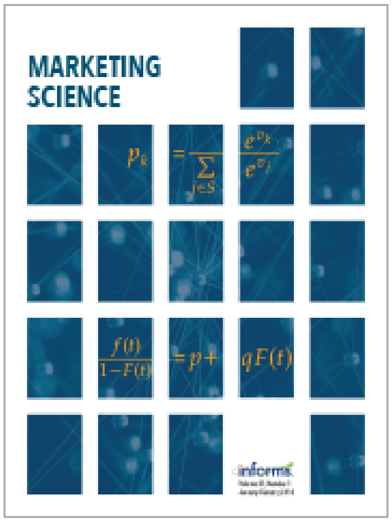

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Demystifying Disruption: A New Model for Understanding and Predicting Disruptive Technologies

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The failure of firms in the face of technological change has been a topic of intense research and debate, spawning the theory (among others) of disruptive technologies. However, the theory suffers from circular definitions, inadequate empirical evidence, and lack of a predictive model. We develop a new schema to address these limitations. The schema generates seven hypotheses and a testable model relating to platform technologies. We test this model and hypotheses with data on 36 technologies from seven markets. Contrary to extant theory, technologies that adopt a lower attack ("potentially disruptive technologies") (1) are introduced as frequently by incumbents as by entrants, (2) are not cheaper than older technologies, and (3) rarely disrupt firms; and (4) both entrants and lower attacks significantly reduce the hazard of disruption. Moreover, technology disruption is not permanent because of multiple crossings in technology performance and numerous rival technologies coexisting without one disrupting the other. The proposed predictive model of disruption shows good out-of-sample predictive accuracy. We discuss the implications of these findings.

Key words: technology disruption; firm disruption; demand disruption; correlated hazards; prediction of disruption
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Introduction

Technological change is critically important to firms for several reasons. First, it has the potential to obsolete assets, labor, and intellectual capital of incumbents in the market. For example, electronic commerce has obsoleted many of the old business processes in the banking industry. Second, it can create entirely new markets, with new products, new customers, and exploding demand. For example, MP3 technology facilitated the iPod revolution, with massive demand for products, services, and accessories. Third, technological evolution enables firms to target new segments within a market with improved products. For example, improvements in LCD monitors enabled firms to target the segment of consumers with mobile computing needs. Fourth, and most importantly, incumbents often misinterpret the potential impact of the new technology, and this error causes their demise. For example, microcomputers killed off manufacturers of minicomputers.

The failure of firms in the face of technological change has been a topic of intense research and debate in the strategy literature (e.g., Schumpeter 1934, Freeman 1974, Henderson and Clark 1990, Henderson 1993, Cohen and Levinthal 1990). An early attempt to understand this phenomenon was by Foster (1986). He posited the theory of S-curves, which suggested that technologies evolve along successive S-curves; incumbents fail if they miss to switch to a new technology that passes the incumbent's technology in performance. Tushman and Anderson (1986) refined this theory by distinguishing between competence-enhancing and competence-destroying technological changes. They argued that failure occurred only when the new technology destroyed, rather than enhanced, the expertise of the incumbents. Other researchers built on the theory of punctuated equilibrium (Gould and Eldredge 1977) to propose a demand-side explanation for the phenomenon of disruption (Levinthal 1998, Adner 2002, Adner and Zemsky 2005, Mokyr 1990). They suggested that disruption occurs when a new technology that starts in one domain moves to a new domain with potentially higher demand and additional resources. Christensen (1997) proposed the theory of disruptive innovations. It posited that disruption occurred when an initially inferior technology introduced by a new entrant improved to meet the needs of the mass market (Bower and Christensen 1995).

Of the three theories, Christensen's (1997) theory has won the most attention and widest acclaim from both managers and researchers (Henderson 2006, Gilbert 2003, King and Tucci 2002, Adner 2002, Adner and Zemsky 2005, Grove 1998, Gilbert and Bower 2002). Books on disruption have sold hundreds of thousands of copies, readings on disruption are among the most used in MBA classes, and a Google search suggests that the term "disruptive innovation" is the most popular innovation term.

However, researchers have pointed to at least four weaknesses in the theory. First, researchers claim that the central thesis about a disruptive technology causing disruption appears to be tautological (Cohan 2000, Danneels 2004, Markides 2006). Christensen's writings alone suggest that the term could take on different meanings (Danneels 2004, Tellis 2006). The major issue is the use of the same term to describe both the causative agent (disruptive technology) and the effect (disruption). For example, Kostoff et al. (2004, p. 142) state, "disruptive technologies...can be revealed as being disruptive only in hindsight."

Second, the theory is ambiguous as to which domain of disruption the theory applies (Danneels 2004, Markides 2006). We identify three domains of disruption: technology domain (performance evolution), firm domain (competitive survival), and demand domain (market acceptance).

Third, many authors point to a scarcity of empirical evidence to validate the generalizability of the claims (Govindarajan and Kopalle 2006, Danneels 2004, Tellis 2006, Utterback and Acee 2005). Danneels (2004, p. 251) calls for new research on a "comprehensive list of technologies" to examine "the mechanisms and effects" of disruptive technologies on firms and markets. Cohan (2000) suggests that the results on the effects of disruptive technologies might not hold as well if the sample were drawn randomly.

Fourth, the theory lacks predictive ability (Tellis 2006, Kostoff et al. 2004). Barney (1997) urges development of a predictive model to rule out cherry-picking or luck as an alternative explanation of why some technologies are more disruptive than others.

To summarize, we seek answers to the following specific questions with the goal of infusing this theory with validity: (1) What is a disruption? (2) Who introduces a disruptive technology, and who survives disruption? (3) What are the causes of disruption? (4) When does disruption occur, and how can we predict it?

We make three contributions to prior literature in this paper. First, we develop a new schema that identifies key variables, defines key terms, and allows us to derive seven testable hypotheses. Second, we conduct an empirical test of the hypotheses by sampling *all* platform technologies in seven markets, rather than selectively sampling those that may or may not fit the hypotheses. Third, we develop a model that can predict the hazard of disruption of a new technology. The next section presents the method and results of the study. The last section discusses the findings, limitations, and implications of the study.

Theory

This section presents a new schema and develops hypotheses about the impact of technological change on markets.

Schema

Our new schema defines constructs, expands the set of drivers of disruption, and provides the foundation for hypotheses and a predictive model. Our definitions cover types of technologies, types of technological attack, dynamics of competition, and domains of disruption. To avoid circularity, we define concepts in terms of technological characteristics rather than effects that lead to premises true by definition, e.g., "disruptive," "sustaining," or "revolutionary."

Definition of Technologies. What is a technology? Following Sood and Tellis (2005), we define a technology as a platform based on a unique scientific principle, on which firms manufacture products to serve customers' needs in a particular market. For example, in the lighting market, incandescence, fluorescence, or light-emitting diodes (LED) are three entirely independent scientific principles, each of which provides a platform on which firms produce products to serve consumers' need for light. Thus, they constitute three independent technologies for lighting. Innovations *within* each technology (platform or scientific principle) could cause it to improve in performance over time. We classify these innovations as belonging either to component innovations (in parts or materials) or design innovations (in layout or links) (see Table 1). However, as long as the scientific principle remains the same, we assign all these innovations to the same technology. For example, large and compact fluorescent bulbs exemplify various design innovations within the fluorescence technology. Carbide and tungsten filaments exemplify component innovations within incandescence technology. The improvement in performance of a platform technology over time is due to these design and component innovations.

