Ashish Sood & Gerard J. Tellis

Technological Evolution and Radical Innovation

Technological change is perhaps the most powerful engine of growth in markets today. To harness this source of growth, firms need answers to key questions about the dynamics of technological change: (1) How do new technologies evolve? (2) How do rival technologies compete? and (3) How do firms deal with technological evolution? Currently, the literature suggests that a new technology seems to evolve along an S-shaped path, which starts below that of an old technology, intersects it once, and ends above the old technology. This belief is based on scattered empirical evidence and some circular definitions. Using new definitions and data on 14 technologies from four markets, the authors examine the shape and competitive dynamics of technological evolution. The results contradict the prediction of a single S-curve. Instead, technological evolution seems to follow a step function, with sharp improvements in performance following long periods of no improvement. Moreover, paths of rival technologies may cross more than once or not at all.

Understanding technological innovation is vital for marketers for several reasons. Technological change is perhaps the most powerful engine of growth. It fuels the growth of new brands (e.g., Gillette's Mach 3), creates new growth markets (e.g., digital video recorders), and transforms small outsiders (e.g., Intel) into market leaders (Chandy and Tellis 1998; Christensen 1997; Foster 1986). To date, the topic of technological evolution has been studied primarily in the technology management literature. A central premise is that performance of a new technology starts below that of an existing technology, crosses the performance of the older technology once, and ends at a higher plateau, thus tracing a single S-shaped curve (see Figure 1). There is scattered empirical support for the premise and limited theoretical support for various aspects of the S-shape curve (e.g., Foster 1986; Utterback 1994a).

Belief in this premise is so strong that it has become almost a law in the strategy literature, from which authors have derived strong managerial implications. For example, they have warned that even though managers might be able to squeeze out improvement in performance from a mature technology at the top of its S curve, improvement is typically costly, short lived, and small. Thus, a primary recommendation in the strategy literature and the trade press is that managers should abandon a maturing technology and embrace a new one to stay competitive (e.g., Christensen 1997; Foster 1986). A central, practical problem that managers face is when to shift investments from the current to the future technology. If the S curve is indeed valid, the appropriate time would be the inflection point of the S curve. After this point, performance improves at a decreasing rate until maturity.

New product development and major investments in research depend on a correct understanding of technological evolution in general and of the S-shaped curve in particular. To foster this understanding, this study addresses the following questions:

- How do new technologies evolve? Do they follow the S-shaped curve or some other pattern? Are technological changes predictable? Is the rate of technological change increasing?
- How do rival technologies compete? What are the performance dimensions of competition? What are the transitions between technological changes?
- Which firms carry out and survive technological evolution? Who introduces radical innovations? Do incumbents survive the change?

The primary focus of the current study is empirical. We test hypotheses derived from prevailing literature and examine the evolution of 14 technologies in four markets or industries. In the next three sections, we present the hypotheses, method, and results. In the final section, we discuss the findings, limitations, and implications of the research.

Hypotheses Development

The field does not enjoy a single, strong, and unified theory of technological evolution. To guide our empirical work, we reviewed available theory from the literature and derived testable hypotheses about the path, shape, source, and speed of technological evolution and the competition among rival technologies. Findings in this area have been partly confounded by the use of circular definitions. Thus, we begin

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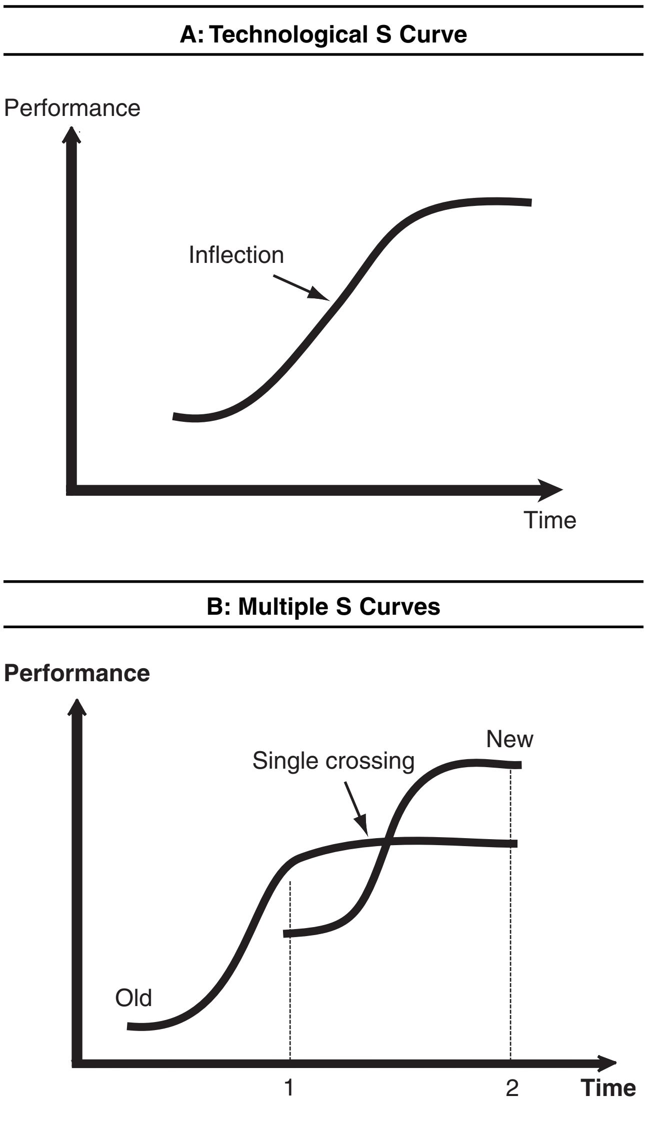
FIGURE 1
Technological Evolution



by defining types of technological innovations independent of their effects.

Definitions

Beginning with Schumpeter's (1939) early study, researchers have used a wide variety of terms to describe innovations. Many terms, such as "revolutionary," "disruptive," "discontinuous," or "breakthrough" (Freeman 1974; Garcia and Calantone 2002; Tushman and Anderson 1986), are intrinsically problematic because they define an innovation in terms of its effects rather than its attributes. If the definitions are then used to predict market outcomes (e.g., new entrants that displace incumbents with disruptive technologies), researchers risk asserting premises that are true by definition. To avoid such circularity, we define technological change in terms of intrinsic characteristics of the technology. As such, we identify and define three types of technological change: platform, component, and design.

We define a "platform innovation" as the emergence of a new technology based on scientific principles that are distinctly different from those of existing technologies. For example, the compact disk (CD) used a new platform, laser optics, to write and read data when the prior technology used magnetism. We define a "component innovation" as one that uses new parts or materials within the same technological platform. For example, magnetic tape, floppy disk, and zip disk differ by use of components or materials, though all are based on the platform of magnetic recording. We define a "design innovation" as a reconfiguration of the linkages and layout of components within the same technological platform. For example, floppy disks decreased from 14 to 8 inches in 1978, to 5.25 inches in 1980, to 3.5 inches in 1985, and to 2.5 inches in 1989, though each was based on magnetic recording (Christensen 1993).

These definitions are refinements of the technological dimension of radical innovations that Chandy and Tellis (2000) define. In our study, we use the term technology synonymously with platform. Furthermore, we note that improved performance in platform innovation results from innovations in component or design. In the interests of parsimony, this study does not explicitly identify the component and design innovations that improve performance in new platforms.

Logic of the S Curve

In the technology literature, a consensus has developed about the shape of technological evolution, and a consensus is emerging about the major explanation for this phenomenon. Regarding the phenomenon, prior research suggests that technologies evolve through an initial period of slow growth, followed by one of fast growth, and culminate in a plateau. When plotted against time, the performance resembles an S curve (see Figure 1, Panel A). Support for this phenomenon comes primarily from the work of Foster (1986), Sahal (1981), and Utterback (1994a). These authors address the progress of a technology on some primary dimension that is critical to consumers when the innovation emerges. Some examples of this are resolution in monitors and printers and recording density in desktop memory products. Subsequent authors have either accepted this view or found additional support for it. We did not find any article that has questioned it.

Authors have not developed any single, strong, and unified theory for the S curve. However, an emerging, and probably the most compelling, explanation revolves around the dynamics of firms and researchers as the technology evolves. We call this explanation the technology life cycle because it explains the occurrences of three major stages of the S curve: introduction, growth, and maturity (see Abernathy and Utterback 1978; Utterback 1994a). We describe these stages as emerging from the interplay of firms and researchers over the life of the technology.

Introduction stage. A new technological platform makes slow progress in performance during the early phase of its product life cycle. Two reasons may account for this: First, the technology is not well known and may not attract the attention of researchers. Second, certain basic but important bottlenecks must be overcome before any new technological platform can be translated into practical and meaningful improvements in product performance. For example, the laser beam was a new platform that required much time and effort to achieve the safety and miniaturization required to use it as a surgical tool.

Growth stage. With continued research, the technological platform crosses a threshold after which it makes rapid progress. This stage usually begins with the emergence of a dominant standard around which product characteristics and consumer preferences coalesce (Utterback 1974). That consensus stimulates research on the new platform, which in turn leads to improvement in its performance. Furthermore, publicity of the standardization draws a large number of researchers to study the new platform. Their cumulative and interactive efforts also lead to rapid increases in performance. The rapid progress leads to increases in sales of products based on the new technology, which increases revenues and profits and offers further support for research. In turn, these added resources fuel further improvement in performance (Klepper 1996).

