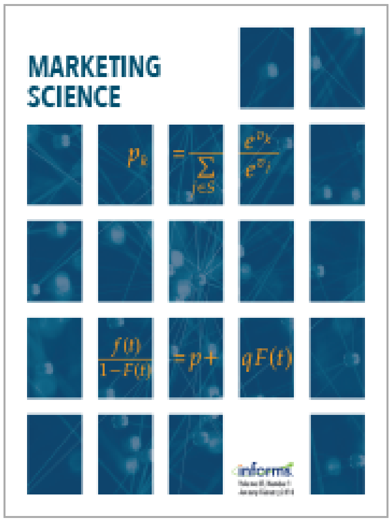

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Predicting the Path of Technological Innovation: SAW vs. Moore, Bass, Gompertz, and Kryder

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Competition is intense among rival technologies, and success depends on predicting their future trajectory of performance. To resolve this challenge, managers often follow popular heuristics, generalizations, or "laws" such as Moore's law. We propose a model, Step And Wait (SAW), for predicting the path of technological innovation, and we compare its performance against eight models for 25 technologies and 804 technologies-years across six markets. The estimates of the model provide four important results. First, Moore's law and Kryder's law do not generalize across markets; neither holds for all technologies even in a single market. Second, SAW produces superior predictions over traditional methods, such as the Bass model or Gompertz law, and can form predictions for a completely new technology by incorporating information from other categories on time-varying covariates. Third, analysis of the model parameters suggests that (i) recent technologies improve at a faster rate than old technologies; (ii) as the number of competitors increases, performance improves in smaller steps and longer waits; (iii) later entrants and technologies that have a number of prior steps tend to have smaller steps and shorter waits; but (iv) technologies with a long average wait time continue to have large steps. Fourth, technologies cluster in their performance by market.

Key words: technology evolution; innovation; SAW model; Moore's law; Kryder's law; Bass model; technological prediction
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Introduction

Competition is intense among rival technologies in many industries. For example, which is the technology for auto batteries of the future: lead–acid, nickel cadmium, fuel cell, or lithium ion? Similarly, which is the technology for display monitors of the future: liquid crystal diode (LCD), light-emitting diode (LED), plasma display panel (PDP), or organic light-emitting diode (OLED)? How should firms choose among competing technologies? This is probably the preeminent challenge facing managers of firms in technology driven markets (Hauser et al. 2007, Tellis 2008).

To resolve this challenge and predict technology change, managers often follow popular heuristics, generalizations, or "laws." Examples of such generalizations are Moore's law, Kryder's law, and the logistic model. Some of these laws gain wide acceptance and begin to serve as self-fulfilling prophecies. For example, Moore (2003) suggests that Moore's law drove semiconductor firms to focus enormous energy and make large investments in a race to achieve the performance predicted by the law ahead of their competitors.

However, most generalizations and long-range predictions fail, offering little help in managerial decision making for at least four reasons (Armstrong 1984, Balachandra 1980, Makridakis et al. 1982, Tashman 2000). First, heuristics or laws may be based on cursory observations of short-term patterns instead of on a scientific study of long-term data (e.g., by Moore 1965). Such heuristics or laws may not survive careful testing. Second, the law itself may be vague in specification, with many contradictory versions. For example, at least two versions of Moore's law are popular (performance doubling every year and doubling every 18 months). The implications of this uncertainty can be substantial. For example, a technology that doubles its performance every 18 months improves to 100 times its initial performance over 10 years, whereas a technology that doubles every year improves to more than 1,000 times its initial performance in the same period. Third, the popularity of a law may encourage indiscriminate extension to many fields, technologies, and industries. For example, Moore's law has been claimed to apply to several metrics of technology performance, including the size, cost, density, and speed of components in the semiconductor industry, and many other technologies besides semiconductors, such as biotechnology, nanotechnology, and genomics (Edwards 2008, Wolff 2004). In fact, Moore (1995, p. 1) suggests that the law has come to refer to "almost anything related to the semiconductor industry that when plotted on a semi-log paper approximates a straight line." Note that without the exact specification of the slope of the straight line, the law is intrinsically flexible and susceptible to hindsight bias. Fourth, prior research is inconclusive on whether the path of technology evolution is smooth or irregular, suggesting that a data-driven approach is better for prediction than dependence on generalized heuristics. All four reasons suggest the need for a better model for predicting the path of technology evolution. The current research addresses these limitations in the literature on technology evolution and addresses these research questions:

- How valid are the traditional laws and models for describing technology evolution?
- Which model can best predict the path of technological innovation?
- What are the key drivers of technology evolution?

To address these questions, we propose a new model called Step And Wait (SAW) and test it against extant models for 25 technologies and 804 technologies-years across six markets for over several decades. We make four contributions to the current literature. First, we propose a model to predict the evolution of technological performance that provides better predictions than traditional models. Such prediction allows both marketing and technology managers to identify dimensions on which to focus their new product design efforts. Second, the proposed model allows for predicting the path of an entirely new technology based on the similarity of its characteristics to those of prior technologies. Third, the exercise enables us to test the validity and generalizability of some popular laws about technology evolution. Fourth, we identify key drivers of technology evolution.