Definition of Technological Attack. How does a new technology attack the dominant technology? To answer this question, we first identify an objective measure of the performance of a technology, which is important to the mainstream segment and forms the primary dimension of competition in the market. We define a market as a set of consumers whose similar needs are being served by a set of competing technologies, firms, and brands. For example, storage

Table 1 Definition of Technologies

Our schema		Christensen's (1997) schema		
Our terms	Our basis	Christensen's terms[a]	Christensen basis	Examples
Platform	Unique scientific principle	Disruptive[b]	New technology inferior on primary but superior on secondary dimension	Digital vs. analog cameras
		Sustaining breakthrough	New technology superior on primary	Fiber optics vs. analog communications
Design	Linkages or layout within same scientific principle	Disruptive[b]	(disruptive as defined above)	5.25" vs. 3.5" floppy drives
		Sustaining incremental	Small improvement in current technology on primary dimension	Compact vs. regular fluorescent
Component	Materials or parts within same scientific principle	Disruptive[b]	(disruptive as defined above)	Thin-film vs. ferrite heads
		Sustaining incremental	Small improvement in current technology on primary dimension	DVD vs. CD

[a]Christensen's (1997) terms will never perfectly match with ours because ours are defined on characteristics of technology, whereas his seem to be defined on effects happening to firms.
[b]Christensen uses the term disruptive for all three levels: platform, design, and component.

capacity is an important primary dimension of competition in the market for computer storage technologies. All other attributes of technologies would be secondary dimensions of competition. We then define two types of attacks: lower and upper attacks. A *lower attack* occurs when, at the time of its entry, a new technology performs worse than the dominant technology on the primary dimension of performance. An *upper attack* occurs when, at the time of its entry, a new technology performs better than the dominant technology on the primary dimension of performance.

Dynamics of Competition. What are the dynamics of competition between the new technology and dominant technology? For simplicity of exposition, following Christensen (1997), we assume the market has two technologies (dominant and new), two dimensions (primary and secondary), and two segments: a mainstream and a niche. (The empirical analysis allows for multiple technologies and dimensions.) Figure 1 illustrates the dynamics of competition between the dominant technology and the new technology on the primary and secondary dimensions in one market. Both segments have similar needs but differ in their preferences: the mainstream segment favors the primary dimension, whereas the niche segment favors the secondary dimension, as shown by their locations in Figure 1. However, both dimensions are both objective and vector—i.e., more is better. At time t_1, the dominant technology is strong on the primary dimension but weak on the secondary dimension, whereas the reverse holds for the new technology. Given this preference distribution, at time t_1, the mainstream segment prefers the dominant technology, whereas the niche segment prefers the new technology.

Again, following Christensen (1997), we assume the segments have fixed preferences but technologies improve over time, as shown by the arrows in Figure 1. Both technologies improve on the primary dimension over time. At time t_2, the dominant technology exceeds the needs of the mainstream segment on this dimension. However, the new technology improves sufficiently on the primary dimension so as to appeal to the mainstream segment, because it now meets its needs on both the primary and secondary dimensions. Thus, at time t_2, demand of both segments shifts from the dominant technology to the new technology. Christensen refers to this event as disruption. The niche segment plays the role of providing a demand for the new technology while it improves

Figure 1 Theory of Disruptive Innovations

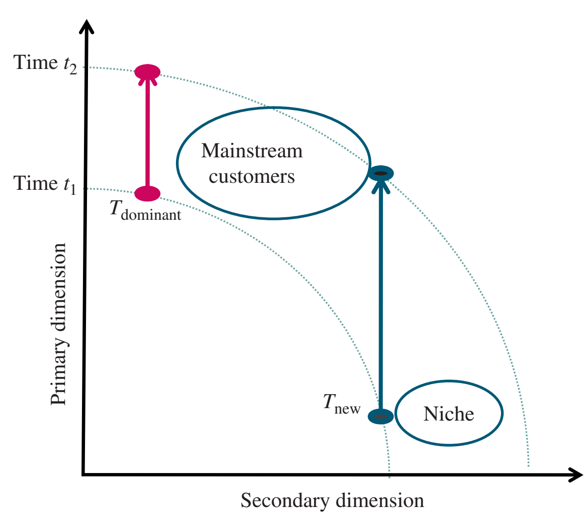


Table 2 Classification of Studies in Literature Based on Proposed Schema

	Performance (entry) of new technology		
Domain of disruption	Lower attack	Upper attack	Both attacks
Firm (competitive survival)	Disruptive innovations (Christensen 1997), potentially disruptive innovations (Raffi and Kampas 2002), radical innovation (Utterback and Acee 2005), low-end disruptions (Govindarajan and Kopalle 2006)	Sustaining breakthrough innovations (Christensen 2003), technological discontinuity competence enhancing/destroying innovations (Tushman and Anderson 1986)	Low-end and high-end disruptions (Govindarajan and Kopalle 2006)
Demand (market acceptance)	Disruptive technologies (Adner 2002), new technology (Levinthal 1998, Utterback and Acee 2005)	Down-market progression (Utterback and Acee 2005), new technology (Levinthal 1998)	Attack from below and down-market progression (Utterback and Acee 2005)
Technology (performance evolution)	New technology (Levinthal 1998), radical innovation (Utterback 1994), theory of S-curves (Foster 1986), discontinuous innovation (Dosi 1982)		Platform technologies (Sood and Tellis 2005)
All domains			This paper

in performance on the primary dimension and meets the needs of the mainstream segment. Note that for this analysis, it is sufficient to assume segments with fixed preferences, as does Christensen (1997), so long as technologies improve over time.

Domains of Disruption. We identify three domains of disruption, in each of which disruption could occur independently: technology, firm, and demand. *Technology disruption* occurs when the new technology crosses the performance of the dominant technology on the primary dimension of performance. We use the term dominant technology to refer to the technology with the best performance on the primary dimension at the time a new technology enters the market. *Firm disruption* occurs when the market share of a firm whose products use a new technology exceeds the market share of the largest firm whose products use the highest-share technology. We use the term *highest-share technology* to refer to the technology with the highest market share at the time a new technology enters the market. Note that by this definition, either an entrant or an incumbent can disrupt the largest firm whose products use the dominant technology.[1] *Demand disruption* occurs when the total share of products in the market based on a new technology exceeds the share of products based on the dominant technology. We use the term *market disruption* to refer inclusively to all three domains of disruption.

Summary. These constructs for technology, direction of attack, and domains of disruption constitute our new schema. The schema allows us to organize terms used in the prior literature (see Table 2). In particular, Christensen's (1997) term *disruptive technology* would be equivalent to a new technology adopting a lower attack that is also superior to the dominant technology on a secondary dimension (see Tables 1 and 2). The term used by Christensen et al. (2004), *sustaining breakthrough*, would be equivalent to a new technology adopting an upper attack. Note that Christensen's (1997) term *sustaining incremental* seems equivalent to design and component innovations that improve a *current* technology's performance along the primary dimension of performance. Design innovations are also what Henderson and Clark (1990) call architectural innovations. From Table 2, note also that relative to the literature, this is the only study that covers all three domains of disruption and both types of attacks in one empirical analysis.

Hypotheses

With the help of the above schema, we formulate seven testable hypotheses—three on technological entry and four on the hazard of disruption.

Technological Entry. Who introduces technologies that use a lower attack (potentially disruptive)? Proponents of the theory of disruptive innovations assert that "the firms that led the industry in every instance of developing and adopting disruptive technologies were entrants to the industry, not its incumbent leaders" (Christensen 1997, p. 24). Why does this occur? According to the theory, entrants are willing to experiment with new technologies targeted toward niche segments (Christensen 1997). These firms are also not deterred by the lower profit margins and smaller sales volumes from niche segments relative to the mainstream segment (Christensen and Rosenbloom 1995).