Maturity stage. After a period of rapid improvement in performance, the new technology reaches a period of maturity after which progress occurs slowly or reaches a ceiling (see Brown 1992; Chandy and Tellis 2000; Foster 1986; Utterback 1994b). Authors propose several reasons for this change. Foster (1986) suggests that maturation is an innate feature of each platform; a technology is good for only so much improvement in performance. Utterback (1994b) and Adner and Levinthal (2002) suggest that as a market ages, the focus of innovation shifts from product to process innovation. As such, performance increases are few and modest, leading to technological maturity. Reinganum (1985) and Ghemawat (1991) suggest that maturity occurs when there is less incentive for incumbent firms to innovate because of fears of obsolescence or cannibalization from a rival platform. Thus, the rate of innovation reduces relative to the growth stage. Perhaps the best explanation is that of Sahal (1981). He proposes that the rate of improvement in performance of a given technology declines because of limits of scale (i.e., things become either impossibly large or small) or system complexity (i.e., things become too complex to work flawlessly). When these limits are reached, the only possible way to maintain the pace of progress is through radical system redefinition—that is, a move to a new technological platform.

Hypotheses

On the basis of the preceding explanation, we derive hypotheses about six aspects of technological evolution: shape, path, and dynamics of technological change on a primary dimension; progress on secondary dimensions; and the source of innovations and pace of technological transition.

Shape of Technological Progress

Although the extant literature suggests that technological evolution follows an S curve, it does not indicate the slope of this S curve, the duration of the stages, or the timing or steepness of the turning points. We try to determine whether it is possible to identify any patterns or generalizations about these parameters. However, in terms of a testable hypothesis regarding shape, the most precise hypothesis we can formulate is as follows:

> H_1: Technological progress on a primary dimension follows a single S-shaped growth curve.

Technological Transition and Performance of Competing Technologies

Do the paths of two technologies ever cross? If so, how many times? A crossing signals whether a new technology is robust and productive enough to supplant the old one. The existing literature suggests that such paths cross once. This conclusion is based on three implicit premises. First, performance of successive technologies each follows an S curve. Second, the performance of the new technology starts below that of the old technology. Third, performance of the new technology ends above that of the old technology.

Support for the first premise follows from that for H_1. Support for the second premise is widespread. Utterback (1994a, p. 158) asserts that "[a]t the time an invading technology first appears, the established technology generally offers better performance or cost than does the challenger, which is still unperfected." Foster (1986) claims that the performance of competing new technologies is much less than that of established technology during the fast growth phase of the established technology. Adner and Levinthal (2002, p. 56) claim, "It is unlikely that a new technology will initially dominate an established technology in its primary domain of application." Christensen (1992a, b) and Anderson and Tushman (1990, 1991) support the general phenomenon that when it first appears, any new technology provides much lower benefits than the old technology. Several authors provide arguments and examples in support of the third premise. Utterback (1994a, p. 160) states that "the new technology often has so much more potential for better performance that it" ultimately "surpasses the old." Two common examples cited in support of these arguments are steamships replacing wind-powered ships (Foster 1986) and airplanes' turbo jet engines replacing internal combustion engines (Constant 1980).

On the basis of the preceding premises, Foster (1986) and Christensen (1997, p. 398) postulate the following chain of events in the evolution of competing technologies: Sometime in the life of an old technology, a new technology emerges. Initially, it makes slow progress on the primary dimension. However, at some point, it enters its growth phase and improves rapidly. In contrast, the old technology improves at a much slower rate even though major commitments are made to develop products using old technology. As a result, a point is reached when the new technology crosses the old technology in performance (see Figure 1, Panel B). This crossing of the old technology is a signal of the end of its efficient progress. Thus, the threat to the old technology on the primary dimension is always from below.

This pattern of intertechnology competition results in overlapping S curves, with each new S curve starting below but ending above the old. For example, some empirical studies indeed show a single crossing between any two technologies (Christensen 1997; Foster 1986). This line of argument is represented in the following hypotheses:

> H_2: When a new technology is introduced, its performance is lower than that of the old technology.
>
> H_3: When a new technology reaches maturity, its performance is higher than that of the old technology.
>
> H_4: The performance path of a pair of successive technologies intersects once when the new technology surpasses the old technology in performance.

Pace of Technological Transition

Pace of technological change refers to the rate at which innovations are introduced in the market. The pace may be essentially stochastic because of the uncertainties in both the frequency of improvements and the magnitude of gain realized through each innovation. However, some authors believe that innovations are occurring more rapidly for three reasons. First, every year, greater resources are devoted to research and development (R&D). Second, every year, an increasing number of countries and people become involved in this R&D. Third, progress in one area (e.g., computers) enables greater efficiencies in another area (e.g., materials design).

At least two studies have found empirical support for this thesis. For example, Qualls, Olshavsky, and Michaels (1981) find that the percentage of products in the introductory and growth phases of the product life cycle increased over the past 50 years. In addition, research in diffusion of new technologies (Danaher, Hardie, and Putsis 2001; Pae and Lehmann 2003) also suggests a reduction in intergenerational time over time in many markets. Thus:

> H_5: The time interval between successive introductions of a new technology (i.e., a new platform) decreases over time.

Similarly, Golder and Tellis (1997, 2004) and Tellis, Stremersch, and Yin (2003) find that the time for takeoff of new products is shorter now than in previous decades. This finding implies that the rate of innovation within technologies is higher now than in previous decades, and new technologies improve at a quicker rate. Kayal (1999) finds that in the past 25 years, there had been increasing recency in the median age of the patents cited on the front page of a patent document. This finding suggests that the cited patents are relatively recent and that the technology is experiencing a frequent replacement of one generation of inventions with another, which is a sign of a rapidly progressing technology. Fernald and Ramnath (2004) find the greatest increase in total factor productivity in industries that use emerging information technologies. Total factor productivity is defined as the growth of real output beyond that which is attributable to increases in the quantities of labor and capital that are used. Economists often use this measure to represent the improvements in productivity that result from technological change (Hulten 2000). The increase in the pace of technological change could result from the larger size of successive jumps in performance, more frequent jumps, or both. Thus, we propose the following two hypotheses:

> H_6: The time interval between successive improvements in performance of a given technology decreases over time.
>
> H_7: The percentage increase in performance, calculated relative to the previous year, increases over time.

Conversely, Bayus (1994, 1998) believes that even though more products and product variations are available in the market at any point, the current rate of change is no higher than in previous decades.

Source of New Technologies

Which types of firms are more likely to introduce platform innovations: incumbents or new entrants, large firms or small firms? This topic has been the subject of research for decades. The conventional wisdom is that platform innovations come primarily from small firms or new entrants. These firms are ridiculed and ignored by incumbents in the beginning, but subsequently, they become successful with the progress of the new technology. Scherer (1984) shows how new entrants contribute to a "disproportionately high share" of revolutionary industrial products. Previous studies proposed many reasons for large incumbents' failing to introduce innovations, including incumbents' technological inertia (Ghemawat 1991), complacency (Robertson, Eliashberg, and Rymon 1995), arrogance (Lieberman and Montgomery 1988), and unwillingness to cannibalize their current products (Chandy and Tellis 1998). Thus, the dominant view in the literature is as follows:

> H_8: Platform innovations are introduced primarily by small entrants.

Method

A ready-made database does not exist for the study of technological evolution. We collected our own data using the historical method, following a growing trend in marketing (see Chandy and Tellis 2000; Golder 2000; Golder and Tellis 1993). The benefits of using the historical method include lower survival and self-report bias, ability to assess causality through longitudinal analysis, and new insights from a fresh reading of history (Golder 2000; Tellis and Golder 1996). Next, we detail our sample selection, sources, and procedure for data collection.

Sample Selection

We used two criteria to select categories: some overlap with prior research and an adequate number of platform innovations. We selected a portfolio of categories such that it included some that had been investigated in prior studies (e.g., memory) and others that had not been researched (e.g., data transfer). This coverage enables us to compare our results with prior studies and to validate these findings in new categories. However, the current study goes further than previous studies in one important aspect: Within each category, we selected all technologies. We also required that the category have had at least two platform innovations. On the basis of these criteria, we chose data transfer, computer memory, desktop printers, and display monitors. Note that the first is utilities, and the next three are consumer electronics. Thus, the sample crosses a broad spectrum of products.

Sources

The information required for this study is technical data on product performance for various technologies at different stages of their evolution. The primary sources of our data were reports in technical journals, industry publications, white papers published by R&D organizations, and annual reports of industry associations. We sourced industry reports of market research firms (e.g., Disk/Trend, Stanford Resources), press releases, timelines of major firms, and records in museums that profiled innovations and the development of industries. We recorded the current performance of many technologies from product information bulletins released by firms.

Procedure

We followed the general rules for data collection for the historical method (Golder 2000). We explain specific problems we encountered and the rules we used to resolve them. First, within a technology, as the performance of that platform, we used the performance of the best component or design or the combination of the two. Second, if two sources provided conflicting data for a period within the series, we chose the one whose starting and ending values were more consistent with the rest of the series. Third, we used the date of first commercialization of a product based on each technology as the standard starting point to compare the relative performance of any two technologies.

