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Employee Spinoffs and the Choice of Technology

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Most existing models of employee spinoffs assume they are driven by a desire to implement new ideas. However, history is replete with examples of spinoffs that were launched to continue with old ideas that their parents were in the process of abandoning. We develop a model of technology choice in which spinoffs may form to implement new or old technologies. A team of managers engaged in production using technology x , is considering switching to technology y . The value of y is not known and disagreements may emerge among team members. Managers who develop sufficiently strong disagreements with their colleagues choose to form new companies to implement their preferred strategy. Two distinct classes of spinoffs arise. A type 1 spinoff forms when an employee comes to believe it is worth adopting y but the firm does not. A type 2 spinoff arises when an employee sufficiently disagrees with the firm's decision to adopt y that he is willing to invest in order to continue with x . We explore the implications of the model for the comparative dynamics of spinoff formation, and the performance of firms.

JEL Classification: L2, D70, D83.

Keywords: Spinoffs, learning, disagreement, technology choice.

* Emails: peter.thompson2@fiu.edu, jchen002@fiu.edu. This paper owes an intellectual debt to Steven Klepper, who has been a constant source of insights about the spinoff process. Comments received during seminar presentations at the University of Toronto were also very helpful. We are also indebted to two anonymous referees, whose insights were instrumental in improving the exposition.

1. Introduction

Employee spinoffs -- new firms founded by former employees of incumbent firms in the same industry -- have played a particularly prominent role in the early evolution of many high-tech industries. They have frequently accounted for a significant fraction of entrants, and on average have out-performed other types of entrants. In many industries, spinoffs have been more likely than other types of entrants to pioneer new technologies [Franco and Filson (2006)]. As a result, employee spinoffs have often been identified as an important engine of an industry's growth.

In certain industries, spinoffs have also played an important role in shaping a region's economic character. Klepper (2007a), for example, attributes much of Detroit's eventual dominance of the US automobile industry to a sustained process of spinoff formation that was initiated by the coincidental presence in the industry's earliest days of a small number of unusually fecund parent companies. More generally, regions in which spinoffs are easier to establish, for example because the law does not permit enforcement of non-compete covenants, are more likely to attract the high-ability workers and inventors that are most likely to establish new firms [Marx, Strumsky, and Fleming (2009)]. Indeed, Saxenian (1994) has attributed much of the success of Silicon Valley relative to the Route 128 high-tech corridor to institutional and cultural factors that in Silicon Valley facilitate the movement of workers between incumbent firms and to newly founded firms.

Because of their prominent role, spinoffs have been the subject of a fair amount of theoretical attention. Although the models differ, most are founded on the notion that spinoffs are particularly innovative types of new firms: they implement ideas that their parents have not, and often will not, pursue. In this vein, one class of theories proposes that new ideas have limited value to incumbent firms because their implementation would cannibalize existing rents [Christensen (1993), Klepper and Sleeper (2005)].¹ In a second class, ideas occur only to individual employees who may choose not to reveal them to their employers, and instead to develop and implement them in a spinoff [Amador and Landier (2003), Chatterjee and Rossi-Hansburg (2007), Hellman (2007)].² The model of Chatterjee and Rossi-Hansberg is the most

¹ This is, of course, a particular example of the Arrow effect [Arrow (1962), Cozzi (2007)].

² In a third class of models, spinoffs are not based on the discovery of a particular idea. Rather, employees learn from their employers and they exploit this knowledge by forming a spi-

explicit about the innovativeness of spinoffs. Workers have private information about the quality of their idea, but adverse selection prevents the price at which they can sell the idea to an incumbent firm from being conditioned on the worker's information. As a result, workers sell ideas of moderate quality to incumbents, but implement the very best ideas in spinoffs.

However, many spinoffs are not motivated by a desire to implement new technologies that their parents dismiss or don't know about. To the contrary, history is replete with examples of spinoffs that are formed in opposition to the parent company's decision to abandon existing products and processes. Many of these spinoffs remain relatively obscure, and they rarely attract the status of examples *par excellence* of spinoffs. But it is also the case that some spinoffs that subsequently became highly innovative and successful began as a negative reaction to the pursuit of new ideas by the parent. For example, Fairchild Semiconductor, a spinoff of Shockley Semiconductor Laboratory, was founded to continue work on transistors that Shockley was in the process of abandoning.³ Similarly, Herbert Austin founded the Austin Motor Company, which came to dominate the British market during the interwar years in much the same way as Ford's Model T did in the United States, to continue the production of an engine design that his employer was abandoning [Georgano *et al.* (2000)].⁴

This paper develops a model that serves as a counterpoint to the singular focus of most existing models on innovative spinoffs. In the model, firms are presented with an opportunity to adopt a new technology and individuals may leave their employer to create a new firm. The value of the new technology is not known in advance, but must be learned over time from noisy signals. Management teams are initially formed

noff [Agarwal *et al.* (2004), Franco and Filson (2006)]. But even in this case, spinoffs are likely to be founded by especially innovative individuals.

³ In 1956, William Shockley was actively pursuing development of a four-layer diode, a device that would combine the work of three separate transistors into one. Addison (2006) describes the fallout: "The researchers wanted to continue working on silicon transistors, which they considered had a better commercial future. [Robert] Noyce and [Gordon] Moore wrote a memo imploring Shockley not to abandon the transistor, but to no avail. It was typical Shockley, who didn't yield once he made up his mind. 'He defined carefully the device he wanted to work on,' said [chemist Harry] Sello. 'I felt he rammed it down the throat of everybody who was working there.' . . . [S]even of the employees decided it was time to leave."

⁴ More examples are given in the Appendix.

of like-minded individuals who subsequently observe diverse signals about the new technology. Although the value of private signals are communicated to the entire team, each individual puts less weight on the signals observed by others. As a result, short-term disagreements about the value of the new technology are inevitable.⁵ If disagreements are sufficiently profound, a member of the management team may leave the firm to establish a spinoff.

The model predicts the existence of two distinct classes of spinoffs. First, a type 1 spinoff forms when an employee comes to believe it is worth adopting the new technology, but the firm does not.⁶ Second, a type 2 spinoff arises when an employee sufficiently disagrees with the firm's decision to adopt the new technology that he is willing to invest in order to continue with the old technology. We show that the comparative dynamics of the formation of type 1 and type 2 spinoffs are distinct, and yield some novel testable implications. We show that type 1 spinoffs are more common, and they are on average launched earlier, than type 2 spinoffs. Type 1 spinoffs are more likely to fail. However, surviving type 1 spinoffs on average outperform surviving type 2 spinoffs.

There is an emerging literature documenting empirical regularities about the quality of spinoffs and their parents, and the influence of incumbent quality on the likelihood of employees spinoffs.⁷ We explore what our model has to say about quality. For both types of spinoffs, average performance is increasing in the quality of the parent. Type 1 spinoffs outperform their parents when the cost of adopting the new technology, either for the incumbent firm or for the spinoff, is not trivial. However, when adoption costs are sufficiently low, type 1 spinoffs under-perform relative to their parents.

⁵ The model builds on the theory of disagreement and spinoff formation in Klepper and Thompson (2010), although the mechanism by which disagreements arise is based on Thompson's (2008) model of marital discord and dissolution.

⁶ Cabral and Wang (2009) also develop a model with two types of spinoffs. In their model, type 1 spinoffs are formed by individuals that discover they have entrepreneurial ability, while type 2 spinoffs are formed by individuals that learn their parent's prospects are poor. Their typology is closely related to previous work on the distinction between opportunity and necessity entrepreneurs that has been documented in the Global Entrepreneurship Monitor [Reynolds *et al.* (2005)]. See Buenstorf (2007) for an explicit analysis of opportunity and necessity spin-offs.

⁷ Klepper and Thompson (2010) review the evidence.

Type 2 spinoffs also outperform their parents when the cost of launching a spinoff is high, but they perform worse than their parents when the incumbent’s adoption cost is sufficiently high. These subtleties are absent from models in which spinoffs are driven by employee discovery of superior ideas.

The quality of parents also influences the likelihood of spinoffs. First, the model predicts that spinoffs are most likely to be spawned by parents of intermediate quality, a prediction at odds with much prior theorizing. Second, among firms that spawn spinoffs, high-quality parents are more likely than low-quality parents to spawn type 1 rather than type 2 spinoffs. There are no spillovers across technologies, in the sense that the distribution of the value of new technology is independent of the value of the firm’s current technology. Thus, the correlations between parent quality and spinoff probabilities and performance are induced by pure selection effects.

The layout of the paper is as follows. Section 2 analyzes the technology adoption problem treating the firm as a single decision maker. Section 3 introduces a team of managers who may develop divergent beliefs about the value of the new technology, and derives the implications of endogenous disagreement for the hazard of spinoff formation. Section 4 examines the relationships between the qualities of spinoffs and their parents. Section 5 concludes.

2. The Firm’s Problem

The model is cast in discrete time. Let the per period profit from a firm’s current technology, x , be given by

$$\pi(x, n) = \max_{n \geq 0} \begin{cases} x^{1-\gamma} n^\gamma - n, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad (1)$$

where n is employment. Although labor is the numeraire, equation (1) contains no explicit output price, which is subsumed into x . Thus, x represents, *inter alia*, the value of technology choices that alter the physical productivity of labor, of technology choices affecting product quality, and of associated strategic choices that also affect the firm primarily through the price of output. We refer to x as the quality of the firm.

The value of x is known, so optimal employment is

$$n(x) = \begin{cases} \gamma^{1/(1-\gamma)}x, & \text{if } x > 0 \\ 0, & \text{if } x \leq 0 \end{cases}, \quad (2)$$

and maximized profits are

$$\pi(x) = \begin{cases} \phi x, & \text{if } x > 0 \\ 0, & \text{if } x \leq 0 \end{cases}, \quad (3)$$

where $\phi = \gamma^{\gamma/(1-\gamma)}(1-\gamma)$. High-quality firms are more productive, they have higher employment and output, and they generate more profit. Thus, quality, size, and profitability are interchangeable terms.