[1] However, if the firm with the highest market share is farsighted and *itself* builds the highest market share in this new technology, then no firm disruption would occur.

On the other hand, incumbents' firms get most of their revenues and profits from the existing technology marketed to the mainstream segment (Raffi and Kampas 2002). So they devote all their efforts and energies to perfect their current technology marketed to the mainstream segment. The established routines within the incumbent firms do not provide sufficient incentives to develop these new skills and knowledge associated with the new technology. These arguments suggest the following hypothesis.

Hypothesis 1 (H1). *Technologies using a lower attack (potentially disruptive) come primarily from entrants.*

Who introduces technologies that use an upper attack (sustaining breakthrough)? Christensen et al. (2004) suggest that the technologies adopting an upper attack (sustaining breakthrough) are introduced mainly by incumbents. Incumbents focus on satisfying their current demanding customers with both simple incremental improvements and breakthrough jumps up the current trajectory of performance improvement. Incumbents have more resources, higher profits, and more at stake than new entrants. Incumbents can readily deploy sustaining breakthrough innovations because they may not require substantial changes to their overall value-creating system (business model). They can use the same manufacturing and distribution process if the new technology fits their R&D capabilities and delivers benefits that are consistent with the brand promise. These arguments lead to the following hypothesis.

Hypothesis 2 (H2). *Technologies using an upper attack (sustaining breakthrough) come primarily from incumbents.*

How do technologies using a lower attack differ from the dominant technology? The theory of disruptive innovations suggests that firms target the less-demanding niche customers with lower-performing technologies. The technologies using a lower attack are "typically simpler, cheaper, easier, and more convenient than dominant technologies" (Christensen 1997, p. 267). Even though these technologies may improve over time, at entry these technologies are crude but more affordable than dominant technologies. Underlying all these arguments is Christensen's (1997) assumption that performance and cost are correlated, and a lower attack also makes the technology less expensive. Moreover, new technologies are initially less feature-rich and focus on primarily providing the basic consumer benefit. By targeting only the small niche segments, firms also reduce costs by limiting the product range. These arguments suggest the following hypothesis.

Hypothesis 3 (H3). *Technologies using a lower attack (potentially disruptive) are priced lower than dominant technologies at entry.*

Hazard of Disruption. Which type of firm is more likely to disrupt? The theory suggests that incumbents are unlikely to disrupt because they focus predominantly on their current customers for several reasons. First, incumbents get their revenues primarily from their current mainstream segment, whereas entrants target the less profitable segments and the less demanding customers (Christensen et al. 2004). Second, incumbents do not possess appropriate resources and competencies to compete with entrants, who introduce a new value proposition and serve demand on a new secondary dimension (see Figure 1). For example, incumbents making CRT monitors could not compete effectively with entrants making LCD monitors on the secondary dimension of compactness even though they made efforts to reduce the size of old CRT monitors by introducing flat-screen CRT monitors. Third, incumbents often do not appreciate the real threat of a new technology (Christensen and Raynor 2003, Henderson 2006, Gilbert 2003). For example, incumbents making CRT monitors discounted the potential increase in resolution of LCD monitors. These arguments suggest the following hypothesis.

Hypothesis 4 (H4). *The hazard of disruption is higher from an entrant than from an incumbent.*

What type of technological attack is more likely to cause firm or demand disruption? The theory suggests that a lower attack is deceptively more dangerous than an upper attack because firms that focus on the dominant technology often do not perceive the new technology as a threat until it is too late. The lower performance lulls incumbents into thinking that these new technologies will not appeal to the mainstream segment, which values the high performance of the dominant technology. Over time, the improvement of the dominant technology on the primary dimension exceeds the needs of the mainstream segment creating conditions of "performance oversupply" (Christensen 1997, p. 211). Disruption occurs when the improvement of the new technology increases its appeal to the mainstream segment. When this change occurs, Utterback (1994) asserts that incumbents lack the required set of capabilities to compete with entrants regardless of how well they are positioned to serve the mainstream segment. These arguments suggest the following hypothesis.

Hypothesis 5 (H5). *The hazard of firm or demand disruption is higher if a new technology uses a lower attack.*

How does firm size affect disruption? Extant theories relate strategies on technology to size of firms. Small firms lack the weaknesses that often beset large firms like technological inertia (Ghemawat 1991), complacency (Robertson et al. 1995), arrogance

(Lieberman and Montgomery 1988), and reluctance to cannibalize existing products (Chandy and Tellis 1998). Small firms are more research productive than large firms, especially in highly innovative industries requiring skilled labor (Acs and Audretsch 1988). During the early life of technologies, these capabilities are more important than the advantages of scale and scope of large firms (Pavitt and Wald 1971, Acs and Audretsch 1988). These arguments suggest the following hypothesis.

Hypothesis 6A (H6A). *The hazard of disruption is higher if a new technology is introduced by a small firm.*

However, some recent research suggests that incumbents may be better positioned to take advantage of new technologies because of superior financial and managerial resources (Hill and Rothaermel 2003, Rothaermel 2001), R&D capability (Rothaermel and Hill 2005), and complementary assets (Tripsas 1997). Chandy and Tellis (2000) find that in recent decades, radical innovations come mainly from large firms. These arguments lead to the following rival hypothesis.

Hypothesis 6B (H6B). *The hazard of disruption is lower if a new technology is introduced by a small firm.*

Is the hazard of disruption higher if a technology is priced lower than the dominant technology at entry? The theory of disruptive innovations suggests that products based on technologies that adopt a lower attack are initially priced lower and are of a cruder design than the dominant technology. Characteristics of such technologies make them attractive to niche customers but not the mainstream segment. For example, lower costs reduce the perceived risk, whereas crude designs reduce the perceived complexity of the new technology (Rogers 2003). Moreover, such technologies target new consumers or those in low-end markets (Christensen 1997) avoiding direct competition with the dominant technology. Reduced competition may help firms to maintain lower costs by reducing marketing expenditures and to transfer these advantages to customers via lower prices. These arguments suggest the following hypothesis.

Hypothesis 7 (H7). *The hazard of disruption is higher if a new technology is lower priced than the dominant technology at entry.*

Control Variables. We use two control variables: change in performance of new technology and order of entry for two reasons. First, extant theory suggests that higher performance of the new technology increases its appeal to the mainstream segment. This improved performance of the new technology increases the hazard of disruption of the dominant technology. So we use change in performance of the new technology as a control variable. Second, prior literature suggests that technological change increases with time (Sood and Tellis 2005). New technologies may find it easier to disrupt older technologies than other technologies. Hence, we also include the order of entry of technologies in a market as an additional control variable.

In summary, our new schema leads to seven distinct, falsifiable hypotheses about disruption and two control variables, which we now proceed to test.

Method

We test these hypotheses using data from seven markets. We collected these data using the historical method (Golder and Tellis 1997, Sood and Tellis 2009). Below we detail the sample selection and sources for collecting the data. Online Appendix A in the electronic companion describes the procedure. An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

Sample Selection

We used three criteria in selecting markets. First, we need markets with a minimum of two technologies per market to observe the phenomenon of disruption. Second, we need a mix of relatively young and relatively old markets. Third, we need some overlap with past research to enable comparison. On the basis of these criteria, we chose seven markets: electrical lighting, data transfer, computer memory, computer printers, display monitors, music recording, and analgesics markets. Note that the first two are utilities, the next four are consumer electronics, and the last is pharmaceutical. Thus, the sample crosses a broad spectrum of technologies, markets, and products with technologies that vary in age from a few years to more than a century. A unique feature of our sample is that we selected all platform technologies that were ever commercialized within each market. Some of these technologies did not achieve much of a presence in the mainstream segment and remained limited to a niche. In all, we identify 36 technologies: nine in computer memory, six in display monitors, five each in computer printers, electrical lighting, and music recording, and three each in analgesics and data transfer. Online Appendix B in the electronic companion describes these 36 technologies briefly. In each of these technologies, improvements occur because of design and component innovations. Because the latter number in the hundreds, for ease of analysis and exposition, we track disruptions only in platform technologies and not in design and component innovations. Thus, our results apply to platform technologies.