Results

First, we present the identification of platform innovations and the performance attributes in each category. Second, we present findings on the hypotheses regarding the shape, path, and dynamics of technological changes. Third, we present findings on the competition, rate of improvement, and source of new technologies. We used nonlinear regression to test the first and primary hypothesis, the existence of the S curve. We used cross tabulations, chi-square and binomial tests, and regression analysis for the other hypotheses.

Identification of Platform Innovations and Performance Attributes

We identified various technologies in each of the markets, each of which was initiated by a platform innovation: four in desktop printing and display monitors and three in desktop memory and data transfer. We describe these 14 technologies briefly in the Appendix. (Detailed definitions for these innovations are available on request).

We found that some of the platform technologies may not be readily distinguishable to the customers for one major reason: Even when a new technology differs radically from an old one, firms try to facilitate consumer adoption by maintaining a uniform interface for the new product based on the new technology. For example, many secondary storage devices based on magnetic and magneto-optical principles used almost identical housings and interface accessories. We considered the underlying technologies distinct if they were based on fundamentally different scientific principles. We adopted this rule to avoid the confusion of differences in technologies based on their characteristics with superficial differences based on derived products.

The literature is quite consistent in recommending the use of performance as the key dependent variable when testing the S curves (e.g., Christensen 1999, p. 19; Foster 1986, p. 274; Utterback 1994a, p. 158). In each category, at a particular stage of technological evolution and consumer needs, certain dimensions of performance assume primacy. We did not have difficulty identifying these dimensions based on the historical description of the technologies. Fortunately, each of the dimensions has fairly clear performance metrics. In choosing metrics, we were careful to take into account output per unit of input (see Table 1).

Shape of Technological Evolution

In H_1, we predict that technologies evolve through S curves. We plotted the performance of technologies on the y-axis against time on the x-axis (see Figure 2, Panels A–E). We excluded organic light emitting device (OLED) technology from the formal tests of shape because it has only two data points. As we hypothesized, these figures reveal that technologies have a slow start and a sudden growth spurt. However, we found a single S-shaped path with a single inflection point followed by a permanent plateau or maturity in only four technologies. In nine technologies, we did not find a single S curve. Rather, we found long periods of static performance interspersed with abrupt jumps in performance. The plots suggest a series of step functions, each of which could approximate an S curve. To test H_1 that evolution follows an S-shaped function, we performed the following two tests.

First, we fit the generalized logistic function to the four technologies that reveal a single S-shaped curve:

$$Y_t = d + \frac{a}{1 + e^{-b(t - c)}}, \tag{1}$$

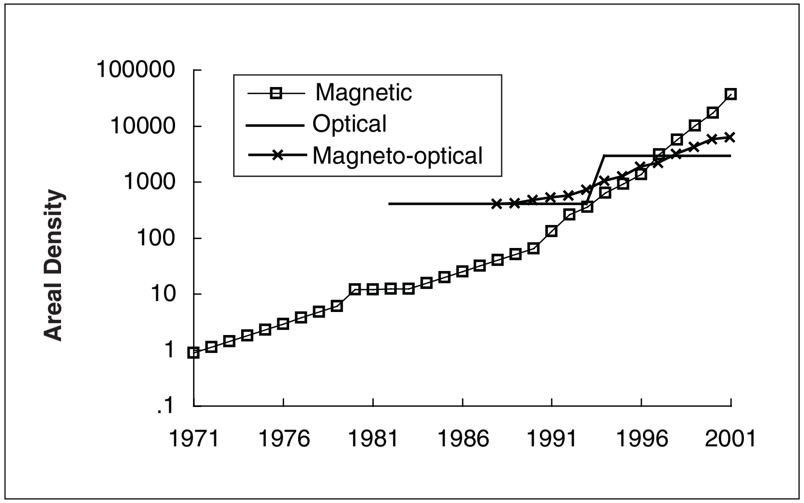
where Y_t = performance of the technology in year t, and a, b, c, and d are parameters to be estimated: b is the growth rate, c is the time of maximum growth or the inflection

TABLE 1
Metrics of Primary Dimensions in Each Category

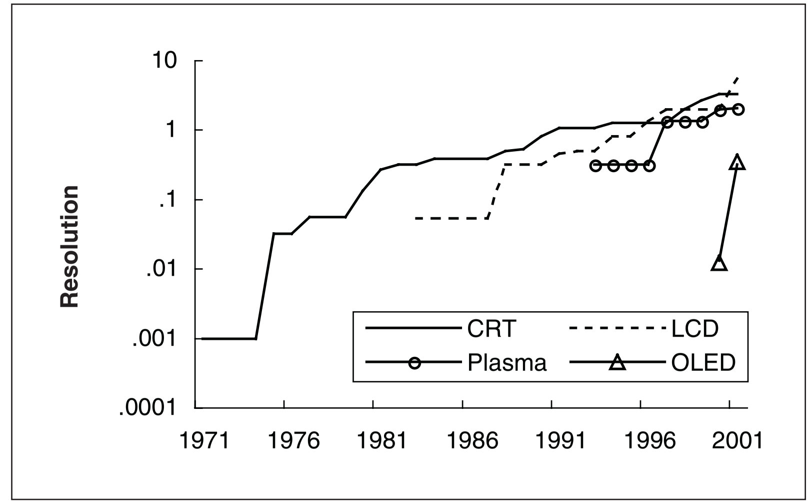
Category	Primary Dimension	Metric
Desktop memory	Storage capacity	Bytes per square inch
Display monitors	Screen resolution	Dots per square inch
Desktop printers	Print resolution	Pixels per square inch
Data transfer	Speed of data transmission	Megabits per second

FIGURE 2
Technological Evolution in Four Categories

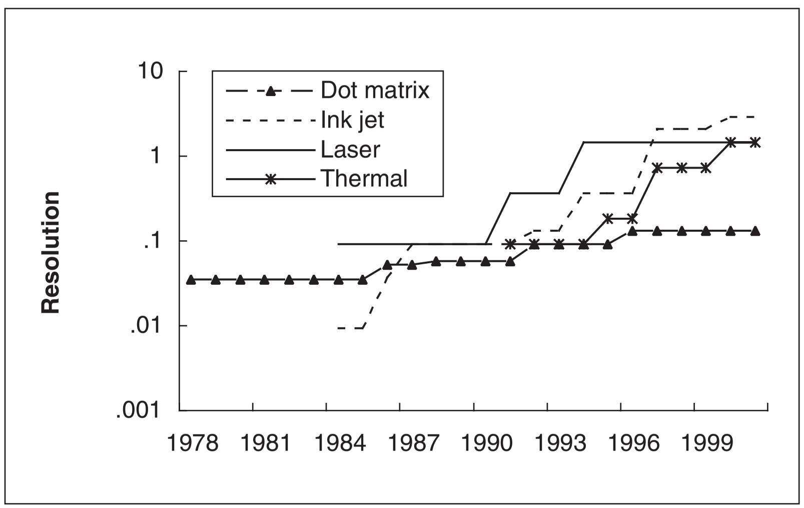
A: Desktop Memory[a]



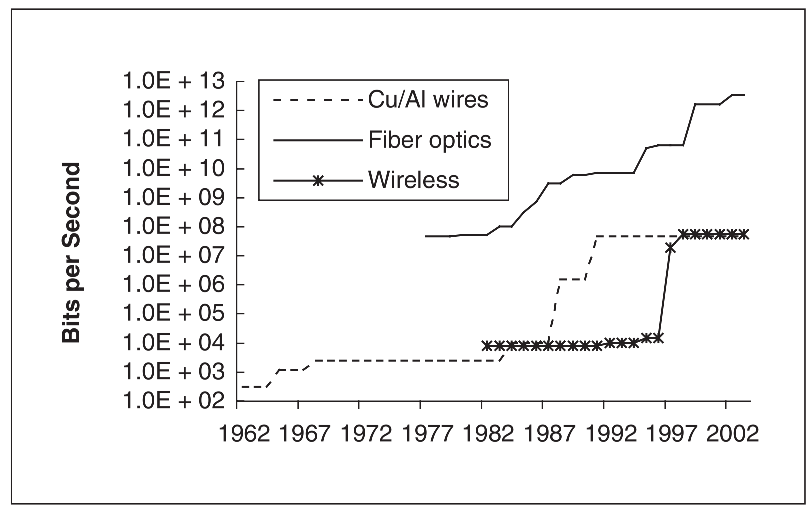
B: Display Monitors[a]



C: Desktop Printers[a]



D: Data Transfer[a]



[a]Performance on y-axis is in log scale.

point, and a + d is the upper asymptote of the S curve. We used the nonlinear regression techniques in SAS to estimate the model over the entire data. Second, for the nine technologies that seemed to exhibit multiple S curves, we fit the generalized logistic function both to the entire series of data and to a subsample of data that exhibited an S curve. We used two criteria to select a subset of data for this purpose: (1) Performance of the technology during the subsample had an upper plateau that was longer in duration than was the duration of the just-preceding growth phase, and (2) the subsequent jump in performance in the one year immediately after the plateau was almost double the performance during the entire plateau. Our practical goal is to test how well an S curve fits on the whole sample and whether it fits better on a subsample than on the whole data.