The next five sections present the theory, hypotheses, models, method, and results. The last section discusses the findings, implications, and limitations of the research.

Theory of Technology Evolution

Technology evolution is the improvement in the performance of a technology over time. We are interested in a better understanding of the path of such improvement. Prior literature has debated the shape of the path (whether smooth or discontinuous) and the drivers of the path (explanatory variables that influence its course). We cover both of these topics next.

Shape of Path

Prior literature suggests both smooth change through incremental improvements occurring frequently (Basalla 1988, Dosi 1982) and nonsmooth change through relatively stable periods of smooth change punctuated with discontinuous steps of big changes (D'Aveni 1994, Eldredge and Gould 1972, Tushman and Anderson 1986).

Proponents of smooth and incremental technological change (e.g., Basalla 1988) argue that technology evolution is a process of continual improvement in performance of a technology through novel recombination and synthesis of existing technologies (Henderson and Clark 1990). These researchers suggest that changes in technology performance are a result of changes in a number of domains, including beliefs, values, culture, technology, operating routines, organizational structure, resources, and core competencies (Gersick 1991, Tushman and Romanelli 1985, Wollin 1999). Invention is a social process that rests on the accumulation of many minor improvements, not the heroic efforts of a few geniuses (Basalla 1988, Dosi 1982).

Proponents of irregular change (e.g., Adner 2002, Eldredge and Gould 1972, Tushman and Anderson 1986) suggest that technologies improve through eras of smooth change punctuated by discontinuous shifts. Products that draw upon fundamentally new technologies enter an industry and create ferment till the emergence of dominant designs (Nelson and Winter 1977, Utterback and Abernathy 1975). After a dominant design is established, firms focus more on process innovations than on product innovations (Henderson and Clark 1990). Jumps in product performance could occur from both product and process innovation related to the focal technology. Tushman and Anderson (1986) explain the discontinuous nature of technological change through two types of change—competence enhancing and competence destroying. Levinthal (1998) extends the concept of natural speciation (Eldredge and Gould 1972) to technology speciation. Substantial improvements in performance occur because a shift of a technology from one domain to another alters the relative preference for attributes, demands different price/performance ratio for older attributes, and often releases substantially higher resources for research and development (R&D) (Levinthal 1998). This shift may be due to (1) changes in problem-solving heuristics; (2) fusion with other domains; and (3) other technological, social, or economic aspects. Such shifts provide access to new customers, resources, and performance metrics (Adner 2002). As a result, the technology exhibits sharp steps in performance.

In summary, even though debate in prior research is inconclusive as to whether technology evolution is smooth or irregular, the question remains important to managers. Thus, good forecasting capabilities may spell the difference between success and failure in the market.

Drivers of Path of Technological Change

Our review of the theory in this area suggests four covariates that could drive the path of technological change. We discuss the role of each of these covariates next.[1]

Year of Introduction. This covariate reflects the newness of the technology. We hypothesize that new technologies improve in larger and more frequent steps than old technologies as a result of the improvement in the supporting environment for innovation in recent years. In particular, improvements in supporting environment are characterized by (1) higher total R&D expenditures, (2) more researchers devoted to technology research, (3) use of better tools, (4) better laboratories, (5) better communication of research, and (6) more countries focused on research.

In addition, the pace of improvement in new technologies may occur more frequently and in larger steps than old technologies for three reasons. (1) After a period of rapid improvement in performance, old technologies may reach a period of maturity (Foster 1986, Brown 1992, Chandy and Tellis 2000, Sood and Tellis 2011). Foster (1986) suggests that maturation may be an innate feature of each technology. Sahal (1981) proposes that maturity occurs because of limits of scale or system complexity. Fleming (2001) suggests that old technologies reach recombinant exhaustion and improvements become smaller. And Golder and Tellis (2004) suggest that maturation can result from abandonment following a cascade. (2) Newer technologies attract the interest of firms. Market power acquired from successful innovation in the old technologies spurs greater inventive activity in new technologies. They seem mysterious yet promise huge benefits. As such, they attract. (3) New technologies also introduce new performance dimensions unrelated to those offered by old technologies. For example, before the advent of LCD monitors, firms making CRT (cathode ray tube) monitors competed mainly on higher screen resolution. LCD monitors promised compactness as a new performance dimension. Old technologies strive to compete as customer demand for these dimensions increases. This slows performance improvements on the existing dimension. Thus, we hypothesize the following.

Hypothesis 1 (H1). *Performance of more recent technologies increases in* (1) *larger steps and* (2) *more frequent steps* (*shorter wait times*).

Order of Entry. After controlling for the basic effect of calendar time, the order of entry of a technology in a particular market could affect its improvement. We need to emphasize that the time effect probably holds for large time spans such as decades. The order of entry works for small time spans such as a few years within a market, within which one technology follows another pretty rapidly. We identify two rival theories: preferential attraction versus precommitment.

The preferential attraction theory holds that the earlier technology gets more (or better, and initially, all) of the limited set of resources (dollars, locations, and researchers) than those technologies that follow. Risk aversion of investors and researchers prevents them from investing in new technologies. Prior literature also suggests that pioneers outperform later entrants (Lambkin 1988, Urban et al. 1986). If this line of reasoning is valid, the earlier technology will have larger and more frequent improvements in performance than later technologies within the same market. The above argument leads to the following hypothesis.