Sources

The primary sources of our data are technical journals, industry publications, press releases, time lines of major firms, white papers published by R&D organizations, annual reports of industry associations, and records in museums that profiled innovations and the development of markets. We collect information on technologies available in each market, the performance of these technologies at various stages of technological evolution, the supplier of these technologies, and the market success of each technology. We also collect information on technological performance on both primary and secondary dimensions.

Model

We develop a correlated hazards model based on the method developed by Lillard (1993). The model may be characterized as follows. A new technology is introduced in an existing market. From the point of introduction, the new technology threatens to disrupt both old technologies and incumbent firms using old technologies in the market. The hazards of both technology and firm disruption are influenced by a number of time-related factors, including performance of the technology and age of the market, and by a set of exogenous covariates like relative price, order of entry, direction of attack, and source of new technology. We limit the analyses to only firm and technology disruption because demand disruption is conflated with firm disruption in our sample; i.e., demand disruption generally occurs with firm disruption or always follows it within a short time. However, the same model can be extended to investigate hazard of demand disruption for other data using the same approach. We account for the correlation between the two hazards to avoid inconsistent standard errors (Lillard 1993).

The model is essentially a proportional hazard, with covariates shifting the baseline hazard (Allison 1995). In particular, we model the log hazard of technology and firm disruption, respectively,

$$\begin{aligned}\ln \mathrm{h}_{it}^{T} &= \beta_0 + \boldsymbol{\beta}_1'\mathbf{T}_{1t} + \beta_2 E_i + \beta_3 S_i + \beta_4 C_i \\ &\quad + \beta_5 O_i + \beta_6 P_{it} + \lambda_{it}^{T}, \qquad (1)\end{aligned}$$

$$\begin{aligned}\ln \mathrm{h}_{it}^{F} &= \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{T}_{2t} + \alpha_2 E_i + \alpha_3 L_i + \alpha_4 S_i \\ &\quad + \alpha_5 C_i + \alpha_6 O_i + \alpha_7 P_{it} + \lambda_{it}^{F}, \qquad (2)\end{aligned}$$

where

- E: dummy variable for incumbency, which is 1 if firm is an entrant at the time of entry of new technology and 0 otherwise;
- L: dummy variable for attack, which is 1 if the new technology employs a lower attack at the time of entry and 0 otherwise;
- S: dummy variable for firm size, which is 1 if firm introducing the new technology is small at the time of entry of new technology and 0 otherwise;
- C: dummy variable for relative price, which is 1 if the new technology is priced lower than the dominant technology at the time of entry and 0 otherwise;
- O: order of entry of the new technology; and
- P: percentage change in performance of the new technology over the prior year.

The subscripts i and t refer to technology and time, respectively. λ^T and λ^F are error terms assumed to be normally distributed; $\lambda^T \sim \mathrm{N}(0, \sigma_T^2)$ and $\lambda^F \sim \mathrm{N}(0, \sigma_F^2)$. Further, we allow the two error terms to be correlated and assume joint normality such that

$$\begin{pmatrix} \lambda_i^T \\ \lambda_i^F \end{pmatrix} \sim \mathrm{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_T^2 & \rho_{TF}\sigma_T\sigma_F \\ \rho_{TF}\sigma_T\sigma_F & \sigma_F^2 \end{pmatrix}\right). \qquad (3)$$

Note that we do not include the direction of attack in Equation (1) for the hazard of technology disruption to avoid circularity. The terms $\boldsymbol{\beta}_1'\mathbf{T}_{1t}$ and $\boldsymbol{\alpha}_1'\mathbf{T}_{2t}$ represent the dependence of respective hazards on time via piecewise-linear splines, as follows. We denote the time at which the dominant technology or firm becomes at risk of disruption by t_0 and subdivide the duration $t - t_0$ into $N_i + 1$ discrete periods that sum to the calendar time, but which allow the slope coefficients to differ within ranges of time separated by the N_i nodes. The spline variable for the kth period between nodes μ_{k-1} and μ_k is given by $T_k(t) = \max[0, \min(t - \mu_{k-1}, \mu_k - \mu_{k-1})]$. So the two baseline hazards can be written as

$$\boldsymbol{\beta}_1'\mathbf{T}_{1t} = \sum_{k=1}^{N_1+1} \beta_{1k} T_{1kt} \quad \text{and} \quad \boldsymbol{\alpha}_1'\mathbf{T}_{2t} = \sum_{k=1}^{N_2+1} \alpha_{1k} T_{2kt}. \qquad (4)$$

Let $\mathscr{L}^T(\lambda^T)$ and $\mathscr{L}^F(\lambda^F)$ represent the conditional likelihood functions of the time to next technology and firm disruption, respectively. Then we can write the joint marginal likelihood as

$$\int_{\lambda_T}\int_{\lambda_F} \prod \mathscr{L}^T(\lambda^T) \prod \mathscr{L}^F(\lambda^F) f(\lambda^T, \lambda^F)\, d\lambda^T\, d\lambda^F. \qquad (5)$$

Here, $f(\lambda^T, \lambda^F)$ is the joint distribution of the unobserved heterogeneity components specified in Equation (3). Thus, conditional on λ, technology disruption and firm disruption are independent of each other and the conditional joint likelihood can be obtained by simply multiplying the individual likelihoods. The marginal joint likelihood is obtained by integrating out the heterogeneity term (see Online Appendix C in the electronic companion for details).

We estimate Equations (1) and (2) jointly as a system of equations with technology-specific errors correlated across the two equations with aML, a multiprocess multilevel modeling software (Lillard and Panis 2003). The complete model is estimated using full-information maximum likelihood. Where a closed-form solution does not exist, numerical approximation can be used (Schweidel et al. 2008). This software employs the Gauss-Hermite quadrature to approximate the normal integrals.

Results

We identify the primary dimension of competition among competing technologies for each market and an objective measure of this dimension (see Table 3(a)). The data on the markets range in time from 53 years for the computer printers market to 127 years for the external lighting market. In all, we have 1,942 technology-years of data for testing the seven hypotheses. Across the sample, only 55% of all technologies cause disruption. Of these, 33% cause only technology disruption and 22% cause both technology and firm disruption. The remaining 45% of all technologies cause no disruption at all.

We first present an example of technology evolution and market disruption in the lighting market. We then present the results of descriptive analysis, estimates of the hazard model, and out-of-sample predictions of the hazard model. Finally, we present results on various patterns of disruption, including the emergence of new secondary dimensions and the robustness of results.