We found that for the four technologies with an apparent single S-shaped curve, the generalized logistic function provides a good fit with the data (see Table 2, Panel A, and Figure 3, Panels A and B). For the remaining nine technologies, an S-shaped curve fits better over a subsample of data than over the whole data, even after we take into account degrees of freedom (see Table 2, Panel B, and Figure 3,

TABLE 2
Test of Shape of Technological Evolution

A: Fit of Logistic Model to Technologies with Single S Curves

	Parameter Estimates	
Technology	Upper Asymptote (t-Value)	Growth Rate (t-Value)
1. Magnetic memory	4.28 (8.5)	.50 (24.8)
2. Optical memory	1.20 (7.4E + 06)	30.95 (24.2)
3. Magneto-optical memory	3.51 (5.2)	.51 (7.8)
4. Wireless data transfer	1.57 (234)	6.29 (5.3)

B: Differences of Logistic Model Fit Between Subsample and Full Data (for Technologies with Multiple S Curves)

	Improvement in Fit of Subsample over Full Data (Measured as a Reduction in the Mean Square Error)[a]			
	Full Data		Subsample	
Technology	Number of Years	Mean Square Error	Number of Years	Percentage Reduction
1. Dot matrix printers	24	.04	14	95%
2. Inkjet printers	18	.05	13	97
3. Laser printers	17	.02	10	100
4. Thermal printers	11	.09	9	95
5. CRT monitors	31	.09	27	97
6. LCD monitors	19	.20	18	93
7. Plasma monitors	19	.14	7	100
8. Copper/Al cables	42	.57	21	95
9. Fiber optics	27	.06	25	99
Mean	23.1	—	16	97

C: Differences of Logistic Parameters Between Subsample and Full Data (for Technologies with Multiple S Curves)

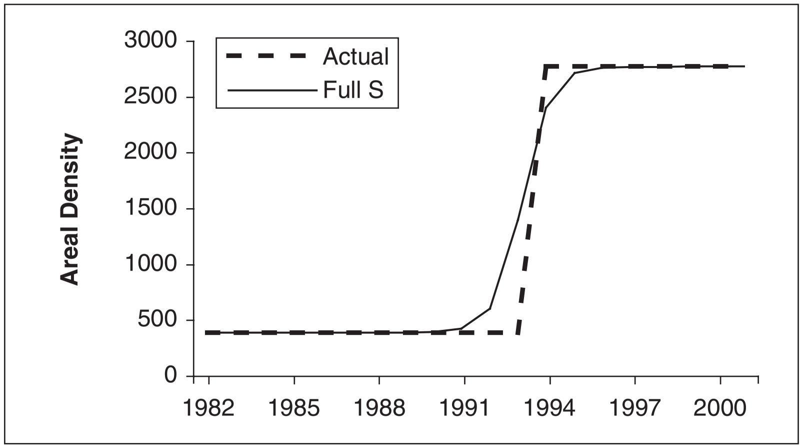
	Difference in Parameter Estimates for	
Technology	Upper Asymptote (a + d): Difference (t-Value)	Growth Rate (b): Difference (t-Value)
1. Dot matrix printers	2.2 (68)	–4.9 (–42)
2. Inkjet printers	2.6 (79)	1.8 (–9)
3. Laser printers	1.6 (63)	–20.8 (–80)
4. Thermal printers	2.5 (14)	–7.2 (–14)
5. CRT monitors	97.3 (44)	–.2 (–11)
6. LCD monitors	89.6 (21)	–.4 (–11)
7. Plasma monitors	1.1 (10)	–28.6 (–222)
8. Copper/Al cables	17.7 (425)	.6 (14)
9. Fiber optics	–1.6E + 12 (–3.0E + 08)	–12.6 (–19)

[a]We excluded OLED displays from the analysis.

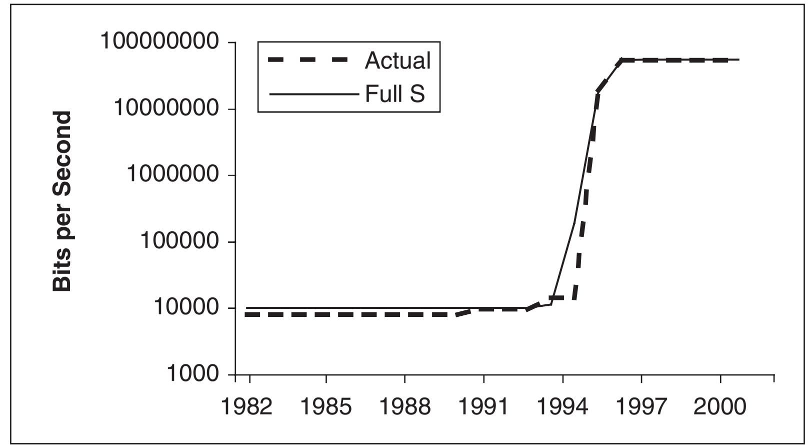
FIGURE 3
Fit of Logistic Model over Multiple and Single S Curves

Technologies with Single S Curve

A: Optical Memory

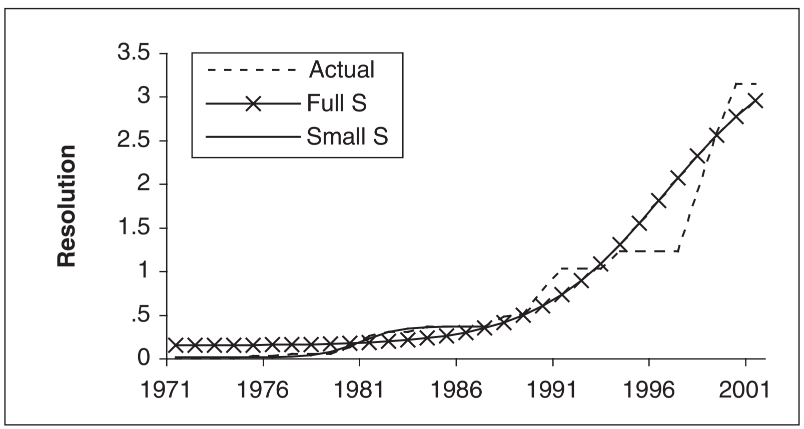


B: Wireless Data Transfer[a]

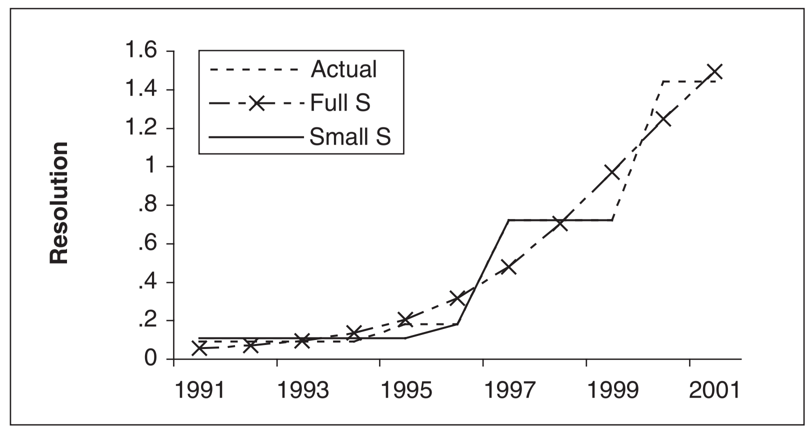


Technologies with Multiple S Curves

C: CRT Monitors



D: Thermal Printers



[a]Performance on y-axis is in log scale.

Panels C and D). Table 2, Panel B, shows that the fit over the subsample gives an average reduction of 97% in the mean square error compared with the fit over the whole sample. Furthermore, Table 2, Panel C, shows that after adjusting for degrees of freedom, the parameter estimates of the fitted generalized logistic function for the subsample are significantly different from the parameter estimates over the whole sample. For this test, we used the t-test for differences in parameters with unequal variances over the two models. More important, the upper asymptote in the subsample is significantly and substantially different from that in the whole series, leading us to reject H_1.

To summarize, the hypothesis of a single S-shaped growth in performance is supported for only 4 of the 13 technologies.[1] For 1 technology, we did not have enough data, and for the remaining 9 technologies, change in performance follows a series of irregular step functions that are better approximated with multiple S curves than with a single S curve. Across these step functions within a technology, estimates of growth rate and especially performance at maturity (the upper asymptote) differ substantially. Using functional analysis, James and Sood (2005) obtain similar results and confirm significant departures from an S curve for these technologies. The importance of this finding is that an analyst expecting a single S curve may prematurely abandon a promising technology at the first plateau in performance.

[1]We also analyzed these and two other categories: analgesics and lighting (Sood and Tellis 2005). Because of reviewers' concerns about the category definitions and the substitutability of technologies, we do not include these analyses in the article.

Performance of Competing Technologies

In H_2, H_3, and H_4, we predict three characteristics of technological competition: performance of a new technology at its introduction and at its maturity (Points 1 and 2 in Figure 1, Panel B) and a single crossing when the new technology crosses the old technology in performance. Our results are contrary to the hypotheses (see Table 3, Panel A). A majority of new technologies performed better than the old technology from the time they were introduced. In addition, many new technologies never improved over the old technology, whereas others enjoyed brief spells of dominance over the old technology before the old technology regained dominance.