Hypothesis 2A (H2A). *Technologies entering earlier improve with* (1) *larger steps and* (2) *more frequent steps* (*shorter wait times*) *than later technologies within the same market*.

The precommitment argument suggests that the earlier technology enters in an environment with less information about potential markets, dimensions of performance, and available resources than the technology that enters later. Thus, the earlier technology precommits to an evolutionary path that may not be the most efficient or effective. The later technology enters in an environment with greater information about markets, technologies, and resources, and it chooses a more efficient and productive evolutionary path (Golder and Tellis 1993). The glamour of the "new" may also result in suppliers switching resources from the old to the new. Thus, a technology entering a market later will have more resources and

[1] Other factors (e.g., market size, technological sophistication) may also affect the evolution but have not been included in the analysis because of a lack of reliable data on these variables. We thank an anonymous reviewer for suggesting these.

more researchers working on it than an older technology. This will result in more frequent but smaller steps in performance. The above argument leads to the following rival hypothesis.

HYPOTHESIS 2B (H2B). *Technologies entering later improve with* (1) *smaller steps and* (2) *more frequent steps* (*shorter wait times*) *than earlier technologies to a market*.

Number of Competing Technologies. Controlling for the effects above, how does improvement relate to the number of competing technologies? We propose two rival theories: competition for limited resources or competition spurring breakthroughs.

The limitation of resources theory is that in any market the amount of dollars, researchers, and labs is relatively fixed in the immediate short term. Thus as the number of competing technologies increases, each resource becomes more scarce. This division of resources results in less frequent breakthroughs and therefore less frequent increases in performance. More competition leads firms to become more risk averse and focus on cost management instead of risky and costly product improvement. Firms generally achieve these objectives by prioritizing process innovation over product innovation (Scherer and Ross 1990). Thus, as the number of competitors increases, improvements in performance are slower.

The rival theory is of competition spurring breakthroughs. This phenomenon could occur for several reasons. First, each technology is supported by a unique set of researchers with their own egos, training, reputation, and emotional attachment. As the number of competing technologies increases, their supporters work harder to promote their own technologies and create improvements in performance. It is also possible that more firms enter a market because (a) there is demand or (b) because they think it is relatively easy to improve existing products (technologies). In other words, if (b) is true, there are more entrants because technological progress is likely to be fast.[2] As a result, the number of improvements in performance increases with the number of competition technologies in a market. Second, Rosenberg (1969) refers to the phenomenon of compulsive sequence, where a breakthrough in one area typically generates new technical problems, creating imbalances that require further innovative effort to fully realize the benefits of the initial breakthrough. For example, the development of high-speed steel improved cutting tools and stimulated the development of sturdier and more adaptable machines to drive them (Rosenberg 1969). Third, new technologies may set up additional opportunities in new niches even for old technologies. Fourth, prior research suggests that a firm's returns from innovation at the margin are larger in an oligopolistic versus a monopolistic environment (Fellner 1961, Arrow 1962, Scherer 1967). Thus, more competition generates more funds to support innovation and faster product improvements. All these reasons suggest that an increase in the number of competitors will increase the number of improvements in technology performance. Thus, we can propose the following rival hypotheses.

HYPOTHESIS 3A (H3A). *As the number of competitors increases*, *performance of technologies increases in* (1) *smaller steps and* (2) *longer wait times*.

HYPOTHESIS 3B (H3B). *As the number of competitors increases*, *performance of technologies increases in* (1) *larger steps and* (2) *shorter wait times*.

Technology Characteristics. We include two covariates to capture technology characteristics—the number of prior steps and average prior wait time. Together, the two covariates capture unique patterns of technological improvement for a technology within its unique technological paradigm (Nelson and Winter 1982, Dosi 1982). A technological paradigm is the common platform on which scientists and technologists agree to do research and explain the speed and pattern of technological advancement. For example, for the past 30 years, firms in the magnetic storage industry pursued higher areal density as a goal to solve design problems and achieve higher productivity. This common understanding led firms to race to introduce improvements in areal density ahead of other firms. In such an urgency, firms may not delay investments in R&D and frequently introduce products with improvements.

In technologies where such a paradigm emerges, a technology evolves with a large number of steps. However, these steps are small and frequent. Firms take advantage of interdependencies with components and advancements in other fields. For example, improvements in the areal density of magnetic storage have been driven in part by advancements in other related disciplines such as semiconductor, fiber optic, and microelectronics.

In the absence of a dominant technological paradigm, firms' efforts scatter in diverse directions. R&D efforts may be targeted toward improvements on diverse performance metrics leading to little synergy across firms' efforts and to fewer steps. Also, competing firms within an industry may wait to introduce products to optimize commercialization costs. As a result, there are few steps with long wait times. Longer average wait times also provide firms more time to develop better products. This results in technological progress with large step sizes and long wait times. Thus, the technological paradigm theory suggests the following two hypotheses.

[2] We thank an anonymous reviewer for suggesting this possibility.