There also exists an alternative technology that the firm has not adopted. Its value $y \in Y$ is not known precisely, and is believed to be a random draw, independent of x , with distribution $F(y)$ and density $f(y)$. In any period the firm may abandon x and adopt y after payment of a cost, c . The realization of y is observed immediately upon switching, but it is assumed that the switch to y is irreversible. However, if it turns out that $y \leq 0$, the firm chooses $n(y) = 0$; a decision to employ no workers will be considered an exit.

2.1 Technology adoption as a stopping rule

The firm faces a dynamic programming problem in which the only link across periods is the evolution of beliefs. These types of problems have been analyzed in quite general terms by Easley and Kiefer (1988). We follow their analysis to establish the existence of a well-behaved solution to our model.

In each period, a signal, z , about the value of the new technology is observed. The signal has conditional density $g(z | y)$, so we can define the one-step-ahead Bayes map as

$$f'(y) = \frac{g(z | y)f(y)}{\int_{y \in Y} g(z | y)f(y)dy}. \quad (4)$$

Equation (4) can be written in terms of the prior and posterior distributions,

$$F' = b(z, F), \quad (5)$$

where $b(z, F)$ is the transition from the prior belief F to the posterior belief F' after observing signal z . Easley and Kiefer (1988) have shown that, under quite general

conditions, $b(z, F)$ is a well defined and stationary function.

The subjective expected value of using technology x when beliefs are F is given by the Bellman equation

$$V(x, F) = \max \left\{ \phi x + \beta \int V(x, b(z, F)) g(z | y) dz dF(y), -c + \frac{\phi}{1-\beta} E_t[y^+ | F] \right\}, \quad (6)$$

where

$$\frac{\phi}{1-\beta} E_t[y^+ | F] = \frac{1}{1-\beta} \int \max\{0, \phi y\} dF(y) \quad (7)$$

is the expected value of immediately switching to y . Because x and y are independent, F , $b(z, F)$, and (7) do not depend on x . And as the per-period profit is strictly increasing in x , it immediately follows that $V(x, F)$ is strictly increasing in x . Therefore, there exists a unique stopping value, $x^*(F)$, satisfying

$$\phi x^* + \beta \int V(x^*, b(z, F)) g(z | y) dz dF(y) = -c + \frac{\phi}{1-\beta} E_t[y^+ | F], \quad (8)$$

where $x^*(F)$ defines the smallest value of x for which continuation with technology x is optimal given beliefs F .

The stopping rule, $x^*(F)$, is a stationary function. However, as the subjective beliefs F evolve over time, the stopping *value* is not constant. In general, one cannot say whether the stopping value rises or falls with the passage of time. The expected values of both continuing with x and switching to y depend critically on the precision of beliefs about y . Because the realized payoff of switching technology is bounded from below at zero, the term $E[y^+ | F]$ generally decreases as the distribution F becomes more concentrated around the subjective mean, and this induces a decline in the stopping value. On the other hand, the value of sticking with x declines with increased precision, because beliefs about y are less likely to change significantly in the future. This reduces the option value of waiting for new information about y , thereby raising the stopping value. It is not possible to show that one of these effects necessarily dominates the other. Moreover, for almost all choices for F and g , the precision of F depends on the history of signals received and may itself rise or fall over time.

2.2 An approximate stopping rule for the Normal conjugate family

Much of the analysis in the remainder of the paper depends on us being able to characterize analytically the distribution of stopping times. To make progress, we first assume that F and g are both Normal. Accordingly, we assume that a firm's realization of y is drawn from a Normal distribution with zero mean and variance σ^2 ; that this is known so the population distribution is also the firm's prior; and that the signals are random draws from a Normal distribution with mean y and variance σ_z^2 . As is well known, this is the only conjugate family for which the precision of F is independent of the signals received.

Let \bar{z}_t denote the mean of the t signals observed up to period t . The posterior belief is normal with mean $\bar{y}_t = t\sigma^2\bar{z}_t(\sigma_z^2 + t\sigma^2)^{-1}$ and variance $\sigma_{y,t}^2 = \sigma^2\sigma_z^2(\sigma_z^2 + t\sigma^2)^{-1}$. Using standard formulae for the normal conjugate family [cf. DeGroot (1970, ch. 9)], the transition function, $b(z, F)$, maps a Normal distribution with mean \bar{y}_t and variance $\sigma_{y,t}^2$, into a Normal distribution with mean

$$\bar{y}_{t+1} = \frac{\bar{y}_t\sigma_z^2 + z_{t+1}\sigma_{y,t}^2}{\sigma_z^2 + \sigma_{y,t}^2}, \quad (9)$$

and variance

$$\sigma_{y,t+1}^2 = \frac{\sigma_z^2\sigma_{y,t}^2}{\sigma_z^2 + \sigma_{y,t}^2}. \quad (10)$$

Clearly, the pair $\{\bar{y}, t\}$ is a sufficient statistic for F and the stopping rule can now be written as $x^*(F) \equiv x^*(\bar{y}, t)$. It will be useful for us to write the inverse stopping rule $\bar{y}^*(x, t)$, but to do so we need to verify that $x^*(\bar{y}, t)$ is a monotonic function of \bar{y} . It is of course readily apparent that $x^*(\bar{y}, t)$ is increasing in \bar{y} , and it is also easily illustrated. Equation (8) can be written more compactly as the solution to

$$\phi x^* + \beta EV(x^* | \bar{y}, t) = -c + \frac{\phi}{1-\beta} E[y^+ | \bar{y}, t]. \quad (11)$$

Figure 1 plots the solution to (11). The right hand side, labeled \mathbf{W} , is a strictly increasing, unbounded, convex function of \bar{y} . Its lower bound, attained as $\bar{y} \rightarrow -\infty$, is equal to the negative of the technology adoption cost, c . The curves labeled \mathbf{V}_0 and \mathbf{V}_1 plot the left hand side of (11) for two values of x , $x_1 > x_0$. These functions are also increasing and convex. However, their slopes can nowhere exceed β times the

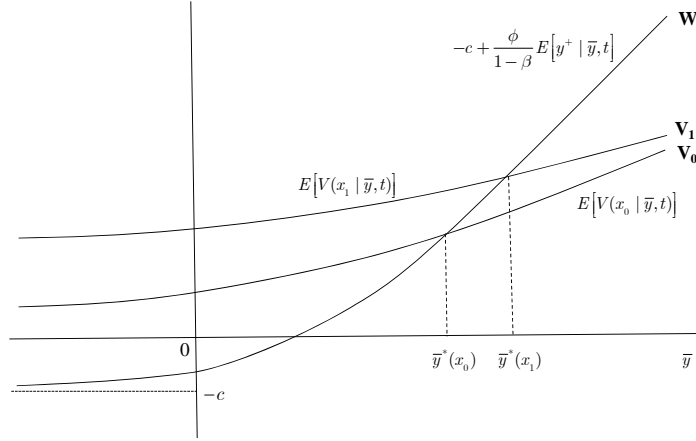


FIGURE 1. The optimal stopping problem for the Normal conjugate family.

slope of \mathbf{W} , and they have a lower bound attained as $\bar{y} \rightarrow -\infty$ that is equal to the payoff, $\phi x(1-\beta)^{-1}$, of continuing with the current technology forever. Thus, there is a unique intersection, with \mathbf{V} crossing \mathbf{W} from above. An increase in the value of x shifts \mathbf{V} up, which raises the stopping value $\bar{y}^*(x, t)$.

As t increases, the decline in the subjective variance of beliefs shifts both \mathbf{W} and \mathbf{V} downward, inducing an ambiguous effect on $\bar{y}^*(x, t)$. In related stopping problems, Jovanovic (1979) and Thompson (2008) have implemented an approximation to the distribution of stopping times by fixing the critical value for switching to y to its asymptotic value. We adopt their strategy here, and defer to the appendix an exploration of some alternative approximations. That is, let $\bar{y}^*(x, t) = \lim_{t \rightarrow \infty} \bar{y}^*(x, t)$ for all t , so the firm switches technology in the first period that $-c + \phi \bar{y}(1-\beta)^{-1} > \phi x(1-\beta)^{-1}$. The approximate stopping value is therefore $\bar{y}^*(x) \approx x + c(1-\beta)\phi^{-1}$. The approximation works in two countervailing directions. On the one hand, it discounts the option value of waiting for additional information, which induces an underestimate of the correct stopping value. On the other hand, it reduces the expected value of adopting the new technology, which induces an overestimate. The appendix provides a numerical example suggesting that $\bar{y}^*(x, t) > \bar{y}^*(x)$ for small values of t , although convergence to $\bar{y}^*(x)$ appears to be rapid.

2.3 Stopping times as a first-passage problem

To explore the timing and probability of switching, we require the distribution of the Markov time, T , that satisfies

$$T = \min_t \left\{ t : \bar{y}_t \geq c(1 - \beta)\phi^{-1} + x \right\}, \quad (12)$$

where \bar{y}_t is a random variable with normally distributed increments in each period, having mean $\bar{y}_t = t\sigma^2 y (\sigma_z^2 + t\sigma^2)^{-1}$ and variance $\sigma_{\bar{y},t}^2 = t\sigma^2 \sigma_z^2 (\sigma_z^2 + t\sigma^2)^{-1}$.