This unexpected pattern of evolution results in three distinct types of crossings between any pair of successive technologies (see Table 3, Panel B). First, three of the ten technology pairs showed no crossing at all. In these cases, new technologies either started higher than the old technology and remained higher or started lower than the old technology and never crossed the old technology long after their introduction. Second, many technologies (three of the ten) showed multiple crossings. In such cases, the new technology passed an older technology but was not able to sustain its advantage. Third, the expectation of a single crossing, of new passing the old from below, was satisfied in only four of the ten technologies, thus rejecting H_4.

In summary, we find no support for any of the three hypotheses on performance of competing technologies. Thus, the final status of each technology cannot be deter-

TABLE 3
Dynamics of Technological Competition

A: Performance of New Technology Compared with Old Technology

Technology Category	H_2: Proportion of New Technologies with Low Performance Compared with Old Technologies at Introduction	H_3: Proportion of New Technologies with High Performance Compared with Old Technologies at Maturity
1. Desktop memory	0/2	1/2
2. Display monitors	3/3	1/3
3. Desktop printers	2/3	1/3
4. Data transfer	1/2	1/2
Total	6/10	4/10

B: Number of Crossings Between New and Old Technologies

Technology	Single Crossing	Multiple Crossing	No Crossing
1. Desktop memory	1	1 (3)[a]	0
2. Display monitors	1	1 (3)[a]	1
3. Desktop printers	2	1 (2)[a]	0
4. Data transfer	0	0	2
Total	4/10	3/10	3/10

[a]Figures in parentheses indicate the total number of crossings in the technology pair with multiple crossings.
Notes: Panel A presents the results of a binomial test to determine the probability that technology performs in accordance with H_2 and H_3, and Panel B presents the results of a binomial test to determine the probability that all crossings are single, and for both, $p < .001$.

mined solely from the direction of the attack or timing of introduction. As such, it would be unwise for an incumbent to scan for competition only among technologies performing worse than its current technology and to make decisions on that basis.

Pace of Technological Transition

Three hypotheses (i.e., H_5, H_6, and H_7) suggest that the pace of technological transition increases over time (the null hypothesis is that the pace of change is constant over time). Tests of all three measures support an increasing pace of technological change (see Figure 4, Panels A–C). The negative slopes of trends for both the measures of duration suggest declining duration between introductions of successive new technologies and declining duration between successive improvements in each technology. The positive slope of trend for the rate of improvement over the past year suggests an increase in the pace of technological change.

To test these three hypotheses, we pooled the categories and estimated the following regression equation for each of the three measures.

$$Y_{mt} = \alpha + \beta_m \log(t) + \varepsilon_t \quad m = 1 - 3 \ldots, \tag{2}$$

where Y_{mt} represents each one of the preceding three measures of pace of technological change in year t, a and b are coefficients to be estimated, m is the measure of technological change, and e_t are the errors assumed to be i.i.d. normal. The coefficients are significantly different from zero for all three measures (see Table 4). Thus, we reject the null hypothesis for H_5, H_6, and H_7 that pace of technological evolution is constant over time. Note that our test is in the same spirit as meta-analyses, which pool estimates across multiple categories (Assmus, Farley, and Lehmann 1984; Tellis 1988). Such pooling increases the power of the test and reduces the probability of a Type II error.

Source of New Technologies

The dominant view in the literature is that new technologies come primarily from small entrants. To shed more light on this issue, we operationalized incumbency and size. An incumbent is a firm that was in the category before the introduction of the new platform technology. All other firms are entrants. For technologies introduced before 1950, we determined the size of a firm on the basis of the total assets (million of dollars) from the COMPUSTAT database. Because of limitations of data, for technologies introduced before 1950, we determined a firm's size on the basis of market share or the range of products across industries.

In contrast to the dominant view in the literature (H_8), we find only 1 platform innovation introduced by small entrants. All the remaining 13 platform innovations came from large firms (7 incumbents and 6 new entrants). Although our results run counter to the dominant view in the literature, they are consistent with two recent findings in the literature (Chandy and Tellis 2000; Sorescu, Chandy, and Prabhu 2003). A possible reason is that in recent decades, innovation has become far more complex. The deeper pockets of large firms enable incumbents to maintain state-of-the-art facilities to conduct research, and incumbency provides them with opportunity and resources for developing and introducing platform innovations. This reason is further supported by the results: Of the 13 innovations introduced by incumbents, none was introduced by small incumbents.

Dimensions of Technological Competition

Prior research suggests that certain secondary dimensions become important as technology evolves. Progress occurs systematically along the first dimension and then moves to the second, then to the third, and so on. These dimensions form the bases of intertechnological competition. They also form the bases by which consumers choose among rival technologies or products.

The literature also suggests that the basis for such competition is standard and occurs in the same form across markets. For example, Christensen (1999) notes four generic dimensions of intertechnological competition: functionality, reliability, convenience, and cost. Product functionality is the primary attribute on which consumers choose products in that category. Similarly, Moore (1991) suggests that products begin to compete on consistent performance, or higher reliability, after subsequent innovations increase functionality beyond a certain point. Christensen suggests that after product functionality and reliability requirements are satisfied, firms become more willing to customize product designs to meet customers' specific requirements, such as convenience. Abernathy and Clark (1985) propose that the product becomes a commodity, and progress occurs through price reductions after the technology has progressed up the S curve sufficiently on functionality, reliability, and convenience. The occurrence of such generic dimensions can be important in guiding firms on the path of evolution and in the direction of the next competitive attack.

However, in contrast to expectations about the dimensions of technological competition, our results suggest a sequence of random, unpredictable secondary dimensions in each of the four categories (see Table 5). Each platform technology offered a completely new secondary dimension of competition while competing on the primary dimension. For example, consider four successive technologies in monitors: CRT, LCD, plasma, and OLED. The CRT monitor was initially introduced on the basis of resolution. Each subsequent technology was inferior in resolution at the time of introduction but introduced a new important secondary dimension: resolution, compactness, screen size, and efficacy.

Discussion

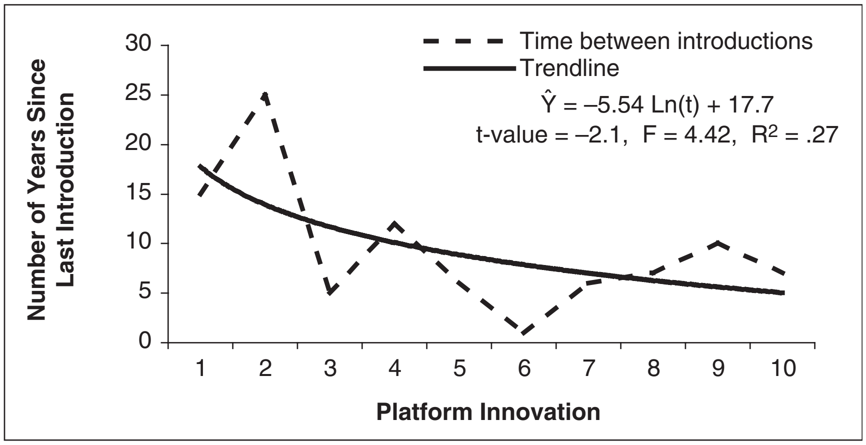
Summary of Findings

The current research leads to six major findings:

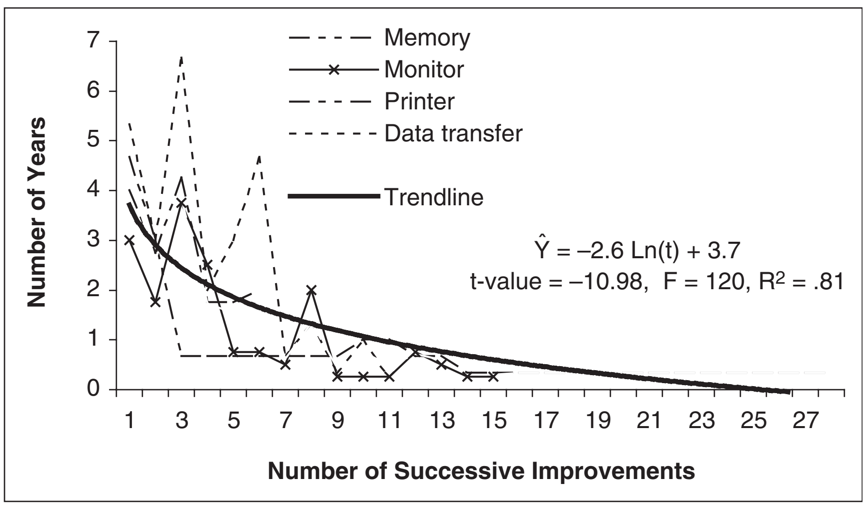
1. Technologies do not show evidence of a single S-shaped curve of performance improvement. Rather, they evolve through an irregular step function with long periods of no growth in performance interspersed with performance jumps. A jump in performance appears to be largest after a long plateau of no improvement.
2. New technologies may enter above or below the performance of existing technologies. The performance curves of