Hypothesis 4 (H4). *Technologies with a large number of* prior steps *have* (1) *small current steps and* (2) *a shorter current wait time.*

Hypothesis 5 (H5). *Technologies with long average* prior wait times *have* (1) *large current steps and* (2) *a long current wait time.*

Models

This section describes eight models in the literature that have been or could be used to predict technological change and one model (SAW) that we propose specifically for this purpose (see Table 1). One of the models is an exponential function used to fit both Moore's law and Kryder's law (see Figure A1a in Online Appendix A, available at http://dx.doi.org/10.1287/mksc.1120.0739). Three more models are the most popular methods used in prior literature to test an S-shaped curve: the Bass, Logistic, and Gompertz models (see Figure A1b in Online Appendix A). All four models are smooth and do not allow the use of explanatory variables in their popular formulation. We propose modified versions of these four models that do include explanatory variables to allow fair comparison with SAW (see Online Appendix B). The next two models are discontinuous and allow the use of explanatory variables: the Gupta model for buyer interpurchase behavior and the Tobit II model used to model technology evolution (see Figure A1c in Online Appendix A). Online Appendix B provides details on the models and explains how they predict holdout periods and technologies. We also include two simple models for comparison—the Naïve method, which does not use covariates, and the Diff Reg approach, which implements a linear regression with covariates. In addition, we develop modified versions of Exponential, Logistic, Bass, and Gompertz models that allow fitting all curves simultaneously and incorporating covariates.

Moore's Law (Exponential Model)

First proposed by Intel cofounder Gordon E. Moore, the law suggests that the density of integrated circuits doubles in performance every year (Moore 1965). Thus, Moore's law specifies an exponential relationship between technology performance and time (see Figure A1a in Online Appendix A and (14) in Online Appendix B). Later, Moore revised the law to a doubling in performance every two years (Moore 1975). Subsequently, Moore claimed that the performance of "almost anything related to the semiconductor industry" (Moore 1997) improves at exponential rates across a number of measures including size, cost (or experience), density, and speed of components. Over the last few decades, many technologies like microprocessors and DRAMs seem to have followed a revised Moore's law that suggests doubling every 18 months (Mollick 2006, Schaller 1997). Researchers suggest that the law also describes technology evolution for many other technologies besides semiconductors, such as biotechnology, nanotechnology, and genomics (Edwards 2008, Wolff 2004). If so, the designation of a "law" would be valid.

Table 1 Unifying Framework for Models Predicting Technology Evolution

	Smooth (continuous)	Discontinuous (irregular)
Symmetric	Logistic, Bass, Gompertz (S shaped)	N/A
Asymmetric	Moore, Kryder (exponential shaped)	SAW, Tobit II, Gupta, Diff Reg (irregular step sizes with irregular wait times)

Note. N/A, not applicable.

Kryder's Law (Exponential Model)

First proposed by Seagate's Chief Technology Officer Mark Kryder, this law suggests that the density of information on hard drives, also known as areal density, "increased by a factor of 1,000 every 10.5 years since introduction of these technologies" (Walter 2005, p. 32). This rate is equivalent to a doubling of performance every 13 months (Shacklett 2008). Grochowski (1998) suggests that the areal density has increased at a compound annual growth rate of 60%. In effect, both Moore's law and Kryder's law specify the same exponential form with differing parameters on time (Figure A1a in Online Appendix A and (14) in Online Appendix B).

Logistic Model

One theory of the evolution of technology is the theory of S-curves (Foster 1986). This theory suggests that a plot of maximum performance of a technology over time follows an S-shaped curve (see Figure A1b in Online Appendix A and (16) in Online Appendix B). The S-curve results from changes in performance on one dimension over the life of the technology. In the early years after introduction, performance improves slowly because of technical problems with mastering the new technology. Once the initial bottlenecks have been resolved, performance improves rapidly as the technology draws researchers and resources. Eventually, the rate of improvement declines because either the technology reaches its limits of scale or size (Sahal 1981) or firms start investing in alternative technologies (Abernathy and Utterback 1978).

Bass Model

Some researchers examining the diffusion of new products suggest a demand-side explanation of the phenomenon of technology evolution (Adner 2002, Bass 1969, Rogers 1962, Young and Ord 1989, Young 1993). These researchers suggest that consumers adopt a new product based on spontaneous innovation driven by word-of-mouth diffusion. This process carves a typical S-shape of sales of a new product (Sood et al. 2009) (see Figure A1b in Online Appendix A and (18) in Online Appendix B). The demand for the new product drives the evolution of a new technology, on which the new product is based, and it also follows an S-curve.

Gompertz's Model

Gompertz's law was first proposed by British actuary Benjamin Gompertz for use in demographic studies and suggests that the rate of human mortality increases exponentially with age (Gompertz 1825). In the current context, Gompertz's law states that the maturity and exit of old technologies pave the way for the new technologies and drive technology evolution (Young and Ord 1989). The rate of change in the performance of a technology increases at an exponential rate, tracing a sigmoid double exponential S-shaped path over the life of the technology from its introduction to its maturity (see Figure A1b in Online Appendix A and (21) in Online Appendix B). Gompertz's law has been used extensively in prior literature to describe technology evolution because it produces S-shaped curves that describe the different phases of evolution—acceleration, inflection, and deceleration of growth over time (Martino 2003; Meade and Islam 1995, 1998, 2006; Young and Ord 1989). The different S-shaped curves have different implications in symmetry around the relative location of the inflection point. These differences may influence the power of these laws to predict technology evolution.