Table 3 Patterns of Entry

(a) Dimensions of competition

Market	Primary dimension	Measure
Electrical lighting	Lighting efficacy	Lumens per watt
Data transfer	Transfer speed	Bits per second
Computer memory	Storage capacity	Megabytes per square inch
Computer printers	Print resolution	Dots per square inch
Display monitors	Screen resolution	Pixels per square inch
Music recording	Storage capacity	Megabytes per square inch
Analgesics	Efficacy in pain reduction	Number needed to treat (NTT)

(b) Frequency of new technologies by attack, source, and price

	Lower attack (%)	Upper attack (%)
Source		
Entrant	47	58
Incumbent	53	42
Total	100	100
Price relative to dominant technology at entry		
High price	88	89
Low price	12	11
Total	100	100

Example of Evolution of Technologies in the Lighting Market

We describe the technological competition and disruption in the external lighting market. The market exhibits a total of five platform technologies between 1879 and 2000 (see Figure 2(a)). Only the first two technologies were introduced by small firms—incandescent lighting by Edison Lamp Works in 1879 and arc-discharge lighting by Cooper Hewitt Lamp Co. in 1908. Some years after the entry of the arc-discharge lighting, General Electric acquired Cooper Hewitt Lamp Co. Philips, an incumbent, introduced two of the other three technologies (gas-discharge lighting and microwave electrodeless discharge lighting) in 1908 and 1932, respectively. RCA, an entrant to the market, introduced LED lighting in 1971. Two technologies, arc-discharge lighting and gas-discharge lighting, used upper attacks at the time of entry. The other three technologies used lower attacks. We observe instances of technology disruption in the market that occurred each time the arc-discharge lighting and gas-discharge lighting crossed each other in performance. Figures 2(b) to 2(d) illustrate the evolution of technologies in three other markets.

Analysis of Technological Entry

We observe only the technologies that enter and not those that do not enter a market. Hence, we use a cross-tabular analysis (and not log-linear models) to test the first three hypotheses. Based on the extant theory, H1 predicts that technologies entering via a lower attack come primarily from entrants. However, contrary to the theory and the hypothesis, 47% of lower attacks are from entrants and the remaining 53% are from incumbents (see Table 3(b)). This difference is not significantly different from 0 ($\chi^2 = 0.1$; $p = 0.80$).

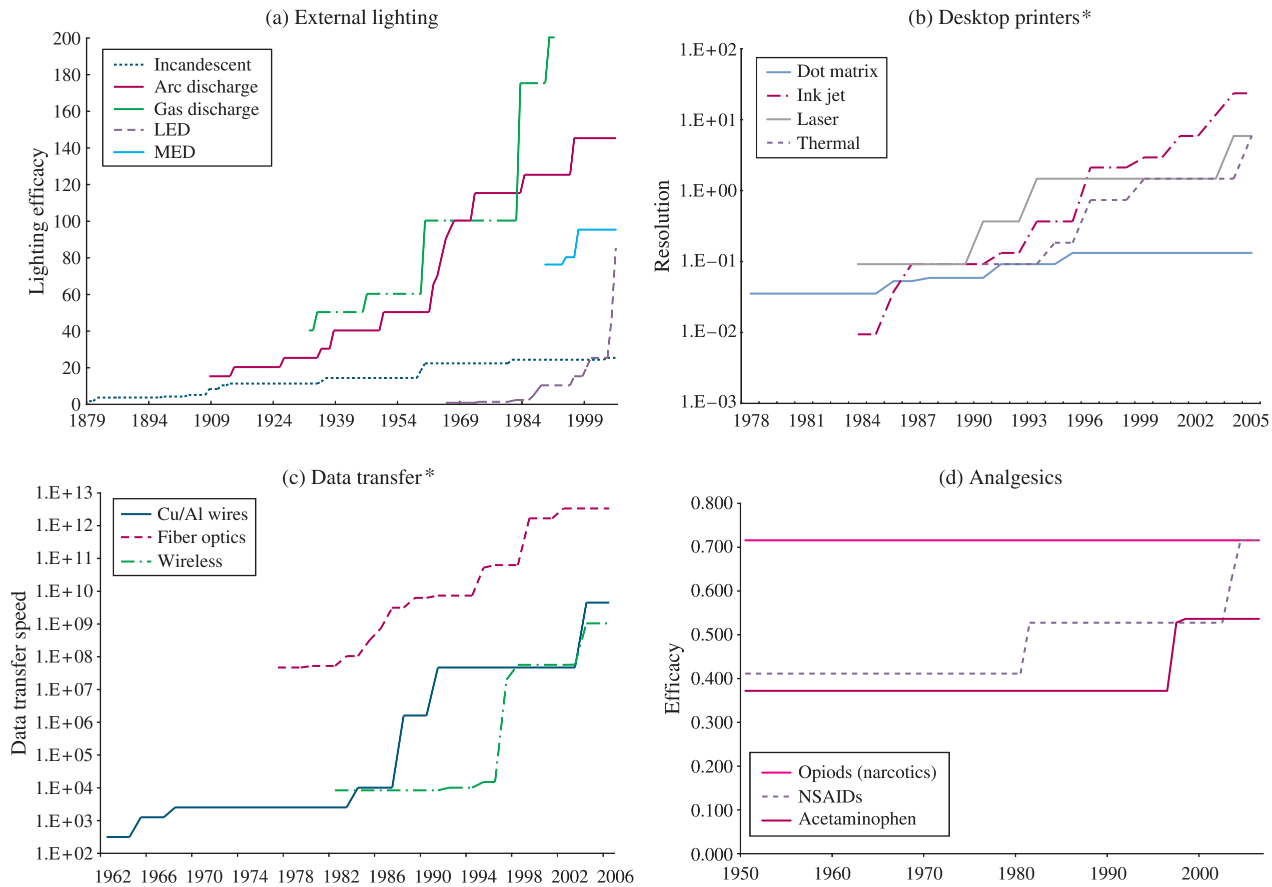
Based on the extant theory, H2 predicts that technologies entering via an upper attack come primarily from incumbents. However, contrary to the theory and the hypothesis, only 42% of upper attacks are from incumbents, whereas the majority (58%) are from entrants (see Table 3(b)). The difference is not significantly different from 0 ($\chi^2 = 0.7$; $p = 0.39$).

H3 predicts that technologies entering via a lower attack are cheaper than dominant technologies at the time of entry. However, contrary to the theory and the hypothesis, only 12% of technologies using a lower attack are cheaper than dominant technologies at entry (see Table 3(b)). The rest (88%) are more expensive. The difference is significant ($\chi^2 = 9.9$; $p < 0.001$).

Analysis of Hazard of Disruption

The results of the hazards model are in Table 4. The coefficients of the independent variables in this model test the hypotheses H4 to H7. We estimated the model for technology disruption and firm disruption

Figure 2 Empirical Path of Technological Evolution in Four Markets



*Performance of Y axis is in log scale.

separately (Equations (1) and (2), respectively) and jointly under the assumption of correlation (Equation (3)). Table 4 shows that ignoring unobserved heterogeneity results in biased and inconsistent estimates. Unobserved heterogeneity for both technology disruption (σ_T^2) and firm disruption (σ_F^2) are significant ($t = 2.7$ and $t = 15.2$, respectively). Also, the correlation between the unobserved heterogeneity coefficients (ρ_{TF}) is statistically significant ($t = 5.4$). In addition, the maximized value of log-likelihood is much higher for the correlated hazard model. Thus, we only discuss the results of the joint model.

The baseline hazards are specified as splines. To identify the location of splines, we used the following procedure. First, we estimate the hazard model with only an intercept and a linear log-hazard, i.e., a spline without nodes. This run provides us with estimates of an intercept and a slope. We then specify two or three nodes, spread out roughly evenly over the years, to approximate the occurrences of disruption in our sample. If the slopes of any two adjacent splines are not significantly different, then we combine them into one spline in the interests of parsimony. For the baseline hazard, we select nodes at 5, 15, and 25 years for technology disruption and at 8 and 28 years for firm disruption. The difference in the distribution of nodes reflects the different distributions of disruptions for technologies and firms.