This is a first passage problem that is easier to analyze in the continuous-time analog to our problem. Define

$$\omega_t = \left(\frac{\sigma_z^2 + t\sigma^2}{\sigma_z \sigma^2} \right) \bar{y}_t - \frac{ty}{\sigma_z}. \quad (13)$$

The random variable ω_t is normal with zero mean and variance t , while the increments to ω_t are independent standard Normals. The continuous time stochastic process that gives rise to the same distribution as ω_t at $t=0,1,2, \dots$, is a standard zero-drift Wiener process, $\omega(t)$, with boundary condition $\omega(0)=0$. The absorbing barrier for \bar{y}_t is $c(1 - \beta)\phi^{-1} + x$. Hence, the corresponding barrier for $\omega(t)$ is obtained by replacing \bar{y}_t in (13) with $(1 - \beta)\phi^{-1}c + x$. The transformed first passage problem is therefore given by the distribution of the Markov time, T , that satisfies

$$T = \min_\tau \left\{ \tau : \omega(\tau) \geq \zeta_1 + \zeta_2 \tau \right\}, \quad (14)$$

where

$$\zeta_1 = \frac{\sigma_z}{\sigma^2} \left(c(1 - \beta)\phi^{-1} + x \right) \quad (15a)$$

and

$$\zeta_2 = \frac{1}{\sigma_z} \left(c(1 - \beta)\phi^{-1} + x - y \right). \quad (15b)$$

Equations (14) and (15) define the problem for the first passage of a Wiener process to a single linear boundary, $\zeta_1 + \zeta_2 t$, that is positively sloped, moving away from the origin, when $y < c(1 - \beta)\phi^{-1} + x$ and negatively sloped when $y > c(1 - \beta)\phi^{-1} + x$ (see Figure 2).

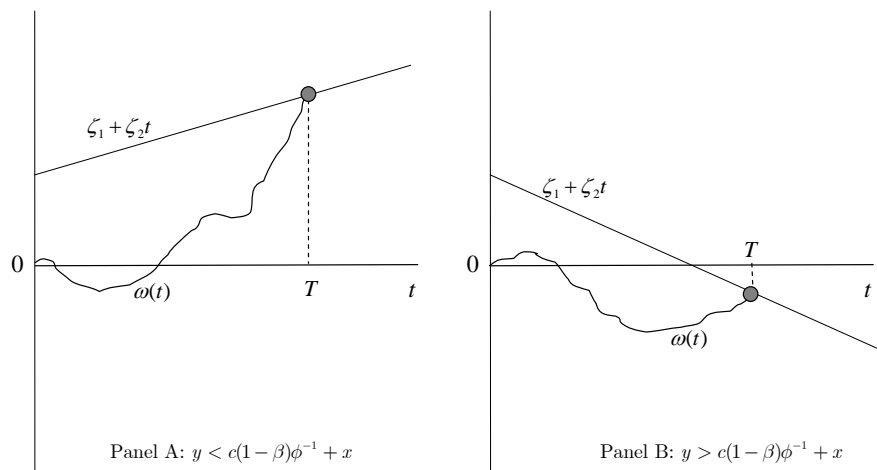


FIGURE 2. First passage problems for adoption of y . Sample paths are drawn excessively smooth for visual clarity.

2.4 The distribution of stopping times

The distribution of first passage times, $P(T; \bullet)$, for this problem is given by the well-known Bachelier-Lévy formula [e.g., Cox and Miller (1965:221)],

$$P(T; \zeta_1, \zeta_2) = \Phi\left(-\frac{\zeta_1 + \zeta_2 T}{\sqrt{T}}\right) + e^{-2\zeta_1\zeta_2} \Phi\left(-\frac{\zeta_1 - \zeta_2 T}{\sqrt{T}}\right), \quad (16)$$

where $\Phi(\bullet)$ is the distribution function of a standard normal random variable. Taking the limit of (16) as $T \rightarrow \infty$ yields the probability that the firm ever adopts technology y :

$$P^\infty(\zeta_1, \zeta_2) = \lim_{T \rightarrow \infty} P(T; \zeta_1, \zeta_2) = \begin{cases} 1, & \text{if } y \geq c(1 - \beta)\phi^{-1} + x \\ e^{-2\zeta_1\zeta_2} < 1, & \text{if } y < c(1 - \beta)\phi^{-1} + x \end{cases}. \quad (17)$$

All firms for whom it is *ex post* optimal to switch technology will eventually do so; all that is needed is sufficient passage of time to learn y . When adoption of y is not optimal, the probability of adoption is strictly less than one. However, a fraction of firms for whom it is not *ex post* optimal to switch technology will do so as a result of observing misleading signals about y . In this case, P^∞ is decreasing in $c(1 - \beta)\phi^{-1}$, so an undesirable switch into y is more likely when the discount factor is high, and when switching costs are low. P^∞ is increasing in σ^2 , so a noisy prior induces more

frequent switches that turn out to be unprofitable. A somewhat more surprising result is that the variance, σ_z^2 , of the signals has no bearing on the probability of an *ex post* undesirable switch. Equation (17) also shows that larger firms (with higher values of x) are less likely to adopt y than smaller firms. First, high quality firms are less likely to draw a y that satisfies $y > c(1 - \beta)\phi^{-1} + x$, so they are less likely to belong to the set of firms for which switching is (eventually) guaranteed. Second, P^∞ is decreasing in x , so large firms that fall into the set $y < c(1 - \beta)\phi^{-1} + x$ are less likely to switch.

3. Team Decisions and the Evolution of Disagreement

Assume that a firm's management team is composed of m individuals, each of whom earns a fraction $1/m$ of the firm's profits. Each individual observes private signals about y and has some influence on the firm's decision about whether or not to adopt the new technology. In period t , individual $i=1, 2, \dots, m$, believes y is a draw from a Normal distribution with mean \bar{y}_{it} and variance $\sigma_{y,it}^2$. The "belief" that governs the firm's decision is a compromise, $\bar{y}_t = \sum_{i=1}^m \psi_i \bar{y}_{it}$, of everyone's beliefs. The parameters ψ_i are time-invariant weights attached to individual expectations, with $\sum_{i=1}^m \psi_i = 1$. The weight ψ_i can be interpreted as i 's decision-making influence.

Team members must express their beliefs in order to participate in the group decision. But in doing so each individual inevitably reveals the mean of his private signals to his colleagues, who can use this information to update their own beliefs. Consequently, private signals become public and disagreements cannot arise without further assumptions.⁸ There are two ways in which Bayesians can disagree despite observing each other's signals. First, one can drop the assumption that the prior distribution about y is common to all team members [e.g., Harrison and Kreps (1978), Van den Steen (2001, 2004)]. Second, one can drop the assumption of a common belief about the distribution of the signals. By construction, the first approach introduces disagreements right from the beginning, and one might wonder why individuals with disparate opinions would have ever decided to form a team. Consequently, we take the second approach, by assuming that each individual believes that his own signals are more accurate than those of his colleagues.

⁸ This inability to disagree is a particular example of general results obtained by Aumann (1976), and Geanakoplos and Polemarchakis (1982).

Specifically, assume that in period 0 all m individuals share the same prior that y is a random draw from $N(0, \sigma^2)$, and that all signals have mean y and variance σ_z^2 . However, while each individual correctly believes his own signals have variance σ_z^2 he maintains a belief that his colleagues' signals have variance $\lambda\sigma_z^2$, for some $\lambda > 1$.⁹ Our assumption that individuals overweigh private information relative to public information has found support in the laboratory [Anderson and Holt (1996)] and among financial analysts [Chen and Jiang (2003)]. Their findings are also consistent with the broader notion that people expect good things (such as receiving accurate signals) to happen to them more often than they do to others [Weinstein (1980), Kunda (1987)].

Beliefs evolve as follows. In period t , individual i forms beliefs as though he has observed t private signals with variance σ_z^2 , and $(m-1)t$ signals with variance $\lambda\sigma_z^2$ from his colleagues. As a consequence, his expectation of the quality of technology y is

$$\bar{y}_{it} = \frac{t\sigma^2}{\lambda\sigma_z^2 + (\lambda + m - 1)t\sigma^2} \left(\lambda \bar{z}_{it} + \sum_{j \neq i} \bar{z}_{jt} \right), \quad (18)$$

while the firm's subjective mean, a weighted average of each team member's subjective mean, is

$$\begin{aligned} \bar{y}_t &= \frac{t\sigma^2}{\lambda\sigma_z^2 + (\lambda + m - 1)t\sigma^2} \left(\lambda \sum_{i=1}^m \psi_i \bar{z}_{it} + \sum_{i=1}^m \psi_i \sum_{j \neq i} \bar{z}_{jt} \right) \\ &= \frac{t\sigma^2}{\lambda\sigma_z^2 + (\lambda + m - 1)t\sigma^2} \sum_{i=1}^m \left(1 + (\lambda - 1)\psi_i \right) \bar{z}_{it}. \end{aligned} \quad (19)$$

Hence, i 's disagreement with the firm is given by

$$d_{it} = \bar{y}_{it} - \bar{y}_t = \frac{(\lambda - 1)t\sigma^2}{\lambda\sigma_z^2 + (\lambda + m - 1)t\sigma^2} \left((1 - \psi_i) \bar{z}_{it} - \sum_{j \neq i} \psi_j \bar{z}_{jt} \right). \quad (20)$$

If $\lambda = 1$, then $d_{it} \equiv 0$. That is, when team members do not discount the accuracy of their colleagues' signals, disagreement is not possible.

⁹ An essentially isomorphic approach would be to assume that each individual correctly believes his colleagues signals have variance σ_z^2 , while he maintains the belief that his own signals are more accurate than they really are, with variance σ_z^2 / λ .

The unconditional variance of d_{it} is obviously zero before any signals have been observed; it then rises monotonically to a maximum at $t = \lambda\sigma_z^2\sigma^{-2}(\lambda + m - 1)^{-1}$ before declining asymptotically to zero. Thus, it takes time for disagreements to emerge, but eventually learning dominates the effects of signal noise. Significant disagreements are more likely when signals are noisy, when the prior beliefs about y are imprecise, in small management teams, and when individual i has little decision-making authority.¹⁰ The variance of disagreements is also increasing in $\sum_{j \neq i} \psi_j^2$: when decision-making authority is unequally distributed among team members $j \neq i$, especially if it is concentrated in just one or two members of the team, individual i is more likely to disagree with the team.