Gupta Model

The model of Gupta (1988) is a well-known and popular approach for modeling consumer purchase decisions. This model consists of three separate stages: brand choice (for modeling the probability of purchasing a particular brand), interpurchase time (for modeling time until purchase), and purchase quantity (for modeling the amount of goods purchased). We use two stages of this model—interpurchase time and quantity—to model the wait time and size of step, respectively. This model provides a natural approach for predicting the discontinuous nature of technology evolution (see Figure A1c in Online Appendix A and (23) and (24) in Online Appendix B).

Tobit II Model

The Tobit II models the evolution of technologies as a series of step functions with random improvements over irregular periods of time (see Figure A1c in Online Appendix A and (25) and (26) in Online Appendix B). The model includes a latent variable that represents the probability of a step as a function of explanatory variables.

Simple Models: Naïve and Diff Reg

We also include two simple alternatives. The first method, Naïve, models technology curves as constant in the holdout period. In other words, we assume that the curve for each technology is horizontal; i.e., if our last observation in the estimation sample is θ, we predict θ for the entire holdout period. The second method, Diff Reg, performs a single linear regression on all technologies simultaneously using a technology-specific indicator variable and the covariates from the previous section as the independent variables. The indicator variable is modeled as a random effect. The change in (log) technology performance between two successive periods is used as the dependent variable. So, for example, if a technology remained constant between two periods, we set $Y = 0$ for the response. After fitting the linear regression model, we use the covariates of a technology to predict its change in each time period and hence the entire trajectory.

SAW Model

We propose a new approach that models technologies as exhibiting periods of constant performance followed by discontinuous steps (see Figure A1c in Online Appendix A). We call this model *Step And Wait* because it predicts steps in performance followed by a flat "waiting" period before the next step. Hence, it is in line with the theory that technologies evolve according to irregular change. Our motivation in proposing SAW is to test whether such a discontinuous model could better predict the evolution of a technology. SAW works by modeling the improvement in performance using the *Step submodel* and the time between changes in performance using the *Wait submodel*. We describe the specification and prediction of SAW here and the fitting in Online Appendix C.

Specification. Let J_{ij} and t_{ij} respectively represent the size of and the duration until the jth step for technology i. Let T_{ij} represent the time between the $(j-1)$th and jth steps for technology i, so $t_{ij} = t_{i(j-1)} + T_{ij}$. SAW uses two submodels—the Step submodel and the Wait submodel.

The Step submodel uses a hierarchical approach to estimate the size of the jth step for the ith technology, J_{ij}, as a function of three quantities, M, μ_i, and γ_{ij}, as follows:

$$J_{ij} \sim \text{Gamma}(M, \mu_i \gamma_{ij}), \tag{1}$$

$$\mu_i^{-1} \sim \text{Gamma}(\rho, \eta), \tag{2}$$

$$\gamma_{ij} = \exp(rT_{ij} + \alpha_1 Y_{ij1} + \cdots + \alpha_q Y_{ijq}), \tag{3}$$

where Y_{ijk} represents the value of the kth covariate for technology i, at time t_{ij}, that is used to predict the size of the step J_{ij}. In this formulation, ρ, η, M, r, and $\alpha_1, \ldots, \alpha_q$ are parameters to be estimated from the data. The parameter M is a global value that contributes to the average step size for all technologies. The value of r controls the level and type of correlation between the step at time j, J_{ij}, and the wait until this step, T_{ij}. For $r > 0$, increased wait times imply larger steps. The term γ_{ij} is a function of the various covariates, such as the last wait time.

The random effect term, μ_i, is unique to each technology and reflects its typical step size. SAW builds strength across all the data by estimating μ_i using both the previously observed step sizes for the ith technology and the typical step sizes of the other technologies. Modeling μ_i as a random effect allows us to borrow strength across multiple technologies by assuming that the μ_i for each technology is drawn from a common distribution.

In theory, one could model J_{ij} or μ_i as coming from a variety of distributions. However, the Gamma distribution has the following advantages. (a) It is extremely flexible (it can model the memoryless exponential and the chi-square distributions, and it provides good approximations to Normal and t-distributions). (b) Using a Gamma allows us to calculate an exact likelihood function for the Step and Wait submodels, which, in turn, provides a relatively simple way of fitting the models by computing the maximum likelihood estimates. For a given μ_i, the expected step size is a function of the covariates Y_{ijk}, the wait time T_{ij}, and μ_i:

$$\begin{aligned} E(J_{ij} \mid \mu_i) &= M\mu_i\gamma_{ij} \\ &= M\mu_i \exp(rT_{ij} + \alpha_1 Y_{ij1} + \cdots + \alpha_q Y_{ijq}). \end{aligned}$$

Hence, a technology with a small μ_i will tend to have small step sizes, and vice versa, but this effect can be moderated by the observed covariates (e.g., a large investment in research and development at time t_{ij}) through the parameter γ_{ij}. Since $E(\mu_i^{-1}) = \rho\eta$, ρ and η provide information about the typical step size over all technologies. However, the individual covariates for each technology will also affect the step size. The coefficients $\alpha_1, \ldots, \alpha_q$ dictate the relationship between the covariates and the step size; for example, a positive value for α_k indicates that increases in the kth covariate are associated with larger step sizes, whereas $\alpha_k = 0$ would suggest no such relationship.