FIGURE 4
Pace of Technological Transition

A: Declining Time Between Introduction of New Platform Innovations



B: Declining Duration Between Successive Improvements in Technology



C: Increasing Average Percentage Improvement Over the Past Year

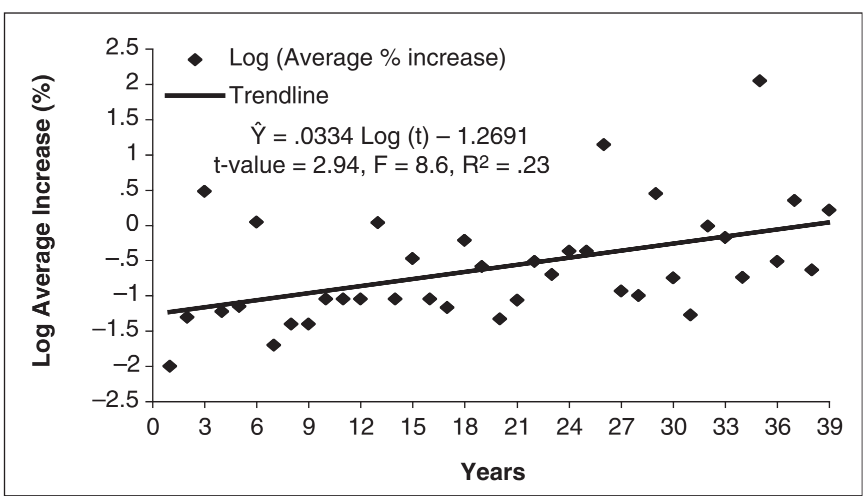


TABLE 4
Regression Results for Different Measures of the Pace of Technological Change

	Effect of Independent Variable: Time		
Measure of Dependent Variable: Technological Change	**β**	**t-Value**	**R^2**
1. Time interval between introductions of successive technologies	–5.54	–2.1	.27
2. Time interval between successive improvements in performance within a technology	–2.64	–10.9	.81
3. Percentage increase in performance relative to the previous year	.03	2.9	.23

TABLE 5
Emergence of Secondary Dimensions of Competition

Market	Secondary Dimensions
1. Desktop memory	Areal density, reliability, and cost
2. Display monitors	Resolution, compactness, screen size, and efficacy
3. Desktop printers	Resolution, graphics, speed, and continuous color rendition
4. Data transfer	Transfer speed, bandwidth, and connectivity/mobility

a pair of competing technologies rarely have a single crossing.

3. The path of technological evolution seems partially predictable. Previous improvement in performance of the same technology, improvement or crossing by a rival technology, and especially crossing by a rival firm tend to signal immediate improvement in performance.
4. The rate of technological change and the number of new technologies increase over time.
5. New technologies come as much from new entrants as from large incumbents.
6. Each new technology introduces a sequence of random, seemingly unpredictable secondary dimensions as a new basis of competition.

Robustness of Results

To test the robustness of the results, we performed several analyses that covered reference technology, gestation time, censoring bias, survival bias, criterion variables, and multiattribute performance.

Reference technology. Our results are based on comparing one technology with another technology introduced just before it. To address the question whether these results are in any way sensitive to the reference point of the comparison technology, we redid our analyses using the first technology and the dominant technology in the category. The results were not materially different from those that we report herein.

Gestation time. We also examined the gestation time of each technology, which is defined as the time it takes for a firm to convert a patent to a commercial product. The average gestation time for technologies is 14.5 years for display monitors, 14.3 years for desktop printers, 9.7 years for desktop memory, and 22.7 years for data transfer technologies. The overall average for all categories is 15.1 years. Given this long gestation period, our results show that investors must be patient and managers must persevere to bring a new technology to fruition.

We examined whether the gestation period shrinks over time given the increasing pace of technological change. To examine this hypothesis, we did a median split of the gestation period by the year 1970. Each group had technologies from all four categories. Pre-1970 technologies have a significantly larger ($t = 2.5$) gestation time (25 years) than do post-1970 technologies (7.8 years). This result further supports H_5, H_6, and H_7 regarding the pace of technological change.

Censoring bias. To check whether our results were at the cost of a censoring bias from not allowing enough time for the new technology to improve, we compared the time taken for the technologies that failed to cross old technologies with those that did cross. The average number of years for new technologies to reach the point of first crossing the old technology is 6.3 years. In contrast, categories in which the new technology never crossed the old have been in existence for 14.6 years. Thus, the lack of a crossing cannot be due to a censored time frame.

Survival bias. It is impossible to rule out survival bias, though we took great pains to minimize its role. First, we tried to include every technology that was commercialized in the markets that we covered for the time period that we studied. Second, to examine the possible effect of inadvertently excluding any technologies from the analyses, we defined a class of technological failures: nonstarters. Nonstarters are those that were used in related fields and could have been used in the target markets with some modification but were either never used or failed to show sufficient improvements in performance, cost, and features soon after initial introduction (e.g., chain printers in desktop printers, wire recorders in desktop memory). In other words, these are potential technologies that were never mass commercialized. The key issue is whether the exclusion of failures biased our results, just as survival bias upwardly biases the alleged advantages of market pioneers (Golder and Tellis 1993).

We believe that nonstarters do not affect any of our results for three reasons: First, our definition of nonstarters is stringent; they are technologies that were never commercialized. Second, most of our analysis tracks the progress of individual technologies without averaging performance across technologies. As such, the exclusion of nonstarters does not bias computed performance levels. Third, our entire analysis tracks the performance of a technology given that it was commercialized. We do not make any predictions or test any hypotheses about the productivity of R&D, in which case nonstarters would loom large.

We find common factors in each of these cases. First, each of the nonstarter technologies failed to develop an acceptable standard or to be included in a prevailing standard. For example, wire recorders were excluded from the standard-setting process in favor of magnetic tape technology by the recording industry. Such exclusion in the standards-setting process, also termed "technological lockout" (Schilling 1998), leaves the technology in a weak market position (Shapiro and Varian 1999). Second, either a new and better technology was introduced early in the life of the nonstarter technology (e.g., magnetic tape and wire recorders) or the performance of the new technology was exceptionally superior to (or growing at a fast rate than) the nonstarter technology (e.g., dot matrix printers and chain printers). Perhaps as a result of these two factors, the nonstarter technology did not show any improvement in performance on all dimensions that we tracked.

The exclusion of these technologies does not lend support to any of the alternative hypotheses that we tested and rejected, such as a single S-shaped curve, single crossing, or generic dimensions of competition. However, because we excluded nonstarter technologies, it would be wrong to conclude from our results that performance always improves over time.

Alternative criterion variable. Some authors propose that when testing the S curves, benefits per dollar should be used as the key dependent variable instead of performance (Chandy and Tellis 1998). Although all our current performance measures also have a denominator for proper scaling (e.g., megabits per second), we investigate the sensitivity of our results to using this alternative metric. We collected data on benefits per dollar for three categories: desktop printers, desktop memory, and display monitors. For each technology, we identified the product that offers the highest benefit per year and the price at which it was offered at its introduction. The results in Figure 5, Panels A–C, do not provide support for any of the hypotheses that we rejected. For example, we observed multiple crossings in all categories and new technologies being introduced with higher benefits per dollar. Moreover, we found that the evolution of technologies is not even a monotonic function of benefits per dollar. One possible reason is that firms charge higher prices for technologically advanced products until competition drives the price down.

Multiattribute performance. To address the question whether our results hold when we take into account multiple dimensions of performance simultaneously, we repeated the analysis using multiple dimensions in two categories: desktop printers and display monitors. For printers, we collected data on the speed of printers, which we measured as pages per minute, and print resolution. For monitors, we collected data on screen size, which we measured in diagonal inches, and resolution. Note that our findings on shape, path, and crossing patterns are robust to the use of this second dimension (see Figure 6, Panels A and B). We also calculated standardized values of performance on each dimension over the category for each platform, computed the sum of these standardized values over all dimensions of performance, and then plotted the latter index by time (see Figure 6, Panels C and D). The use of multiple dimensions simultaneously using this crude index fails to yield any patterns that might support consistency with S curves.

Implications

Although the results of our study are not strictly normative, this study has several implications for managers. First, using the S curve to predict the performance of a technology is quite risky and may be misleading for two reasons: (1) Most of the technologies do not demonstrate an S-shaped performance curve, and (2) several technologies show multiple S curves, suggesting that a technology can show fresh growth after a period of slow or no improvement. The critical importance of this issue is the following: An analyst expecting an S-shaped curve would conclude that the first curve (on the subsample) meets the hypothesis. He or she would then wrongly conclude that the technology has matured at the upper asymptote when indeed it has not. As a result of this incorrect conclusion, the analyst would suggest abandoning the old technology. The average period for the subsample S curves is 16 years, compared with an average of 23 years for the full period. Thus, this error may result in premature abandonment of a promising technology as early as at least 7 years before its life to date.