3.1. The distributions of spinoff probabilities and times (theory)

Suppose the firm, as before, can adopt the new technology at cost c . And suppose that individuals in the firm can form a spinoff at cost $k > c$. If a spinoff is formed, the founder heads a new team of m individuals, so he continues to have a claim to a fraction $1/m$ of the new firm's profits. A spinoff may be attractive under two circumstances. First, a team member may come to believe that y is sufficiently profitable to justify payment of k when the firm has never yet decided that it justifies payment of c . We call a spinoff launched under these circumstances a type 1 spinoff. We apply the same asymptotic approximation to the spinoff stopping problem as we did to the firm's problem. Hence, individual i forms a spinoff at

$$\begin{aligned} T_s^1 &= \min_{\tau} \left\{ \tau : \bar{y}_{i\tau} \geq k(1 - \beta)\phi^{-1} + x \wedge \left\{ \bar{y}_t < c(1 - \beta)\phi^{-1} + x \forall t \leq \tau \right\} \right\}. \\ &= \min_{\tau} \left\{ \tau : \bar{y}_{i\tau} \geq k(1 - \beta)\phi^{-1} + x \wedge T > \tau \right\}, \end{aligned} \quad (21)$$

where T is the time the firm switches to y , and T_s^1 denotes the time of a type 1 spinoff. The first term in (21) states that i believes y to be sufficiently superior to x that it justifies investment k . The second term states that firm has not chosen to adopt y at any time up to τ .

Second, individual i forms a spinoff if the firm comes to believe that switching to y

¹⁰ Taylor and Zimmerman (1992) surveyed 646 managers about why productive middle managers voluntarily leave their jobs. Although perceived causes of turnover varied across organizational levels, the most common explanations were a lack of control and input on the job.

justifies the payment of c , he has not previously found y attractive enough to justify implementing it himself through a type 1 spinoff, and at the time the firm switches he believes that y is sufficiently unattractive that payment of k to continue with technology x is warranted. That is, i launches a type 2 spinoff at

$$\begin{aligned}
T_s^2 &= \min_{\tau} \left\{ \tau : \bar{y}_{i\tau} \geq c(1-\beta)\phi^{-1} + x \wedge \bar{y}_{i\tau} < (c-k)(1-\beta)\phi^{-1} + x \right. \\
&\quad \left. \wedge \left\{ \bar{y}_{it} < k(1-\beta)\phi^{-1} + x \quad \forall t \leq \tau \right\} \right\} \\
&= \begin{cases} T, & \text{if } \bar{y}_{i\tau} < (c-k)(1-\beta)\phi^{-1} + x \wedge T_s^1 > T \\ \infty, & \text{otherwise} \end{cases} . \tag{22}
\end{aligned}$$

Because x is known, type 2 spinoffs can only be launched out of parents with $x > k(1-\beta)\phi^{-1}$.

Calculating the probabilities of spinoffs is somewhat challenging for two reasons. First, the random variables \bar{y}_{it} and \bar{y}_t are not in general independent: the extent to which they are correlated depends on the parameters of the model, most especially the degree to which signals of others are underweighted, λ , and the decision weights, ψ_i . Second, a spinoff may be formed by any of m individuals, so the distributions of spinoff times depend on the order statistics $\bar{y}_{(1)t} = \min\{\bar{y}_{1t}, \bar{y}_{2t}, \dots, \bar{y}_{mt}\}$ and $\bar{y}_{(m)t} = \max\{\bar{y}_{1t}, \bar{y}_{2t}, \dots, \bar{y}_{mt}\}$. We therefore proceed with the simpler case in which only one individual, i , may form a spinoff, and the random variables, \bar{y}_{it} and \bar{y}_t , are independent. This requires that (i) i has no weight in the firm's decision making (i.e., $\psi_i = 0$), and (ii) individuals place no weight at all on their colleagues signals (i.e., $\lambda \rightarrow \infty$).

With these simplifying assumptions, expectations about y are given by

$$\bar{y}_t = \frac{t\sigma^2}{\sigma_z^2 + t\sigma^2} \sum_{j \neq i} \psi_j \bar{z}_{jt} , \tag{23}$$

and

$$\bar{y}_{it} = \frac{t\sigma^2 \bar{z}_{it}}{\sigma_z^2 + t\sigma^2} . \tag{24}$$

We next need to define crossing barriers for the firm and for both types of spinoffs.

We follow the steps used in Section 2. First, we transform \bar{y}_t and \bar{y}_{it} to obtain new variables, ω_t and ω_{it} , that are standard random walks. Second, we pass into continuous time to obtain independent diffusion processes, $\omega(t)$ and $\omega_i(t)$, for the firm and for individual i . Third, we apply the same transformation to the stationary stopping values for \bar{y}_t and \bar{y}_{it} . As in Section 2, doing so yields stopping values that are linear functions of time.

The absorbing barrier for the firm is the same as given in (14) and (15), with the exception of the addition of a Hirfindahl index for the concentration of decision making, which was by construction equal to unity in Section 2.

$$B(t) = \frac{\sigma_z (c(1-\beta)\phi^{-1} + x)}{\sigma^2 (\sum_{j \neq i} \psi_j^2)^{1/2}} + \left(\frac{c(1-\beta)\phi^{-1} + x - y}{\sigma_z (\sum_{j \neq i} \psi_j^2)^{1/2}} \right) t. \quad (25)$$

The barrier for a type 1 spinoff is given by

$$B_s^1(t) = \frac{\sigma_z (k(1-\beta)\phi^{-1} + x)}{\sigma^2} + \left(\frac{k(1-\beta)\phi^{-1} + x - y}{\sigma_z} \right) t, \quad (26)$$

and $\omega_i(t)$ must reach this barrier before $\omega(t)$ has reached $B(t)$.

The boundary for type 2 spinoffs is not a crossing barrier in the same sense as (25) and (26). When type 2 spinoffs are formed, they happen at the time that $\omega(t)$ first hits $B(t)$. But for this event to induce a type 2 spinoff, $\omega_i(t)$ must at that time be below the boundary given by

$$B_s^2(t) = \begin{cases} \frac{\sigma_z}{\sigma^2} ((c-k)(1-\beta)\phi^{-1} + x) \\ \quad + \frac{t}{\sigma_z} ((c-k)(1-\beta)\phi^{-1} + x - y), & \text{if } x \geq k(1-\beta)\phi^{-1}, \\ -\infty, & \text{otherwise} \end{cases} \quad (27)$$

and $\omega_i(t)$ cannot have yet hit $B_s^1(t)$.

Figure 3 illustrates some sample paths for the spinoff problem. $B(t)$ has a positive slope, so the figure illustrates the case $y < c(1-\beta)\phi^{-1} + x$; in this case, $B_s^2(t)$ may have a positive or negative slope, as long as $x > k(1-\beta)\phi^{-1}$. The figure has been

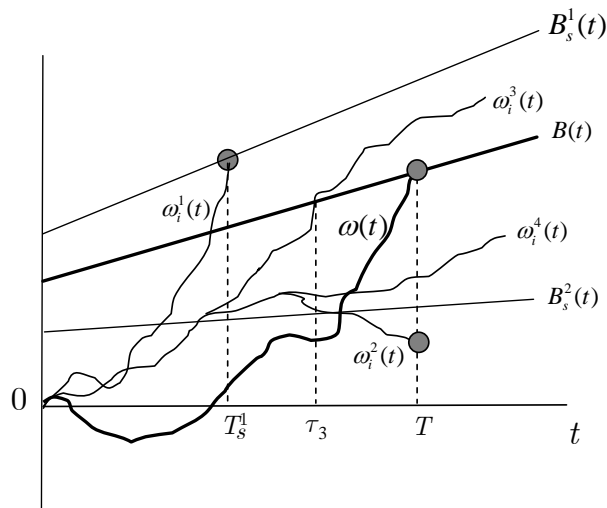


FIGURE 3. Sample paths for type 1 and type 2 spinoffs.

drawn with $B_s^1(t)$ lying everywhere above $B(t)$, but this need not be the case. The relative locations of these two barriers depend on the values of, *inter alia*, $(k - c)$ and $\sum_{j=i} \psi_j^2$. Large values of $(k - c)$ tend to place $B_s^1(t)$ above $B(t)$, but this is offset by the fact that small values of $\sum_{j=i} \psi_j^2$ shift $B(t)$ upwards.

A single sample path for the firm, $\omega(t)$, is plotted showing an adoption time of T . Four possible sample paths, $\omega_i^j(t)$, $j = 1, 2, 3, 4$, are illustrated for individual i 's beliefs. Sample path $\omega_i^1(t)$ hits boundary $B_s^1(t)$ before T , so this path corresponds to a type 1 spinoff at time T_s^1 . Sample path $\omega_i^2(t)$ lies below $B_s^2(t)$ at time T , without having previously crossed $B_s^2(t)$; this sample path yields a type 2 spinoff at time $T_s^2 = T$. The paths illustrated by $\omega_i^3(t)$ and $\omega_i^4(t)$ do not produce a spinoff by individual i . With beliefs $\omega_i^3(t)$, i begins to believe the firm should pay c to switch technology from time τ_3 , but he is not willing to pay the greater cost, k , of launching a type 1 spinoff at any time before T . With beliefs $\omega_i^4(t)$, he does not think the firm should switch technology at T , but his disagreement with the firm's choice is not sufficiently strong to induce him to launch a type 2 spinoff.