The Wait submodel works in a similar fashion, estimating the wait time until the $(j+1)$th step for technology i, $T_{i,(j+1)}$, as a function of three quantities, λ_i, ω_{ij}, and K, as follows:

$$T_{ij} \sim \text{Gamma}(K, \lambda_i\omega_{i(j-1)}), \tag{4}$$

$$\lambda_i^{-1} \sim \text{Gamma}(\kappa, \theta), \tag{5}$$

$$\omega_{ij} = \exp(sJ_{ij} + \beta_1 X_{ij1} + \cdots + \beta_p X_{ijp}), \tag{6}$$

where X_{ijk} represents the value of the kth covariate used to predict T_{ij} for technology i at time t_{ij} and K, κ, ω, θ, s, and $\beta_1, \ldots, \beta_p$ are parameters. The parameter K is a global value that contributes to the average wait time for all technologies, and s controls the correlation between the jth step, J_{ij}, and the wait time until the $(j+1)$th step. A positive value of s implies longer wait times after larger steps. The term ω_{ij} is a function of the various covariates for technology i (including the step size J_{ij}) at time t_{ij}.

The random effect, λ_i, is unique to each technology and reflects its typical wait between steps. Again, SAW builds strength across all the data by estimating λ_i using both the previously observed wait times for the ith technology and the typical wait times of the other technologies. For a given λ_i, the expected wait until the next step is a function of the covariates X_{ijk}, K, and λ_i:

$$\begin{aligned} &E(T_{i(j+1)} \mid \lambda_i) \\ &\quad = K\lambda_i\omega_{(ij)} = K\lambda_i \exp(sJ_{ij} + \beta_1 X_{ij1} + \cdots + \beta_p X_{ijp}). \end{aligned}$$

Hence, a technology with a small λ_i will tend to have short time periods between steps, and vice versa, but this effect can be moderated by the observed covariates at time t_{ij} through the parameter ω_{ij}. For example, a technology may have a large λ_i and hence typically experience long waits between steps, but at a given time, this might be moderated by a change in the number of competing technologies, resulting in a small ω_{ij} and, hence, a smaller wait time. The expected value of λ_i^{-1} is $\kappa\theta$. So κ and θ provide information about the typical wait time over all technologies. However, the individual covariates for each technology also affect the wait time. The coefficients $\beta_1, \ldots, \beta_p$ dictate the relationship between the covariates and the wait time. For example, a positive value for β_k indicates that increases in the kth covariate are associated with a longer wait, whereas $\beta_k = 0$ suggests no relationship between the kth covariate and the wait time. Because the covariates can change over time, the typical T_{ij} may increase or decrease.

Predictions. Suppose for a given technology i we observe n_i steps, $J_{i\bullet} = (J_{i1}, \ldots, J_{in_i})$ with wait times $T_{i\bullet} = (T_{i1}, \ldots, T_{in_i})$. Note that t_{i0} represents the time of introduction. So T_{i1} corresponds to the duration from the introduction of a technology until the first step, and J_{i1} is the size of the first step. Then natural estimates for the size of the next step, $J_{i(n_1+1)}$, and the wait until the next step, $T_{i(n_i+1)}$, are $E(J_{i(n_1+1)} \mid J_{i\bullet})$ and $E(T_{i(n_i+1)} \mid T_{i\bullet})$. Using the Step submodel given by

Equations (1)–(3), by the law of iterated expectations and the fact that $J \mid \mu$ has a gamma distribution,

$$\begin{aligned} E(J_{i(n_i+1)} \mid J_{i\bullet}) &= E(E(J_{i(n_i+1)} \mid \mu_i) \mid J_{i\bullet}) \\ &= E(M\gamma_{i(n_i+1)}\mu_i \mid J_{i\bullet}) = M\gamma_{i(n_i+1)}E(\mu_i \mid J_{i\bullet}). \end{aligned}$$

To compute the final expectation we need to derive the expected value of $\mu \mid J$. The distribution of μ^{-1} conditional on $J_\bullet$ is given by

$$\begin{aligned} &f(\mu^{-1} \mid J\bullet) \propto f(J\bullet \mid \mu^{-1}) f(\mu^{-1}) \\ &= \left(\prod_{j=1}^{n_i} (\mu_i \gamma_{ij})^{-M} J_{ij}^{M-1} \exp\left(-\mu_i^{-1} \sum_{j=1}^{n_i} J_{ij}\gamma_{ij}^{-1}\right) \eta^{-\rho} \mu_i^{-(\rho-1)} \right. \\ &\qquad \left. \cdot \exp(-\mu_i^{-1}/\eta) \right) \cdot (\Gamma(\mathrm{M})^{n_i} \Gamma(\rho))^{-1} \\ &\propto \mu_i^{-(Mn_i+\rho-1)} \exp\left(-\mu_i^{-1}\left(\frac{1}{\eta} + \sum_{j=1}^{n_i} J_{ij}\gamma_{ij}^{-1}\right)\right). \end{aligned}$$