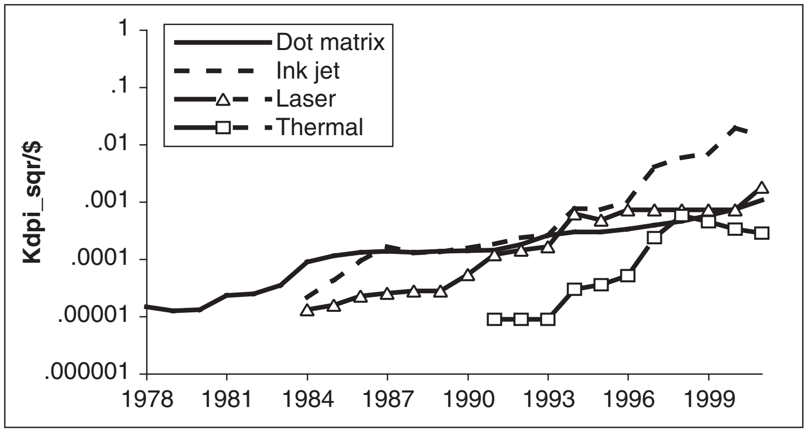
Second, the continuous emergence of new technologies and the steady growth of most technologies suggest that relying on the status quo is deadly for any firm. Moreover, technological progress is occurring at an ever-increasing pace. As such, vigilance for the emergence of new technologies coupled with efforts to improve the old technology can help an incumbent sustain and advance its position or even preempt competitors.

Third, our findings indicate that the attack from below remains a viable threat. Many new technologies start by offering low performance but subsequently threaten old technologies by improving at a much quicker rate. Incumbents are prone to disregard these new technologies initially because they often cater only to a niche and not to the mass market. However, these niches can grow into mass markets and eventually replace the old technology. Furthermore, some new technologies can outperform old technologies even at the time of introduction.

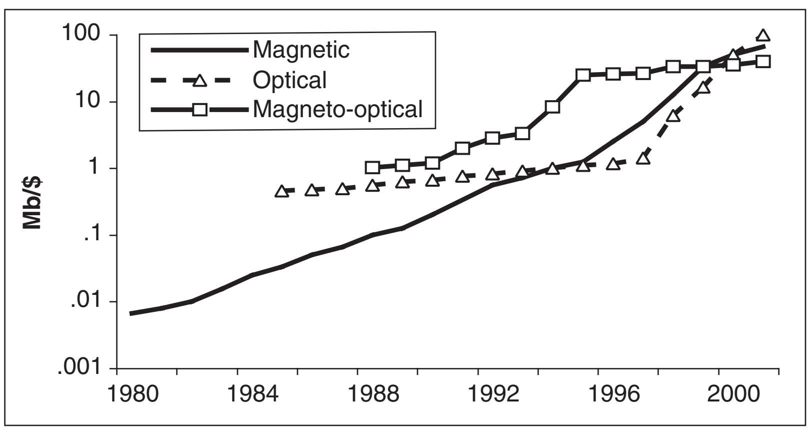
Fourth, another threat to incumbents is the emergence of secondary dimensions of competition. Old technologies may be completely vulnerable to these dimensions. Faced with such threats, incumbents need research to identify technological solutions to improve the value of the old technology and to identify market segments that value the contributions of the old technology. Alternatively, incumbents need to explore R&D options on multiple dimensions to react appropriately to threats posed by entrants. Fifth, first-

FIGURE 5
Performance per Unit Price

A: Desktop Printer Technologies (Resolution per Dollar)



B: Desktop Memory Technologies (Storage Capacity per Dollar)



C: Display Monitor Technologies (Size per Dollar)

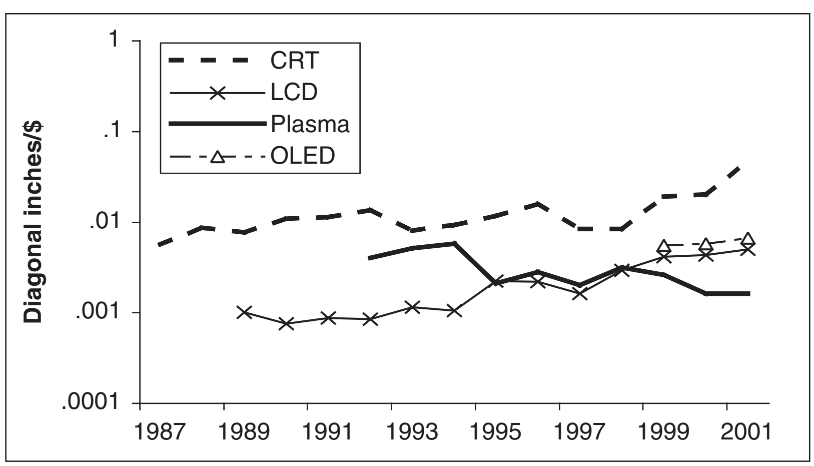
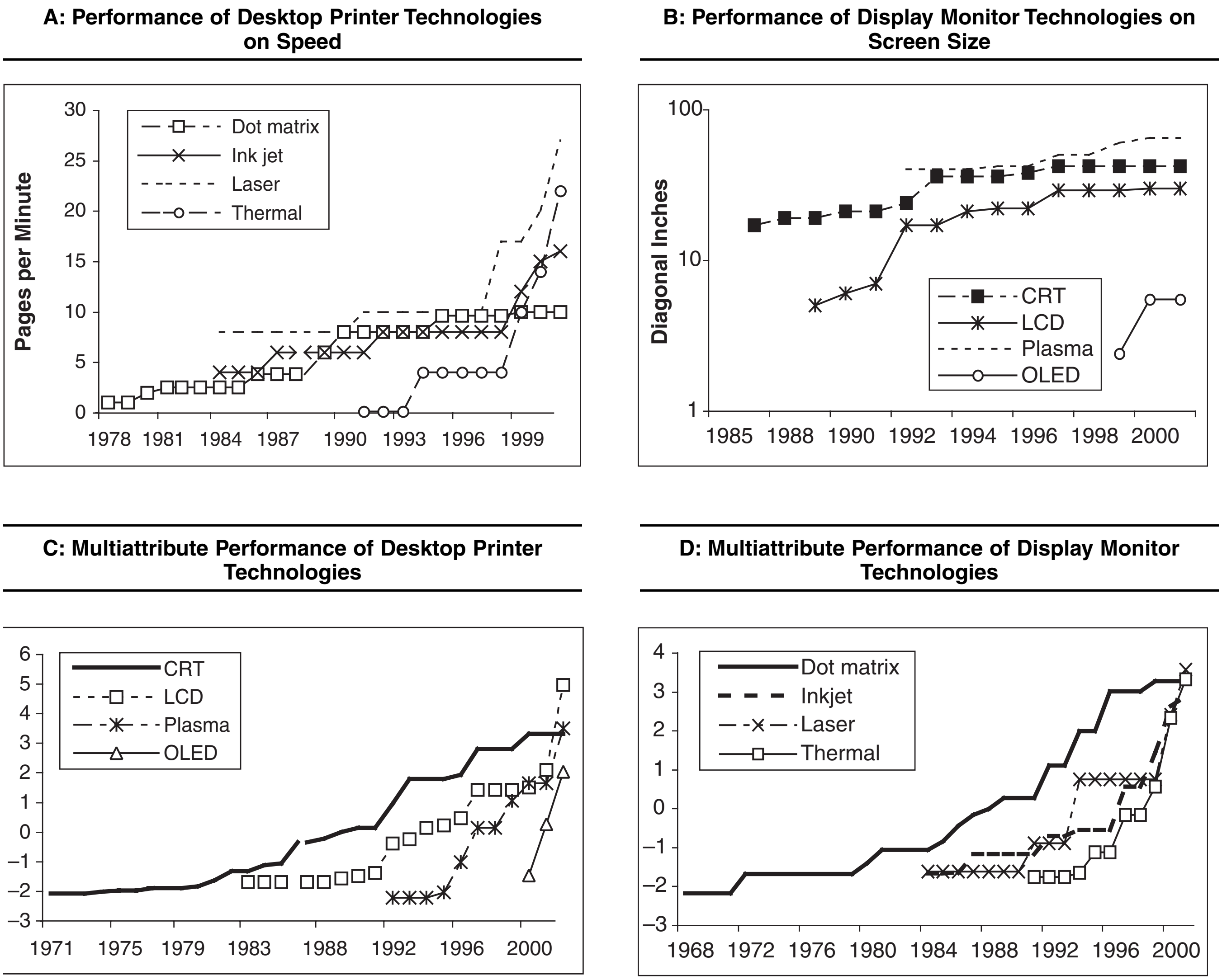


FIGURE 6
Multiattribute Performance



mover advantages may not be lasting because entrants introduce even more innovations than do incumbent firms.

Limitations

This study has several limitations. First, we needed to limit our analysis to only four categories because of the time-consuming nature and difficulty of data collection. Second, our analysis of performance did not include cost to buyers. Third, we did not incorporate sales of products based on each technology within a category. Finally, despite our efforts to be as comprehensive as possible in data collection based on historical records, we must acknowledge the potential limitation of incomplete data availability in the first half of the twentieth century. All of these limitations are potential opportunities for further research. In addition, further research might also explore whether S curves are evident at the subplatform level, why there are long periods of no improvement in performance, and how firms should compete given the pattern of technological evolution.