The distributions of the first passage times to $B(t)$ and $B_s^1(t)$ are given by the Bachelier-Lévy formula, (16), with (25) and (26) providing the appropriate values for ζ_1 and ζ_2 . Let $P_s^1(T)$ denote the distribution of the first-passage time to $B_s^1(T)$, and let

$P(T)$ denote the corresponding distribution for $B(T)$; let $p_s^1(T)$ and $p(T)$ denote their corresponding densities. Then, because of the independence of $\omega(t)$ and $\omega_i(t)$, the probability there is a type 1 spinoff at time τ is $\tilde{p}_s^1(\tau) = p_s^1(\tau)(1 - P(\tau))$, so the distribution of the time that i forms a type 1 spinoff is given by

$$\tilde{P}_s^1(T) = \int_0^T p_s^1(\tau)(1 - P(\tau))d\tau. \quad (28)$$

Evaluating the probability of a type 2 spinoff is just a little more complex. A type 2 spinoff occurs when the firm switches technology, i has never launched a type 1 spinoff, and $\omega_i(t)$ lies below $B_s^2(t)$ at the time the firm switches technology. Let T denote the time the firm switches technology, with distribution function $P(T)$, and let $\omega_i(T)$ denote the value at this time of the Weiner process for individual i . For any admissible $\tilde{\omega}$, the probability that $\omega_i(T) = \tilde{\omega}$ without having first triggered a type 1 spinoff is given by the complement to the crossing probability of a Brownian bridge that begins at $\omega_i(0) = 0$, terminates at $\omega_i(T) = \tilde{\omega}$, and has an absorbing boundary $B_s^1(t)$. This is a well-known distribution [e.g., Scheike (1992), Proposition 3], given by

$$\Pr\{\omega_i(t) < B_s^1(t) \forall t \in [0, T] \mid \omega_i(T) = \tilde{\omega}\} = 1 - \exp\{-2\hat{\zeta}_1(\hat{\zeta}_1 + \hat{\zeta}_2 T - \tilde{\omega}) / T\}, \quad (29)$$

where $\hat{\zeta}_1$ and $\hat{\zeta}_2$ are the coefficients in $B_s^1(t) = \hat{\zeta}_1 + \hat{\zeta}_2 t$ from (26). As the unconditional distribution of $\omega_i(T)$ is normal with mean zero and variance T , it follows that the joint probability that $\omega_i(T) < B_s^2(T)$ and $\omega_i(t)$ had not previously crossed $B_s^1(t)$ is given by

$$g(T) = \int_{-\infty}^{\hat{\zeta}_1 + \hat{\zeta}_2 T} \left(1 - \exp\{-2\hat{\zeta}_1(\hat{\zeta}_1 + \hat{\zeta}_2 T - \omega) / T\}\right) \frac{e^{-\omega^2/2T}}{\sqrt{2\pi t}} d\omega, \quad (30)$$

where $\tilde{\zeta}_1$ and $\tilde{\zeta}_2$ are the coefficients in $B_s^2(t) = \tilde{\zeta}_1 + \tilde{\zeta}_2 t$ from (27). The probability of a type 2 spinoff is therefore given by

$$\tilde{P}_s^2(T) = \int_0^T \int_{-\infty}^{\tilde{\zeta}_1 + \tilde{\zeta}_2 T} 1 - \exp\{-2\hat{\zeta}_1(\hat{\zeta}_1 + \hat{\zeta}_2 T - \omega) / T\} \frac{e^{-\omega^2/2T}}{\sqrt{2\pi t}} d\omega dP(T). \quad (31)$$

3.2 The distributions of spinoff probabilities and times (numerical evaluations)

We have been able to derive explicit expressions for distributions of times for (i) the firm's adoption of new technology [equations (16) and (25)]; (ii) type 1 spinoffs [equation (28)], and (iii) type 2 spinoffs [equation (31)]. However, the expressions are

complex, and we must resort to numerical evaluations in order to characterize them further.

We have eight free parameters to select for our baseline. The discount factor, β , is set to 0.95. We set the value of the current strategy, x , equal to 10. In this subsection, we further set the value of the new technology, y , equal to 15.¹¹ The parameter ϕ appears only as the denominator in the ratios c/ϕ and k/ϕ , which we set to 100 and 150 respectively. With these baseline parameter values, the present value of staying with x indefinitely, or investing in y are both equal to 200 for the firm. Thus, a fully informed firm would be indifferent between the two technologies. Both types of spinoffs are *ex post* undesirable. The present value of a type 1 spinoff is 150; while this is positive, the share of individual i 's earnings from the spinoff, $150/m$, is strictly less than the share $200/m$ that would have been available to i if he had remained with the firm. A type 2 spinoff, with a present value of 50, also yields earnings lower than remaining with the firm. Thus, the formation of either type of spinoff is a mistake. Sufficient prior uncertainty and sufficiently noisy signals are necessary to induce such mistakes at non-negligible rates, so we set the two variances, σ^2 and σ_z^2 , to the rather large value of 100. Finally, the Hirfindahl index of decision-making authority, $\sum_{j \neq i} \psi_j^2$, is set to 0.5. We explored a variety of alternative baseline parameter values; the results described below are robust to these alternatives, except that in some cases our calculations began to suffer from computational difficulties.¹²

Figure 4 plots the hazard functions for the parent switching technology and for type 1 and type 2 spinoffs. All hazards rise rapidly to a unique mode and then decline more gradually. This is a feature of hazards already familiar from related stopping problems with Bayesian learning [e.g., Jovanovic (1979, 1982), Thompson (2008)].

¹¹ In Section 4, which studies the distributions of firm qualities, we take expectations over values of y drawn from the Normal distribution with mean zero and variance 100.

¹² All calculations were conducted using Derive 6.0. Derive approximates integrals with an extrapolated adaptive Simpson's rule. The algorithm can produce serious computational errors if a low order derivative of the integrand has any discontinuities or singularities. A helpful feature of Derive is that it recognizes when such computational errors are possible and suspends the calculations. Calculations were in most cases carried out to ten significant digits. In some cases in Section 4, computational complexity forced us to reduce the accuracy of the numerical computations to six significant digits. Where necessary, the infinite limits on integrals were replaced with finite limits, which were set large enough that there was no discernible effect of a marginal change in them.

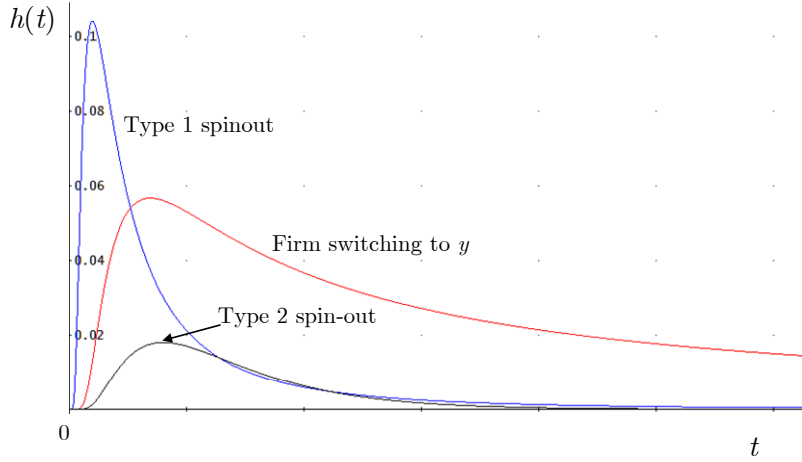


FIGURE 4. Hazards of parent switching technology, and the formation of type 1 and type 2 spinoffs.

As a fully-informed firm would be indifferent between continuing with x and switching to y , the hazard for the firm declines asymptotically to a positive upper bound. For values of y less than $c(1 - \beta)\phi^{-1} + x$, the firm's hazard declines asymptotically to zero, but even in this case the spinoff hazards decline to zero much more rapidly. Because a type 1 spinoff must happen before the firm switches technology, it is not surprising that the hazard of a type 1 spinoff peaks earlier than the hazard of technology switching. In contrast, the hazard of a type 2 spinoff peaks a little later than the hazard of technology switching. Thus, innovative spinoffs that adopt new technologies tend to enter earlier than do spinoffs that implement old technologies.

Numerical evaluation of (28) yields the following comparative statics results for the probability that a firm spawns a type 1 spinoff:

- S1.** *The probability of a type 1 spinoff by time T : (1) is increasing in the variance of prior beliefs (σ^2), the quality of the new technology (y), and the cost of switching technology (c); (2) is decreasing in the cost of spinoff formation (k), and the concentration of decision-making authority ($\sum_{j \neq i} \psi_j^2$); (3) is decreasing in the variance of the signal (σ_z^2) for $T < \infty$; (4) exhibits an inverted U-shaped relationship with x .*

These are, on the whole, intuitive results, although not all could have been unambi-

guously anticipated in advance. For example, it was established in Section 2 that the variance of the signals has no effect on the probability that the firm ever switches technology. In contrast, noisier signals make type 1 spinoffs less likely. The effect of concentration of decision-making authority had *ex ante* ambiguous consequences for the probability of spinoff formation. On the one hand, individual i is more likely to disagree with a decision derived from concentrated authority; on the other hand, a firm with concentrated authority is more likely to mistakenly switch technology, thereby precluding the formation of a type 1 spinoff. S1(2) concludes that the latter effect dominates.

Property S1(4) states that the probability of a type 1 spinoff is increasing in the quality of the parent when x is small, but decreasing when x is large. This result holds both when conditioning on the realization of y and when taking expectations over all possible values of y . When x is low, no one in the management team is likely to conclude that x is better than y , leaving little likelihood that the firm would stick with x when individual i prefers to switch. Conversely, when x is high, it is unlikely that individual i will find switching to y attractive. Thus, the model predicts that type 1 spinoffs are more likely to be spawned by parents of intermediate quality than by low- or high-quality parents.

The evidence on parent quality and spinoff probabilities is mixed, and in any case simple extensions to our model can modify the effect of x on the spinoff hazard. For example, one might suppose that the size of the management team is positively correlated with the size of the firm, and all members of the team may potentially form a spinoff. Alternatively, one might suppose that y is stochastically increasing in x . If either correlation were sufficiently strong, the negative effect on spinoff probabilities of increasing parent quality at high values of x might be reversed. These are not difficult extensions to pursue but, as they would be designed simply to improve the model's concordance with only suggestive evidence, we shall not do so here. In any case, such extensions would do no more than create the *possibility* that spinoffs emerge more frequently from the highest-quality parents.