Hence,

$$\mu_i^{-1} \mid J_\bullet \sim \mathrm{Gamma}\left(Mn_i + \rho,\ \frac{1}{\eta^{-1} + \sum_{j=1}^{n_i} J_{ij}\gamma_{ij}^{-1}}\right),$$

but the expected value of the inverse of a $\mathrm{Gamma}(\alpha, \beta)$ random variable is equal to $1/(\beta(\alpha-1))$. Therefore,

$$E(\mu_i \mid J_{i\bullet}) = \frac{\eta^{-1} + \sum_{j=1}^{n_i} J_{ij}\gamma_{ij}^{-1}}{Mn_i + \rho - 1},$$

and the expected size of the next step conditional on previous steps is

$$E(J_{i(n_i+1)} \mid J_{i\bullet}) = M\gamma_{i(n_i+1)} \frac{\eta^{-1} + \sum_{j=1}^{n_i} J_{ij}\gamma_{ij}^{-1}}{Mn_i + \rho - 1}. \tag{7}$$

Similarly, using the Wait submodel given by Equations (4)–(6), the expected wait time until the next step conditional on previous steps is (derivation is identical to that for (7))

$$\begin{aligned} E(T_{i(n_i+1)} \mid T_{i\bullet}) &= K\omega_{in_i} E(\lambda_i \mid T_{i\bullet}) \\ &= K\omega_{in_i} \frac{\theta^{-1} + \sum_{j=1}^{n_i} \omega_{i(j-1)}^{-1} T_{ij}}{Kn_i + \kappa - 1}. \end{aligned} \tag{8}$$

From Equation (8), we can predict that the next step in technology i will occur at time

$$\begin{aligned} t_{i(n_i+1)} &= t_{in_i} + E(T_{i(n_i+1)} \mid T_{i\bullet}) \\ &= t_{in_i} + K\omega_{in_i} \frac{\theta^{-1} + \sum_{j=1}^{n_i} \omega_{i(j-1)}^{-1} T_{ij}}{Kn_i + \kappa - 1}, \end{aligned}$$

the following step at time

$$t_{i(n_i+2)} = t_{i(n_i+1)} + K\omega_{i(n_i+1)} \frac{\theta^{-1} + \sum_{j=1}^{n_i} \omega_{i(j-1)}^{-1} T_{ij}}{Kn_i + \kappa - 1},$$

and so on.

Together, Equations (7) and (8) can be used to predict the entire remaining trajectory. Note that this approach will work even for a curve for which we have no data. SAW can be used to estimate the size of the first step and the duration until the first step after the introduction of a new technology. In this case, $n_i = 0$; so Equations (7) and (8) simplify as

$$E(T_{i1}) = K\omega_{i0} \frac{\theta^{-1}}{\kappa - 1}, \tag{9}$$

$$E(J_{i1}) = M\gamma_{i1} \frac{\eta^{-1}}{\rho - 1}. \tag{10}$$

Thus, given estimates for μ_i, γ_{ij}, λ_i, K, M, and ω_{ij}, one can predict the evolution of a technology as far into the future as desired by combining the predicted wait time ($K\lambda_i\omega_{ij}$) with the predicted step size ($M\mu_i\gamma_{ij}$).

Connections to Renewal-Reward Process. Our SAW model has similarities to a renewal-reward process (see Cox 1970). In particular, for fixed values of λ_i and μ_i, SAW fits a separate nonhomogeneous RRP to each technology. The nonhomogeneous component is introduced by virtue of the time-varying covariates. However, although conditional on λ_i and μ_i, each technology is independent, so these parameters are unobserved in practice. Thus SAW models the processes (technologies) as unconditionally related via the Gamma distributions given by (2) and (5). In this sense, SAW can be considered a generalization of a standard renewal-reward process because it is building strength across the technologies by jointly modeling a series of related processes.

Extensions of the Exponential, Logistic, Bass, and Gompertz Models. In their standard forms, the Exponential, Logistic, Bass, and Gompertz models all fit individually to a single technology and do not incorporate covariates in their specification. This specification places them at a potential disadvantage relative to SAW, which both utilizes the covariate information and builds strength across technologies by fitting all curves simultaneously. To ensure a fair comparison, we fit modified versions of these methods. In particular, we implemented two new versions of each approach.