Based on extant theory, H4 predicts that the hazard of disruption is higher from an entrant than from an incumbent. However, contrary to the theory and H4, entrants are less likely than incumbents to disrupt (i.e., the sign of entrant is negative) for both technology disruption ($t = -3$) and firm disruption ($t = -4.6$). Consistent with this result, we find that incumbents more often than entrants cause technology disruption (63% versus 57%) and firm disruption (29% versus 16%) more frequently than entrants. Our result contrasts dramatically with Christensen's claim (1997, p. 24) that "the firms that led the industry in every instance of developing and adopting disruptive technologies were entrants to the industry, not its incumbent leaders."

Based on extant theory, H5 predicts that the hazard of firm disruption is higher if a new technology enters via a lower attack. However, contrary to the theory and H5, a lower attack significantly lowers the hazard of firm disruption ($t = -3$). Because technologies

Table 4 Results of Hazard Model on Disruption

	Uncorrelated hazards		Correlated hazards	
	Technology disruption	Firm disruption	Technology disruption	Firm disruption
Parameter	Est. (t-value)	Est. (t-value)	Est. (t-value)	Est. (t-value)
Technology disruption spline				
Spline: 0–5 years	−0.77 (−5.9)		−0.74 (−26.7)	
Spline: 5–15 years	0.52 (8.9)		0.2 (8)	
Spline: 15–25 years	0.51 (9.0)		−0.34 (−12)	
Spline: >25 years	−0.81 (−6.1)		−1.75 (−2.7)	
Firm disruption spline				
Spline: 0–8 years		0.38 (5.8)		0.47 (5.5)
Spline: 8–28 years		−0.06 (−3.7)		−1.88 (−19.3)
Spline: >28 years		−0.22 (−8.2)		−2.59 (−2.1)
Intercept	0.89 (3.9)	0.89 (0.6)	0.69 (0.3)	0.84 (1.2)
Entrants (E)	−5.72 (−9.2)	−3.22 (−4.4)	−3.64 (−3)	−3.15 (−4.6)
Lower attack (L)	NA	−2.00 (−2.2)	NA	−2.66 (−3)
Small firm (S)	1.7 (1.1)	−1.56 (−1.9)	0.34 (0.7)	−1.57 (−2.5)
Low priced (C)	1.22 (5.1)	.32 (4.8)	0.11 (2.4)	0.41 (6.4)
Order of entry (O)	0.004 (8.3)	1.94 (2.5)	0.27 (2.4)	0.88 (1.7)
Performance improvement (P)	0.92 (9.4)	1.33 (5.0)	1.14 (4.7)	1.52 (6.9)
Heterogeneity	σ_T^2 0.9 (7.8)	σ_F^2 1.70 (2.5)	σ_T^2 2.36 (2.7)	σ_F^2 1.92 (15.2)
Correlation			ρ_{TF} 0.15 (5.4)	
Log-likelihood	−799.9	−7,595.2	−7,954.2	

entering via a lower attack are equivalent to "potentially disruptive technologies," and only six technologies in our sample disrupt using a lower attack, the absolute frequencies suggest that potentially disruptive technologies rarely cause firm disruption.

Based on extant theory, H6A predicts that the hazard of disruption is higher if a new technology is introduced by a small firm, whereas H6B predicts the reverse. We find that firms' size only affects the hazard of firm disruption. Small firms do not increase the hazard of technology disruption ($t = 0.7$) but lower the hazard of firm disruption ($t = -2.5$).

Based on extant theory, H7 predicts that the hazard of disruption is higher if a new technology is priced lower than the dominant technology at entry. The results support the hypothesis. Relative price of the new technology at entry relative to the dominant technology increases the hazard of both technology disruption ($t = 2.4$) and firm disruption ($t = 6.4$).

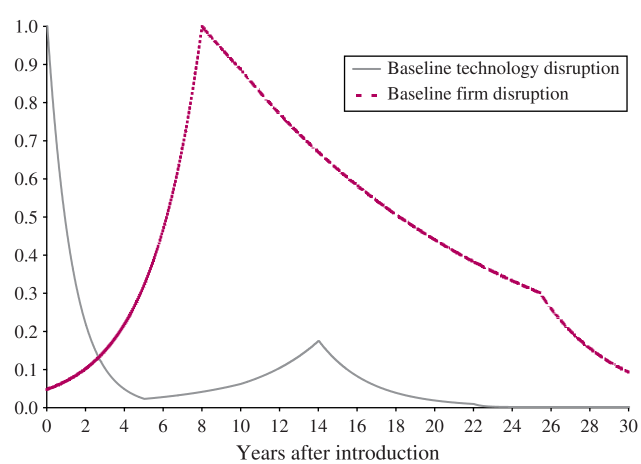
The hazard of technology disruption increases with both an increase in performance ($t = 4.7$) and in the order of entry ($t = 2.4$). However, only an increase in performance affects the hazard of firm disruption ($t = 6.9$), but the order of entry has no impact ($t = 1.7$).

Figure 3 plots the baseline hazard for both technology and firm disruption for a new technology. Both hazards peak early and decline subsequently but follow somewhat different paths. Firm disruption lags technology disruption by approximately 10 years in our sample.

Out-of-Sample Prediction of Disruption

Following Golder and Tellis (1997) and Sood et al. (2009), we use a jackknife approach to ascertain the out-of-sample predictive validity of the hazard model in (Equations (1) and (2)) as follows. We reestimate the model n times, each time excluding one target technology, where n is the number of technologies in our sample. We carry out this analysis by iteratively reestimating this model in aML using a batch mode in DOS. For each of these n runs, we multiply the estimated parameters of the model with the values of the variables of the excluded target technology (in Excel) to predict the hazard of disruption for the excluded target technology. We compare the predicted value

Figure 3 Baseline Hazards: Technology and Firm Disruption



with a cutoff point (as explained under the Predictive Statistics section) to predict a disruption. Based on this approach, we make two types of predictions, one at entry and the other, one year later, updated with the most recent prior-year information. The difference in the two approaches lies in the difference in the information used to estimate the models, either at entry or when including each additional year of the subsequent evolution of the target technology. In the latter case, if the jth technology has m_j years, then there will be a total of $\sum_{j=1}^{36} m_j$ predictions. See Online Appendix D in the electronic companion for more details.

In total, there were 72 iterations for predictions at the time of entry and 1,969 predictions for updated forecasts. We show the predictive accuracy of the hazard model in three ways: predictive statistics, graphical comparison of actual versus predicted disruptions, and error in the prediction of disruption.

Predictive Statistics. Traditional summary statistics of the accuracy of the model in predicting disruption are specificity and sensitivity. *Specificity* and *Sensitivity* are the power of the model to detect true negatives and true positives, respectively, computed as follows:

$$\mathit{Specificity} = \frac{\mathit{True\ Negatives}}{\mathit{Actual\ Negatives}} = \frac{\mathit{True\ Negatives}}{\mathit{True\ Negatives} + \mathit{False\ Positives}}, \tag{6}$$

$$\mathit{Sensitivity} = \frac{\mathit{True\ Positives}}{\mathit{Actual\ Positives}} = \frac{\mathit{True\ Positives}}{\mathit{True\ Positives} + \mathit{False\ Negatives}}. \tag{7}$$

The false-positive rate and the false-negative rate are simply $(1 - \mathit{Specificity})$ and $(1 - \mathit{Sensitivity})$, respectively. The determination of a disruption is made by the analyst when the predicted value falls below a cutoff value. Choosing too low a cutoff leads to low false positives but high false negatives. The reverse is true for choosing too high a cutoff, so we choose a cutoff that balances the two error rates.