In contrast to the ambiguous effect of changes in x , increases in the realized value of y always raise the probability of a type 1 spinoff. Thus, when the new opportunities are more attractive, innovative spinoffs are always more likely. This lack of ambiguity is a little surprising, since an increase in y raises the probability that the incumbent firm switches to y , (which precludes a type 1 spinoff), as well as the probability that a type 1 spinoff is formed if the parent does not switch. However, our calcula-

tions suggest that the latter effect always dominates.¹³

Equation (31) is numerically evaluated to produce the following results:

S2. *The probability of a type 2 spinoff by time T : (1) is increasing in the variance of prior beliefs (σ^2), the quality of the new technology (y), the degree of overconfidence (i.e., a reduction in μ), and the concentration of decision-making authority $\sum_{j \neq i} \psi_j^2$; (2) is decreasing in the cost of spinoff formation (k), and the cost of switching technology (c); (3) is decreasing in the variance of the signal, (σ_z^2), for small T but increasing in the variance for large T ; (4) exhibits an inverted U-shaped relationship with x .*

The majority of the results for type 2 spinoffs parallel those for type 1 spinoffs, but there are some notable exceptions (Table 1 summarizes). First, an increase in the cost of switching technology (holding constant the cost of launching a spinoff) raises the probability of a type 1 spinoff, but reduces the probability of a type 2 spinoff. This is intuitive: a type 1 spinoff must occur before the firm switches technology, and an increase in c tends to delay the latter event and make it less likely over any time horizon; a type 2 spinoff can only occur conditional upon the firm switching

TABLE 1. *Effects of parameters changes on spinoff hazards and probabilities*

	TYPE 1	TYPE 2
Variance of prior beliefs, σ^2	+	+
Quality of new technology, y	+	+
Cost of spinoff formation, k	-	-
Quality of parent, x	+, small x -, large x	+, small x -, large x
Cost of switching, c	+	-
Concentration of decision-making, $\sum_{j \neq i} \psi_j^2$	-	+
Signal noise, σ_z^2	-	-, small t +, large t

¹³ Note that a change in x alters both the intercepts and slopes of the barriers, $B(t)$ and $B_s^1(t)$, while a change in y alters only the slopes.

technology. Second, an increase in the concentration of decision-making authority reduces the probability of a type 1 spinoff while raising the probability of a type 2 spinoff. Greater concentration in decision-making authority increases the likelihood of disagreement between individual i and the firm. As previously shown in the case of type 1 spinoffs, this effect is more than offset by the effect of increased concentration on inducing firms to adopt y more quickly, thereby squeezing out type 1 spinoffs. Finally, increases in signal noise unambiguously reduce the probability of a type 1 spinoff at all finite time horizons, but has ambiguous effects on the probability of a type 2 spinoff. Type 2 spinoffs are no more likely when signals are noisy but those that occur will tend to occur later.

4. Spinoff and Parent Quality

The model's predictions for the survival rates of spinoffs are straightforward. As x is known to be positive, the probability of exit of a type 2 spinoff is zero. In contrast, for a type 1 spinoff, y is stochastically increasing in x , so $\Pr[y < 0 \mid x]$ is decreasing in x .

Q1. (1) *The probability of failure of a type 1 spinoff is greater than the probability of failure of a type 2 spinoff.* (2) *The probability of failure for a type 1 spinoff is decreasing in the quality of its parent.*

We turn now to the average quality of spinoffs. In Section 2 we found that firm productivity after switching to y is stochastically increasing in the quality, x , of the firm. An analogous property holds for spinoffs. The quality of a type 2 spinoff is x , so in this case spinoff quality is identical to the quality its parent had immediately prior to switching and positively correlated with its parent's post-switching quality, y . For a type 1 spinoff, the critical threshold of \bar{y}_i necessary to induce an individual to form a spinoff is increasing in x . Because y and \bar{y}_i are positively correlated (this holds even after conditioning on the fact that \bar{y}_i is too low for the firm to switch technology), the expected value of y among type 1 spinoffs is increasing in x . Note also that the type 1 spinoffs are on average higher quality if their parents subsequently switch, because the probability that a parent ever switches technology is increasing in y .

These observations, which can easily be verified by numerical means, are summarized in Q2:

Q2. (1) *The expected quality of a spinoff is increasing in the quality of the parent.* (2) *The quality of type 1 spinoffs whose parents subsequently switch technology is higher than for spinoffs whose parents do not subsequently switch technology.*

Recall that quality is synonymous with profits, output and employment size; Q2 therefore implies that larger and more profitable firms produce larger and more profitable spinoffs. This is consistent with most existing empirical evidence [Klepper (2007a, 2007b), Buenstorf and Klepper (2009), Brittain and Freeman (1986), Phillips (2002)].

The present model predicts that the average spinoff is a mistake. This is because any decision made by an individual is less likely to be correct than the decision made by the average of m decision makers. If m decision makers conclude it is not worth spending c to switch to y , then an individual who believes it is worth spending $k > c$ to do so is likely to be mistaken. Similarly, m decision makers who conclude it is worth spending c to switch to y are more likely to be correct than an individual who concludes it is worth spending $k > c$ to avoid switching.

However, while the average founder of a spinoff may subsequently regret his decision, there are some cases where the performance of spinoffs may exceed that of their parents. For example, if the sunk cost, k , of launching a spinoff is large, the threshold of beliefs about y for a type 1 spinoff is relatively high; in this case the quality, y , of a type 1 spinoff is greater than the quality, x , of its parent, even though spinoffs are on average mistakes. Similarly, when the switching cost, c , is high, firms will choose not to switch despite more promising signals about y , and this has the effect of raising the average quality of type 1 spinoffs.

These claims about costs and the quality of type 1 spinoffs can be easily verified by numerical means. Recalling that the population distribution of y is Normal with mean zero and variance σ^2 , the expected quality of the spinoff conditional on the quality of the parent is

$$E_s^1[y | x] = \frac{1}{\int_{-\infty}^{\infty} \tilde{P}_s^{1\infty}(x, y) d\Psi(y)} \int_{-\infty}^{\infty} y \tilde{P}_s^{1\infty}(x, y) d\Psi(y), \quad (32)$$

where $\tilde{P}_s^{1\infty}(x, y) = \lim_{T \rightarrow \infty} \tilde{P}_s^1(T | x, y)$ denotes the probability that a type 1 spinoff of quality y is ever spawned by a firm of quality x , and $\Psi(y)$ is the distribution of y . Figure 5 plots the difference between type 1 spinoff quality and parent quality, $E_s^1[y | x] - x$, as a function of k for various values of c . To highlight the ambiguities

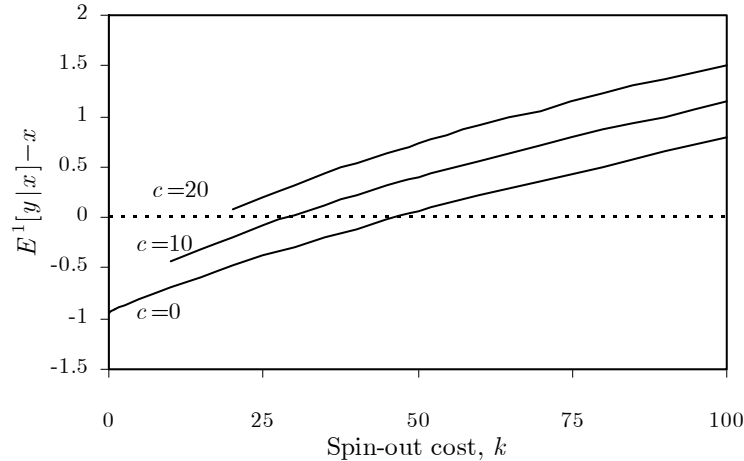


FIGURE 5. Expected value of type 1 spinoff minus value of parent. By assumption $k \geq c$.

described above, we produce plots for values of c considerably lower than our baseline of 100. The remaining parameters have the same baseline values as before. As claimed, increases in c and k are associated with rising spinoff quality, and average spinoff quality is less than parent quality only when both c and k are sufficiently low.

These observations about the quality of type 1 spinoffs are summarized in Q3:

- Q3.** (a) *The average quality of type 1 spinoffs may be higher or lower than the quality of their parents; it is lower only when c and k are sufficiently small.* (b) *The average quality of a type 1 spinoff is increasing in the spinoff cost, k , and the incumbent switching cost, c .*

Q3 implies that in environments where the adoption of new technology is costly (and hence in which doing so is not common), spinoffs perform better: they are more likely to outperform their parents, and they are less likely to exit than is the case when new technologies are cheap.

A somewhat different logic applies to type 2 spinoffs. As in the case of type 1 spinoffs, a low launching cost, k , induces lower quality spinoffs for any given quality of parent. But changes in the switching cost, c , have two effects that together induce an ambiguous effect of c on the quality of type 2 spinoffs relative to the quality of their

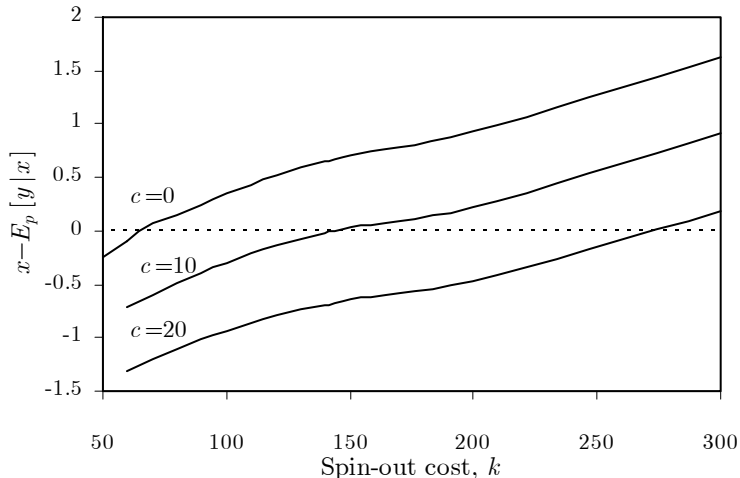


FIGURE 6. Expected value of type 2 spinoff minus value of parent.

parents. First, when c is low, parent firms switch despite only modestly good news about y , and this induces type 2 spinoffs even for modest values of x ; this effect moves the average quality of parents (post-switching) and spinoffs in the same direction. Second, recall that individual i launches a type 2 spinoff in part to avoid paying cost c ; when this is low, a spinoff is attractive only for high values of x , thereby inducing a positive effect of spinoff quality relative to parent quality. We have not been able to deduce analytically the net effect of c on spinoff quality. However, numerical examples, illustrated in Figure 6, show that increases in c reduce the quality of type 2 spinoffs, x , relative to the expected quality, $E_p[y | x]$, of their parents. Figure 6 also confirms our intuition that the average relative quality of type 2 spinoffs is increasing in k , and that the average spinoff quality is less [greater] than the quality of its parent when k is low [high] or c is high [low].