APPENDIX
Operating Principles of Sampled Technologies

Technology	Principle	Technology	Principle
Desktop Memory		**Desktop Printers**	
Magnetic	Records data by passing a frequency-modulated current through the disk drive's magnetic head, thus generating a magnetic field that magnetizes the particles of the disk's recording surface.	Dot matrix	Creates an image by striking pins against an ink ribbon to print closely spaced dots that form the desired image.
Optical	Stores data using the laser modulation system, and changes in reflectivity are used to store and retrieve data.	Inkjet	Forms images by spraying ionized ink at a sheet of paper through micronozzles.
Magneto-optical	Records data using the magnetic-field modulation system, but it reads the data with a laser beam.	Laser	Forms an image on a photosensitive surface using electrostatic charges. Then, it transfers the image onto a paper using toners and heats the paper to make the image permanent.
Display Monitors		Thermal	Forms images on paper by heating ink through sublimation or phase change processes.
CRT	Forms an image when electrons, fired from the electron gun, converge to strike a screen coated with phosphors of different colors.	**Data Transfer**	
LCD	Creates an image by passing light through molecular structures of liquid crystals.	Copper/aluminum	Transmits data in the form of electrical energy as analog or digital signals.
Plasma	Generates images by passing a high voltage through a low-pressure, electrically neutral, highly ionized atmosphere using the polarizing properties of light.	Fiber optics	Transmit data in the form of light pulses through a thin strand of glass using the principles of total internal reflection.
OLED	Generates light by combining positive and negative excitons (holes emitted by anodes and electrons emitted by cathodes) in a polymer dye through the principle of electroluminescence.	Wireless	Encodes data in the form of a sine wave and transmits it with radio waves using a transmitter–receiver combination.

REFERENCES

Abernathy, William J. and K.B. Clark (1985), "Innovation: Mapping the Winds of Creative Destruction," *Research Policy*, 14 (1), 3–22.

——— and J.M. Utterback (1978), "Patterns of Industrial Innovation," *Technology Review*, 80 (7), 40–47.

Adner, Ron and Daniel Levinthal (2002), "The Emergence of Emerging Technologies," *California Management Review*, 45 (1), 56.

Anderson, Philip and M.L. Tushman (1990), "Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change," *Administrative Science Quarterly*, 35 (4), 604–633.

——— and ——— (1991), "Managing Through Cycles of Technological Change," *Research Technology Management*, 34 (3), 26–31.

Assmus, Gert, John U. Farley, and Donald R. Lehmann (1984), "How Advertising Affects Sales: Meta-Analysis of Econometric Results," *Journal of Marketing Research*, 21 (February), 65–74.

Bayus, Barry L. (1994), "Are Product Life-Cycles Really Getting Shorter," *Journal of Product Innovation Management*, 11 (4), 300–308.

——— (1998), "An Analysis of Product Lifetimes in a Technologically Dynamic Industry," *Management Science*, 44 (6), 763–75.

Brown, Rick (1992), "Managing the 'S' Curves of Innovation," *Journal of Consumer Marketing*, 9 (1), 61–73.

Chandy, Rajesh K. and Gerard J. Tellis (1998), "Organizing for Radical Product Innovation: The Overlooked Role of Willingness to Cannibalize," *Journal of Marketing Research*, 35 (November), 474–87.

——— and ——— (2000), "The Incumbent's Curse? Incumbency, Size, and Radical Product Innovation," *Journal of Marketing*, 64 (July), 1–17.

Christensen, Clayton M. (1992a), "Exploring the Limits of the Technology S-Curve, Part I: Component Technologies," *Production and Operations Management*, 1 (4), 334–57.

——— (1992b), “Exploring the Limits of the Technology S-Curve, Part II: Architectural Technologies,” *Production and Operations Management*, 1 (4), 358–66.

——— (1993), “The Rigid Disk-Drive Industry: A History of Commercial and Technological Turbulence,” *Business History Review*, 67 (4), 531–88.

——— (1997), *The Innovator’s Dilemma: When New Technologies Cause Great Firms to Fail*. Boston: Harvard Business School Press.

——— (1999), *Innovation and the General Manager*. Boston: Irwin/McGraw-Hill.

Constant, Edward W. (1980), *The Origins of Turbojet Revolution*. Baltimore: Johns Hopkins University Press.

Danaher Peter J., Bruce G.S. Hardie, and William P. Putsis Jr. (2001), “Marketing-Mix Variables and the Diffusion of Successive Generations of a Technological Innovation,” *Journal of Marketing Research*, 38 (November), 501–514.

Fernald John G. and Shanthi Ramnath (2004), “The Acceleration in the U.S. Total Factor Productivity After 1995: The Role of Information Technology,” *Economic Perspectives*, 28 (1), 52.

Foster, Richard (1986), *Innovation: The Attacker's Advantage*. New York: Summit Books.

Freeman, C. (1974), *The Economics of Industrial Innovation*. London: Printer.

Garcia, Rosanna and R. Calantone (2002), “A Critical Look at Technological Innovation Typology and Innovativeness Terminology: A Literature Review,” *Journal of Product Innovation Management*, 19 (2), 10–32.

Ghemawat, Pankaj (1991), “Market Incumbency and Technological Inertia,” *Marketing Science*, 10 (2), 161–71.

Golder, Peter N. (2000), “Historical Method in Marketing Research with New Evidence on Long-Term Market Share Stability,” *Journal of Marketing Research*, 37 (May), 156–72.

——— and Gerard J. Tellis (1993), “Pioneer Advantage: Marketing Logic or Marketing Legend,” *Journal of Marketing Research*, 30 (May), 158–70.

——— and ——— (1997), “Will It Ever Fly? Modeling the Takeoff of New Consumer Durables,” *Marketing Science*, 16 (3), 256–70.

——— and ——— (2004), “Going, Going, Gone: Cascades, Diffusion, and Turning Points of the Product Life Cycle,” *Marketing Science*, 23 (2), 180–91.

Hulten, Charles R. (2000), “Total Factor Productivity: A Short Biography,” NBER Working Paper No. 7471. Cambridge, MA: National Bureau of Economic Research.

James, Gareth and Ashish Sood (2005), “Performing Hypothesis Tests on the Shape of Functional Data,” *Journal of Computational Statistics and Data Analysis*, forthcoming.

Kayal, Aymen (1999), “Measuring the Pace of Technological Progress: Implications for Technological Forecasting,” *Technological Forecasting and Social Change*, 60 (3), 237–45.

Klepper, Steven (1996), “Entry, Exit, Growth, and Innovation over the Product Life Cycle,” *American Economic Review*, 86 (3), 562–83.

Lieberman, Marvin B. and David B. Montgomery (1988), “1st-Mover Advantages,” *Strategic Management Journal*, 9 (Summer), 41–58.

Moore, G.A. (1991), *Crossing the Chasm: Marketing and Selling High-Tech Goods to Mainstream Customers*. New York: HarperBusiness.

Pae, Jae H. and Donald R. Lehmann (2003), “Multigeneration Innovation Diffusion: The Impact of Intergeneration Time,” *Journal of the Academy of Marketing Science*, 31 (1), 36–45.

Qualls, William, R.W. Olshavsky, and R.E. Michaels (1981), “Shortening of the PLC: An Empirical Test,” *Journal of Marketing*, 45 (October), 76–80.

Reinganum, Jennifer F. (1985), “Innovation and Industry Evolution,” *Quarterly Journal of Economics*, 100 (1), 81–99.

Robertson, Thomas S., Jehoshue Eliashberg, and Talia Rymon (1995), “New Product Announcement Signals and Incumbent Reactions,” *Journal of Marketing*, 59 (July), 1–15.

Sahal, Devendra (1981), “Alternative Conceptions of Technology,” *Research Policy*, 10 (1), 2–24.

Scherer, F.M. (1984), *Innovation and Growth: Schumpeterian Perspectives*. Cambridge, MA: MIT Press.

Schilling, M.A. (1998), “Technological Lockout: An Integrative Model of the Economic and Strategic Forces Driving Technology Success and Failure,” *Academy of Management Review*, 23 (2), 267–84.

Schumpeter, Joseph A. (1939), *Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process*. New York: McGraw-Hill.

Shapiro, Carl and H.L. Varian (1999), “The Art of Standard Wars,” *California Management Review*, 41 (2), 8–32.

Sood, Ashish and Gerard J. Tellis (2005), “The S-Curve of Technological Evolution: Strategic Law or Self-Fulfilling Prophecy,” Working Paper No. 04-116. Boston: Marketing Science Institute.

Sorescu, Alina, Rajesh K. Chandy, and Jaideep Prabhu (2003), “Sources and Consequences of Radical Innovation: Insights from Pharmaceuticals,” *Journal of Marketing*, 67 (October), 82–102.

Tellis, Gerard J. (1988), “The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales,” *Journal of Marketing Research*, 25 (November), 331–41.

——— and P.N. Golder (1996), “First to Market, First to Fail? Real Causes of Enduring Market Leadership,” *Sloan Management Review*, 37 (2), 65–75.

———, Stefan Stremersch, and Eden Yin (2003), “The International Takeoff of New Products: Economics, Culture, and Country Innovativeness,” *Marketing Science*, 22 (2), 161–87.

Tushman, Michael L. and P. Anderson (1986), “Technological Discontinuities and Organizational Environments,” *Administrative Science Quarterly*, 31 (3), 439–65.

Utterback, James M. (1974), “Mastering the Dynamics of Innovation,” *Science, New Series*, 183 (4125), 620–26.

——— (1994a), *Mastering the Dynamics of Innovation*. Boston: Harvard Business School Press.

——— (1994b), “Radical Innovation and Corporate Regeneration,” *Research Technology Management*, 37 (4), 10.