Table 5 presents the results for each domain of disruption. Note that for prediction of both technology and firm disruption at the time of entry, the out-of-sample sensitivity and specificity are both high. For predicting disruption one year ahead, specificity is high for both technology and firm disruption and sensitivity is high for firm disruption. The only prediction that is not good is that of sensitivity of firm disruption for updated forecasts.

Graphical Comparison of Actual vs. Predicted Disruptions. Figure 4 compares the actual disruption at entry with that predicted by the models. Figures 4(a) and 4(b) display the results for technology and firm disruptions, respectively. Note that for both graphs, the model predicts the disruptions reasonably well, even at the time of introduction.

Table 5 Out-of-Sample Predictive Accuracy

At entry	Technology disruption	Firm disruption
Specificity (%)	75	82
Sensitivity (%)	80	75
Updated forecasts		
Specificity (%)	72	82
Sensitivity (%)	65	52
Predictive accuracy		
Mean absolute error in prediction 1[a] (SE[b])	0.22 (0.42)	0.19 (0.40)
Mean absolute error in prediction 2[c] (SE[b])	1.9 (6.1) years	1.8 (5.1) years

[a]We compute the error in prediction as difference in the ability to predict disruption (1) or not (0).
[b]We compute standard error as $\mathrm{SE} = \sqrt{(\sum(|Y - Y'|)^2)/(N-1)}$, where $(|Y - Y'|)$ is the error in prediction and N is the number of predictions.
[c]We compute the error in prediction as the difference in predicted year of disruption and actual year of disruption.

Error in Prediction of Disruption. We calculate this error in two ways: First, the error in correctly predicting the occurrence of disruption (1) versus no disruption (0). Second, the difference in years between when the model predicts a disruption and when the disruption actually takes place. For the first approach, the mean error is 0.22 for technology disruption and 0.19 for firm disruption, respectively. For the second approach, the mean errors range from 1.9 years for technology disruption to 1.8 years for firm disruption, respectively (see Table 5). Although these figures may seem large, recall that these events occur rarely in the life of a technology that spans decades and that as of now the literature has no model whatsoever that can predict disruption, especially so many years ahead of the event. Also, these error rates compare well with past studies using this method (Golder and Tellis 1997).

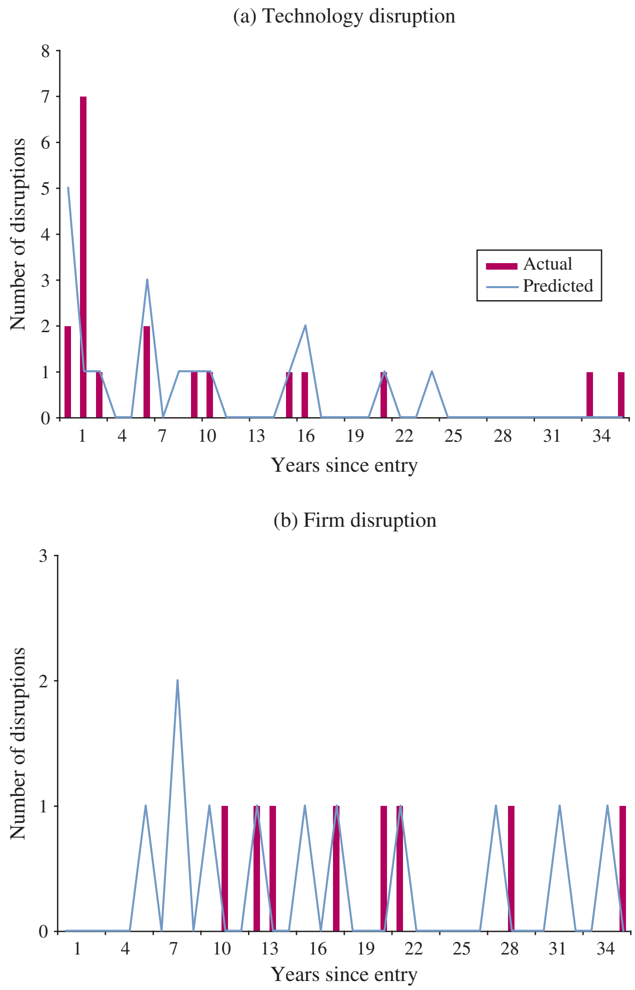
Patterns of Disruption

We find some patterns in the two types of disruption that are noteworthy.

First, at many points in time, competing technologies coexist. In some cases, disrupted technologies continue to survive and coexist with the new technology by finding a niche. For example, impact printers continue to coexist with laser and inkjet printing technologies. This suggests that the phenomenon is not as "fatal" or "final" as the term implies. It is true that some technologies do die, but many continue to survive even after being disrupted.

Second, some technologies experience disruption in one domain but not in another domain. For example, in the lighting market, incandescence continues its

Figure 4 Predictive Ability of Hazard Model



dominance in the demand domain for many decades even though it was disrupted in the performance domain by higher-performing technologies. We also observe that firms that introduce a new technology may not be the ones to cause disruption. In many cases, other firms may subsequently promote the new technology and cause disruption. For example, even though Optel Inc. introduced the LCD technology, it was Samsung that disrupted the incumbents and became the market leader. Hence, first-mover advantages are not sufficient for disruption.

Third, most technologies do not improve smoothly over time (see Figures 2(a) to 2(d)) as the theory of disruptive innovations predicts; neither do most technologies improve in the shape of S-curves (Foster 1986). Rather, improvement is sporadic, with many periods of no improvement followed by spurts of big improvements. For example, gas discharge was stagnant for many years and lost technological superiority to a competing technology, arc discharge, which improved frequently every few years after its entry. However, substantial improvement after almost 20 years propelled gas discharge into a position of superiority again.

Fourth, there is a fascinating dynamic of emergence of new secondary dimensions of performance. We find that a new technology almost always introduces a new dimension of importance even while competing with old technologies on the primary dimension (see Table 6(a)). For example, in display monitors, LCDs introduced the dimension of compactness, plasma brought into focus the dimension of screen size, and organic light-emitting diode brought into play the dimensions of convenience and low power consumption. These secondary dimensions appeal to various niche segments. However, in all cases, the competition for the mainstream segment was still on the primary dimension of performance (e.g., resolution in desktop monitors), which continued to improve substantially over time.

Finally, contrary to current belief, we observe multiple disruptions or crossings between paths of technological performance. This pattern occurs when technology disruption by a new technology is not

Table 6 Patterns of Disruption

(a) Secondary dimensions of competition

Market	Secondary dimensions
Electrical lighting	Cleanliness/safety, brightness, life, size, modularity
Data transfer	Mechanization, bandwidth, connectivity
Computer memory	Mechanization, mutability, accessibility, addressability, transfer speed, life, capacity
Computer printers	Mechanization, graphics quality, speed, simple design
Display monitors	Mechanization, compactness, screen size, brightness, flexibility, low power consumption
Music recording	Play time, duplication, mutability, size, life
Analgesics	Recovery speed, targeted action, risk-benefit balance

(b) Occurrence of disruption by time period

	Technology disruption (%)		Firm disruption (%)	
Time of introduction	No disruption	Disruption	No disruption	Disruption
Before 1960	28	22	41	9
After 1960	17	33	36	14

(c) Technology dynamics in printer market[a]

	Characteristics of new technology at entry			
Printer technology	Lower attack	Entrant	Small firm	Low-priced
Impact	Yes	No	No	No
Pen plotter	No	Yes	Yes	No
Laser	Yes	No	No	No
Inkjet	Yes	No	No	No
Thermal	Yes	Yes	No	No

Note. Percentage of all technologies: 36.
[a]Using resolution per dollar.

permanent, because a technology that has been surpassed in performance regains technological leadership. We find a total of four cases of multiple technology disruptions: two in computer memory and two in electrical lighting. Thus disruption is not permanent as extant theory suggests. At the same time, we do not find cases of multiple firm or demand disruption so far in our sample.