These observations about the quality of type 2 spinoffs are summarized in Q4:

- Q4.** (a) *The average quality of type 2 spinoffs may be higher or lower than the quality of their parents.* (b) *The average quality of a type 2 spinoff relative to its parent is increasing in k , and decreasing in c .*

Figure 5, which compares the average quality of type 1 spinoffs with the quality of

their parents, is also by construction a plot of the average quality of type 1 spinoffs relative to the quality of type 2 spinoffs conditional on the initial quality of the parent. Intuition therefore suggests that, at least when c or k are not too small, type 1 spinoffs are on average higher quality than type 2 spinoffs, even though type 1 spinoffs have a higher failure rate. This is consistent with the notion that being innovative yields higher but riskier returns to costly investment. However, intuition is complicated by the fact that the distribution of x among firms that spawn type 1 spinoffs is not the same as the distribution of x among firms that launch type 2 spinoffs.

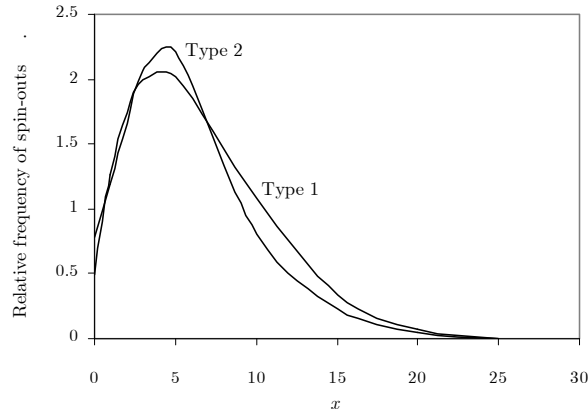


FIGURE 7. Relative frequencies of spinoffs as a function of x .

Figure 7 plots the relative frequency of spinoffs for different values of x . What this implies for the distribution of x conditional on the formation of each type of spinoff depends upon the assumptions made about the distribution of x in the population. However, Figure 7 suggests that, whatever this distribution, x is stochastically greater for parents of type 1 spinoffs than for parents of type 2 spinoffs. In conjunction with Figure 5 and the fact that the expected values of both types of spinoffs are increasing in x , we can conclude that type 1 spinoffs have higher average quality than type 2 spinoffs as long as c and k are not trivially small.

As x is also the initial quality of parents, Figure 7 also implies the following relationship between parent quality and the type of spinoffs likely to be produced:

- Q5.** (a) *As long as adoption costs and spinoff entry costs are not too small, the average quality of type 1 spinoffs is greater than the average quality of type 2 spinoffs.* (b) *The average initial quality of the parents of type 1 spinoffs is greater than the average quality of the parents of type 2 spinoffs.*

5. Discussion

This paper has developed a model in which a team of managers are considering adopting a new, untried technology. Prior to its adoption, the profitability of the new technology is learned slowly over time through the observation of noisy signals. Disagreements about the new technology may emerge over time, and managers who develop sufficiently strong disagreements with their colleagues choose to form new companies to implement their preferred technology. The model identifies two distinct classes of spinoffs that may appear: type 1 spinoffs that implement the new technology when their parents do not (yet) want to, and type 2 spinoffs that are formed to continue with the old technology when the parent is switching to the new one. The paper serves as a counterpart to existing theories in which all spinoffs are technological pioneers.

The paper has focused on the *mechanics* of spinoff formation. As a result, our analysis has not addressed numerous issues that are relevant to disagreements and spinoffs. For example, we have not explored contractual arrangements that might influence spinoff formation [e.g., Amador and Landier (2003), Hellman (2007)], or the strategic transmission of information to influence others [cf. Crawford and Sobel (1982)]. Nonetheless, even without these extensions, our setting yields some distinctive implications for organizational behavior and policy.

Consider, for example, the model's implications for the attitudes that potential parents and policymakers should have toward spinoffs. Employee spinoffs of all colors are potential competitors to their parents; they may lead to undesirable duplication of investment that serves only to dissipate rents, and be a disincentive for research in incumbent firms. Thus, parents frequently discourage them, by means of contractual sticks such as non-compete covenants, legal sticks such as filing suits for intellectual property infringement, and carrots such as schemes to reward employees for revealing their ideas. In many jurisdictions, policymakers support parent firms by creating the institutional and legal support for the sticks that parents use. The present model fea-

tures a potential offsetting benefit to parents that has to date received relatively little attention. Type 1 spinoffs, by engaging in an activity that the parent is unwilling to do without waiting to accrue more information, offer something like a free experiment for the parent whenever the performance of the spinoff is observable. When competition effects are not too strong, the information value of type 1 spinoffs may even be enough to make parents and policymakers supportive of individuals that choose to launch them. In contrast, type 2 spinouts provide no new information. As a consequence, the model predicts that incumbent firms are likely to expend less effort to discourage or fight innovative spinoffs, and that policy should treat type 1 spinoffs more favorably.

Appendix

A. Alternative Approximations to \bar{y}_t^*

In the main text, \bar{y}_t^* was approximated by its limit value:

$$\bar{y}_\infty^* = c(1 - \beta)\phi^{-1} + x, \quad t = 1, 2, 3, \dots \quad (\text{A.1})$$

We consider two approximations which provide lower bounds on the sequence \bar{y}_t^* . Consider first the stopping criterion, \bar{y}_t^{**} , satisfying

$$\frac{\phi x}{1 - \beta} = -c + \frac{\phi}{1 - \beta} \int_0^\infty y dF_t(y | \bar{y}_t^{**}). \quad (\text{A.2})$$

Equation (A.2) incorporates the fact that the expected payoff from switching conditional on \bar{y}_t is increasing in the variance of y . However, it does not incorporate the option value of not switching, which is also increasing in the variance of \bar{y}_t . Thus, (A.2) provides an underestimate of the correct critical value. As the variance of \bar{y}_t is decreasing over time, the size of the error declines to zero for large t .

The second approximation is the solution to the one-step-look-ahead rule (1sla). The rule involves comparing stopping in the current period with the expected value of continuing one period, and then stopping. That is, the 1sla stopping criterion, \bar{y}_t^{***} , is the solution to

$$-c + \frac{\phi}{1 - \beta} \int_0^\infty y dF_t(y | \bar{y}_t^{***}) = \phi x + \beta \left[-c + \frac{\phi}{1 - \beta} \int_{-\infty}^\infty \int_0^\infty y dF_{t+1}(y | \bar{y}') dG_t(\bar{y}' | \bar{y}_t^{***}) \right] \quad (\text{A.3})$$

When 1sla indicates continuation, then continuation is optimal because there exists at least one strategy that dominates stopping. When the 1sla prescribes stopping, stopping

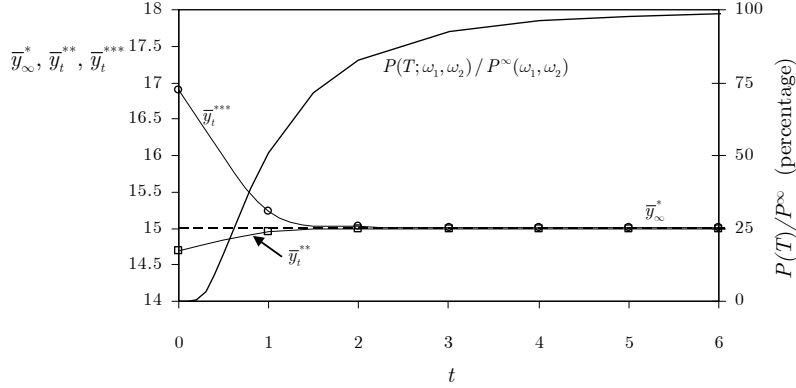


FIGURE A1. Lower bound approximations to critical values, and the fraction of firms that will eventually switch that have switched by time t . Parameter values: $x=10$, $\sigma=10$, $\sigma=10$, $c=100$, $\beta=0.95$, $\phi=1$. These values yield a limiting critical value of 15, and P^∞ is approximately 1.75 percent.

may or may not be optimal.¹⁴ Thus, \bar{y}_t^{***} must also be an underestimate of the correct critical value. However, in many applications it performs quite well.¹⁵

Figure A.1 provides a numerical comparison of (A.1)-(A.3). The parameter values used yield $\bar{y}_\infty^* = 15$ and $P^\infty(\omega_1, \omega_2) = 0.0175$; thus switching is relatively rare. To provide context, the fraction of switching firms that have already switched at each point in time is also plotted for these parameter values. The 1sla, \bar{y}_t^{***} , consistently exceeds \bar{y}_∞^* , while \bar{y}_t^{**} is less than \bar{y}_∞^* . As 1sla is either optimal or an underestimate of \bar{y}_t^* , it follows that \bar{y}_t^{***} is a worse approximation than \bar{y}_∞^* . This is not surprising – it incorporates a feature of the stopping problem that reduces the estimated critical values but ignores the option value that works in the opposite direction. The 1sla results show that, for these parameter values at least, $\bar{y}_t^* > \bar{y}_\infty^*$, with the largest differences at small values of t . The 1sla critical values do converge rapidly on to the limiting value, but this good news is offset by the fact that $P(T)/P^\infty$ rises rapidly. It would be possible to improve upon the constant critical value used in the main text by means of piecewise linear corrections to the absorbing barrier. Wang and Pötzelberger (1997) have derived an explicit formula for the distribution of the first passage time to a piecewise linear barrier. However, although it

¹⁴ For all finite-horizon monotone optimal stopping problems and most infinite-horizon monotone problems with discounting, 1sla is optimal. However, the problem in this paper is not monotone.