Robustness of Results

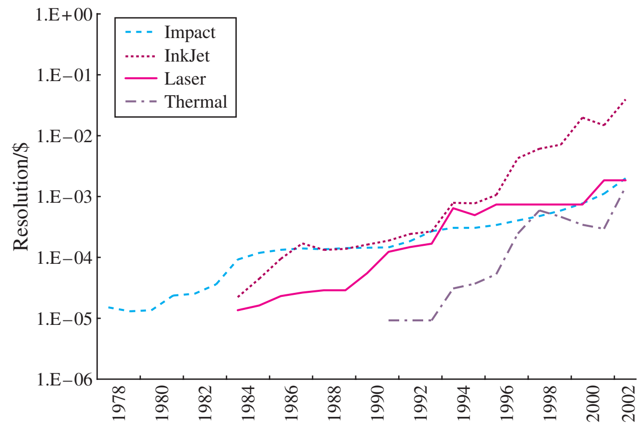
We carried out five analyses to assess the robustness of our results. First, one would be concerned that the theoretical relatedness in some of our independent variables may create a problem of multicollinearity. However, we find that the results of the hazard model are robust to the selection of variables. In particular, the significance and effect of each variable does not change much, whether each variable is included individually or combined with all others. The correlation between the two key variables of interest—incumbency and type of attack—is low (0.1). Estimates of variance inflation factors, using a multiple regression model with the same data and variables, suggest variance inflation factor values of less than 2. Thus, multicollinearity is not a problem in our data (Hair et al. 2006).

Second, one could argue that the frequency of occurrence reported in our results could suffer from censoring bias, because not enough time has elapsed for disruption to occur. To assess the severity of this problem, we do a split-sample analysis, dividing our sample by a median split on the year of entry. This yields two sets of technologies—one introduced before 1960 and the other after 1960, each with 18 technologies. Note that, in general, disruption occurs more frequently in the sample after 1960 than in that before 1960 (see Table 6(b)). However, even in the post-1960 sample, which allows for a time period of at least 40 years, the occurrence of disruption is not high, contrary to the dire warnings of extant theories.

Third, we also tested the impact of two more variables in the hazard model—change in performance of dominant technology and difference in the change in performance of the two competing technologies. Both these variables could affect the hazard of disruption by the new technology for the following reasons. First, disruption may become easier as the dominant technology matures and improves slowly (Foster 1986). Second, difference in the performance of the two competing technologies may increase the hazard of disruption of the dominant. We added these variables in the hazard model to test these expectations. The results were not materially different from those reported here.

Fourth, we redo the analysis for one industry using resolution per dollar rather than only resolution. The results are in Figure 5 and Table 6(c). The results are consistent with the original analyses for all markets using absolute performance. Four technologies use a lower attack, but only one of these (pen plotter) is from an entrant; the rest are from incumbents. The one technology using an upper attack is from an entrant. All five new technologies are more expensive than the dominant technology at the time of entry. There is only one disruption: inkjet disrupts impact printers in 1987. Inkjet was introduced by IBM, which was an incumbent. Thus, in this market, using resolution per dollar, the pattern of results is very similar to that in other markets using absolute performance.

Figure 5 **Technology Dynamics for Desktop Printers (When Performance Is Measured as Resolution per Dollar)**



Fifth, we tested many interactions in the model. However, the correlated hazards model fails to converge when these interaction terms are added to the model, probably because of few events per interaction term. So we chose to retain and test only the variables directly suggested by the theory of disruptive innovations.

Discussion

Although making strong claims that are quite popular, the theory of disruptive innovations lacks precise definitions, suffers from tautologies, lacks adequate empirical testing, and has no predictive model. We attempt to remedy these problems with a new schema, new empirical data, and a new predictive model. The proposed schema has clear definitions and distinguishes between types of technologies, types of attacks, and domains of disruption. The schema allows us to derive seven testable hypotheses. We test these hypotheses with a hazard model on data from all 36 technologies in seven different markets. Further, we carry out an out-of-sample predictive analysis that shows good to high sensitivity and specificity. The test and results apply to platform technologies. This section summarizes the findings from this test, discusses implications, and points out some limitations of the research.

Summary of Findings

Contrary to extant theory,

1. Technologies that adopt a lower attack or "potentially disruptive technologies"
   - are introduced as frequently by incumbents as by entrants,
   - are not cheaper than old technologies, and
   - rarely disrupt firms.
2. The hazard of disruption by incumbents is significantly higher than that by entrants.
3. Lower attack reduces the hazard of firm disruption.

However, consistent with extant theory,

- low price of new technologies increases the hazard of disruption. However, most new technologies, unfortunately, are not priced lower than dominant technologies at entry.

Implication

These results suggest that many aspects of the theory of disruption are exaggerated, if not inaccurate. They raise one big question: Is the theory totally wrong? Not so. The theory is right in one aspect: the hazard of disruption by low-priced new technologies is higher.

Although entrants with lower attacks do cause disruption, this event has been exaggerated. Although an entrant disrupting a well-funded, giant incumbent with a lower attack always makes for a good story, such disruptions account for only a small fraction of all cases. For example, only 8% of all technology disruptions and 25% of all firm disruptions were caused by entrants using a lower attack.

The term "disruptive technology" has been attributed to technologies entering via a lower attack. By our results, the frequency of the latter event has been exaggerated, and so-called "disruptive technologies" rarely disrupt. For example, although 47% of all technologies adopt a lower attack, only 16% of all technologies cause technology disruption and only 14% of all technologies cause firm disruption via a lower attack. However, the threat of lower attacks should not be completely discounted. Lower attacks are important because managers of incumbent firms may tend to ignore or belittle a new technology that initially seems inferior to the dominant technology. Some of these new technologies can improve enough to disrupt the initially superior technology.

Incumbents may take hope from our results in that incumbents cause 50% of all technology disruptions and 62% of all firm disruptions. However, in all markets, even though incumbents introduced more technologies and caused more disruption than entrants, many incumbents lost market dominance and subsequently failed. Hence, there is no room for complacency. Entrants do disrupt, and for entrants to account for many disruptions, often without the expertise, market knowledge, or resources of the incumbents, is quite impressive. A key issue is why some incumbents fail whereas others succeed. We suspect that the internal culture of the firms is probably a key factor responsible for disruption, rather than any external threat per se, such as a new technology or strategy (Tellis et al. 2009).

Limitations

We acknowledge some limitations of the study, which could be the basis of future research. First, because of the time-consuming nature of data collection, we were able to analyze only seven markets. However, that number still yields 36 technologies, which we track for an average of 50 years. This is probably a more comprehensive sampling than prior research in the field. Second, we were not able to get data on the performance per dollar of all technologies for all years. A number of authors emphasize the need to incorporate such metrics for a richer analysis of performance. Third, our results apply to platform technologies because we do not test the disruptive potential of design and component innovations, product innovations, or business model innovations due to both limitations of data and the large number of such innovations. However, each of these levels of innovations may also have disruptive potential. Fourth, because of the extensive technological and historical focus of this study, we did not obtain behavioral and cultural aspects of the firms involved in technology competition. We suspect that these may be important predictors of firm disruption. Fifth, our results may be susceptible to censoring. However, even when given over 40 years of time, the occurrence of disruption never came close to the values claimed by extant theories. Sixth, we did not encounter any cases of an incumbent acquiring a potentially disruptive technology before a disruption occurred. Nevertheless, this could be a viable strategy and needs to be studied.

Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

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