¹⁵ With normal priors and signals, the precision of beliefs rises with time at a declining rate, so the expected gain in precision secured by waiting one more period is monotonically decreasing in t . As a result, we suspect (but cannot prove) that the 1sla is optimal.

“can be very easily calculated, for example by using the Monte Carlo simulation method” [p.55], it is far more complicated than the distribution used in the main text.

A third approximation modifies (A.2) to produce an upper bound for \bar{y}_t^* . Let \bar{y}_t^{****} , be the solution to

$$\phi x + \beta E_t[v | \bar{y}_t^{****}] = -c + \frac{\phi}{1-\beta} \int_0^\infty y dF_t(y | \bar{y}_t^{****}), \quad (\text{A.4})$$

where $E_t[v | \bar{y}_t^{****}]$ is the expected value of waiting one more period under the counterfactual assumption that doing so fully reveals y . That is,

$$E_t[v | \bar{y}_t^{****}] = \int_{-\infty}^\infty \max\left\{\frac{\phi x}{1-\beta}, -c + \frac{\phi y}{1-\beta}\right\} dF(y | \bar{y}_t). \quad (\text{A.5})$$

Because $E_t[v]$ must exceed the true continuation value, the solution to (A.4) yields overestimates of the correct sequence of critical values. Unfortunately, (A.4) does not provide a precise characterization for \bar{y}_t^* , because it yields critical values far in excess of the lower bound, \bar{y}_t^{***} . For example, using the same parameter values as in Figure A1, one obtains $\bar{y}_0^{****} = 26.5$, $\bar{y}_1^{****} = 23.2$, and $\bar{y}_5^{****} = 19.73$. The sequence converges on to \bar{y}_∞^* as it should, but at a very slow rate. So far we have been unable to devise a more informative upper bound.

B. Examples of Type 1 Spinoffs

We reviewed case studies of spinoffs provided in previous work on disk drives [Christensen (1993)], semiconductors [Klepper (2007b)], and lasers [Klepper and Sleeper (2005)]. Some examples of type 1 spinoffs gleaned from this review are given here.

- *Komag and Read-Rite (disk drives)*. In the disk drive industry, established manufacturers generally integrated the development of component technologies to assist their entry into a new product architecture market. However, when new component technologies became available, leading firms often proved reluctant to employ these technologies across their product lines. At the same time there existed non-integrated disk drive manufacturers that were aggressively pursuing innovative system designs requiring the support of new component technologies. As these independent manufactures had little access to new-technology components directly via the leading integrated firms, spinoffs occurred as former engineers at integrated firms formed new start-up companies to produce and sell advanced components to these “bleeding-edge” disk drive manufacturers in the original equipment market.

IBM, for example, was the first to introduce the thin-film head, and led a group of integrated firms to focus on the development of this technology. After commercializing the new component in a limited number of high-end models, these integrated firms became

very slow to incorporate this technology in other product lines as they chose to stick with their current market position with traditional technologies. In contrast, demand for the thin-film technology increased among independent manufacturers such as Maxtor and Micropolis whose strategy was less conservative and focused on the remote market. In response to market demand, spinoffs such as Komag (eventually the leading thin-film disk manufacturer) and Read-Rite (eventually the leading thin-film head manufacturer) emerged as component suppliers for these non-integrated disk drives makers. In this case, IBM and other integrated firms were aware of the value of this new component technology, but their process of product design did not catch up with the pace at which they developed component technologies. As a result, IBM refused to initially adopt this technology and eventually turned out to be the slowest in the industry to utilize this component broadly across its product lines.

- *Amelco and Signetics (semiconductors)*. Although Fairchild became a leader in the development of Integrated Circuits (ICs), it initially chose to focus on its component business because of the initial inferior performance of ICs and its fear that making ICs would cannibalize its current business. A group of its engineers, however, were confident about the future of ICs, and therefore formed Amelco and Signetics to commercialize the technology. Because of its small size, higher reliability, and lower power need, the IC technology was soon favored by the Department of Defense. As a result, Signetics became profitable by producing and selling circuits to military contractors. Its parent, Fairchild, eventually entered the IC market and managed to take over leadership from Signetics by massively producing Signetics' standard circuits and selling them at lower prices. Signetics continued to pursue innovation in IC technology, although it never regained its leadership in this market.

- *Intel (semiconductors)*. Another famous spin-off from Fairchild, Intel, was formed partly because Fairchild was pessimistic about the future of the Metal Oxide Semiconductor field-effect transistors (MOSFE) technology. Although Fairchild was among the earliest to develop this technology, it did not enter the production of the MOS devices due to the instability of the technology. However, after the resolution of technical problems, the MOS devices eventually become popular for many applications. In a similar case, former employees of Advanced Micro Devices formed Cypress to pursue the development of high speed CMOS SRAMS, a new technology that was neglected by its parent and other existing semiconductor firms.

- *Uniphase and Lexel (lasers)*. The origin of spinoffs in the laser industry is somewhat different from what has been described above. As documented by Klepper and Sleeper (2005), spinoffs tended to produce laser types that were closely related to what had been previously produced by their parents. A common practice of these spinoffs was to develop a variant of the parent's laser, using technology which their parents had previously explored but eventually abandoned due to either manufacturing difficulties or the uncertainty of future market. For example, among the spinoff cases studied in detail by Klep-

per and Sleeper (2005), Uniphase was formed by former employees at Spectra Physics to produce a variant of Spectra's HeNe laser when its parent gave up this effort because of the uncertain future market for HeNe. Lexel originated from a disagreement with its parent, which abandoned its effort, because of manufacturing problems, to pursue improvements to its ion laser. Similarly, Laser Diode Laboratories was formed to continue developing a semiconductor laser for defense applications after its parent gave up on it due to technical difficulties. As Bhaskarabhatla and Klepper (2008) document, new lasers developed by spinoffs can often find their application in a submarket that is different from their parents' target. Thus, the majority of these parent firms were able to continue their production of original laser types for a long time after the entry of spinoffs.

C. Examples of Type 2 Spinoffs

The examples that follow, drawn from our own on-going data collection efforts in the British automobile and coach-building industries, are based on information provided in Georgano *et al.* (2000).

- *Austin Motor Company.* The founder of Austin Motors, Herbert Austin, had been a very successful manager at the Wolseley Motor Company. He designed the horizontal-engined Wolseley cars, which sold very well at first. Later on, as losses started to occur, the company was considering a switch to vertical engines. But Austin did not like the proposed switch, which led to his breakup with Wolseley in 1906 and the formation of his own firm, the Austin Motor Company. Wolseley replaced Austin with a new general manager, John Siddeley, who had been making vertical-engined cars in his own company. Directed by Siddeley, Wolseley soon brought out the new vertical-engined cars, under the name of Wolseley-Siddeleys. Output grew dramatically, and in 1911, nearly 1,600 of these cars were produced. Ironically, Austin never continued production of horizontal-engined cars at his own company. Perhaps because he later realized the value of the vertical-engined design, all Austin models he made actually had vertical engines.
- *Pilgrim.* The second example also involves a disagreement about horizontal and vertical engines. Francis Leigh Martineau was one of the original partners at James & Browne Ltd. He designed the early James & Browne cars, which had mid-mounted horizontal engines. In 1905, Martineau left and joined Pilgrim to make Pilgrim(i), also a horizontal-engined car, but with cylinder heads set forward. Although history does not specify the reason for Martineau's departure, it is recorded that around this time, the parent James & Browne switched to a conventional vertical-engined car called Vertex. As there were already many good conventional cars in the market, this switch did not turn out to be successful, and few Vertexes were sold. Martineau was not much more successful, selling only eighteen Pilgrim(i) cars before Pilgrim went into receivership.
- *Eagle Engineering.* The third example relates to Ralph Jackson, who had started as a cycle maker, and later invented a tricar with a 2.25hp single-cylinder engine. These tri-cars were called the Century Tandem, and were built at the Century Engineering Co.

until 1901. In 1901, Century was under control of Sydney Begbie, who was the first importer of Aster engines into England. It appeared that the company soon changed its focus away from Jackson's tricars. In 1903, Begbie launched the first Century cars with 8 or 12hp 2-cylinder Aster engines, French transmissions, and English-built chassis and bodies. Jackson left the company in 1901 and started a new company, the Eagle Engineering Motor Co., where he made a thinly disguised version of the Century Tandem tricar under the name of Eagle.

- *Frazer-Nash and Godfrey-Proctor*. Our last example is probably more about a disagreement over production strategy than choice of technology. Frazer Nash and H.R. Godfrey founded G.N Motors Ltd. in 1910 and made the first British cyclecars. In 1913, sporting models of these cyclecars came out and, by the outbreak of war in 1914, the G.N. had become the best-known of British cyclecars. Sales fell after the war and in 1922 the company was bought by a Mr. Black, who wanted to move away from sports cars and focus on the mass production of a water-cooled 4-cylinder shaft-drive tour model. Both Godfrey and Nash preferred to continue making sports cars and therefore left to start their own car companies. Nash founded Frazer-Nash Ltd., where he built his sports model with a chain-drive system that he had employed on the G.N. Godfrey founded Godfrey-Proctor Ltd., where he made sports cars in the style of a miniature Aston Martin with an Austin engine and gear box. As for G.N. Motors, its switch to shaft-drive touring cars was not a success for two reasons. First, there were already many of these cars in the market. Second, traditional G.N. owners preferred the older designs. Despite attempts to improve the G.N., production soon ended.

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