In the first implementation, we used a nonlinear mixed effects model (Pinheiro and Bates 2000), which fitted the standard functional forms of each method but modeled the various parameters as random effects coming from a Gaussian distribution. The parameters for the Gaussian distribution were estimated using all technologies simultaneously. Hence it built strength across technologies in a similar fashion to SAW. Our second implementation also modeled the parameters using a random effects formulation but, in addition, incorporated the covariates as a multiplicative adjustment to the original prediction. In this implementation, we modeled each technology using

$$P_{ij} = f_i(t_{ij}) \exp\left(\beta_0 + \sum_{k=1}^{q} \beta_k X_{ijk}\right) e^{\varepsilon_{ij}}, \tag{11}$$

where P_{ij} is the performance of technology i at time t_{ij}; $f_i(t)$ is the general formulation of the Exponential, Logistic, Bass, or Gompertz model, exclusive of covariates; and X_{ijk} is the kth covariate for technology i at time t_{ij}. For example, the Exponential model (11) becomes

$$P_{ij} = \tau_{i1} e^{\tau_{i2} t_{ij}} \times \exp\left(\beta_0 + \sum_{k=1}^{q} \beta_k X_{ijk}\right) e^{\varepsilon_{ij}},$$
$$\tau_{i1} \sim \mathrm{N}(\mu_1, \sigma_1^2), \quad \tau_{i2} \sim \mathrm{N}(\mu_2, \sigma_2^2),$$

with τ_{i1} and τ_{i2} modeled as coming from a Gaussian distribution. Equivalently, using a log transformation,

$$\log(P_{ij}) = \log(\tau_{i1}) + t_{ij}\tau_{i2} + \beta_0 + \sum_{k=1}^{q} \beta_k X_{ijk} + \epsilon_{ij}.$$

When $f_i(t_{ij})$ is set to the Bass model, (11) has a similar form to the Generalized Bass model (Bass et al. 1994), though the latter method does not use a mixed-effects fitting procedure.

We used a multiplicative covariate adjustment to f_i because this ensured the basic shape for each model was maintained while still allowing the covariates to influence the fit. This second implementation had the twin advantages of building strength by simultaneously fitting all curves and incorporating the covariates. Hence, these models can be seen as a direct competitor to SAW. To our knowledge, neither the first nor second mixed-effects formulations have been previously implemented in such a setting, except in the Bass model. So our specification can be considered a contribution in its own right. For more details of our fitting procedure, see Online Appendix B.

Method

This section describes the data collection and the method of prediction.

Data

We collected data on 26 technologies drawn from six markets: external lighting, desktop printers, display monitors, desktop memory, data transfer, and automotive battery technologies (see Table 2). We chose these six markets to ensure sufficiently long periods of study, a wide variety of technologies, and diversity of markets. We collected the data using the historical method (Sood and Tellis 2005). The primary sources of our data are technical journals, white papers, press releases, timelines of major firms, museum records on the development of industries, and annual reports of industry associations.

Table 2 Technologies Sampled and Primary Dimensions of Competition

Market	Primary basis of competition	Metric
External lighting	Lighting efficacy	Lumens per watt
Desktop memory	Storage capacity	Bytes per square inch
Display monitor	Screen resolution	Pixels per square inch
Desktop printer	Print resolution	Dots per square inch
Data transfer	Transfer speed	Megabits per second
Automotive battery	Energy density	Watt-hour per kilogram

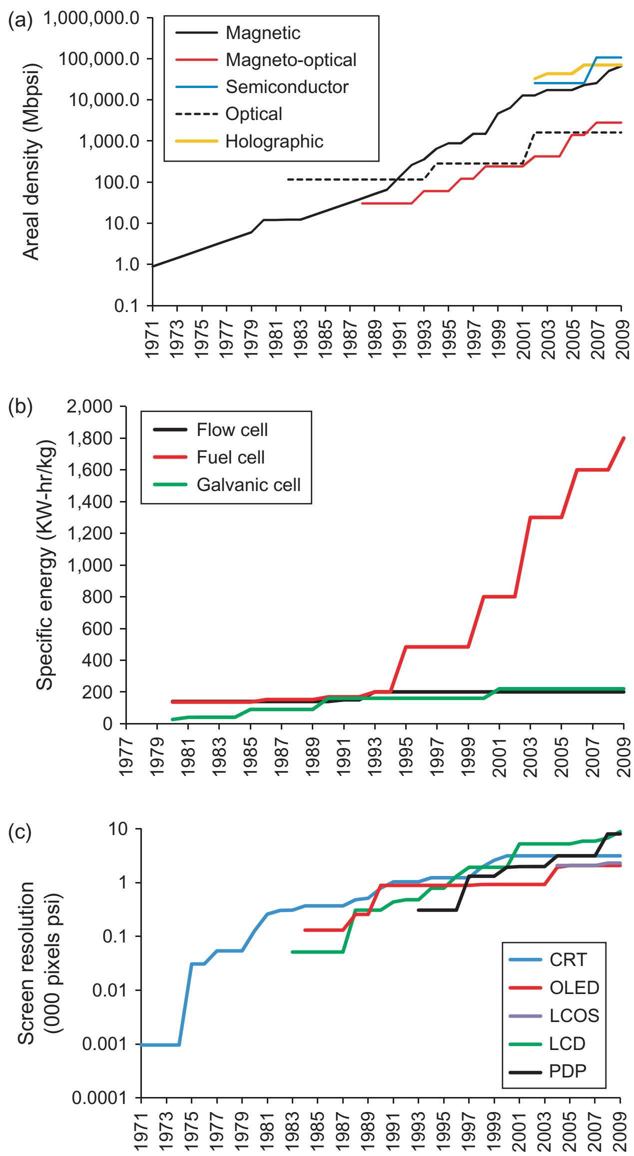
Note. Adapted from Sood and Tellis (2005).

For each technology, we collected the performance record on the most important attribute to consumers—the primary basis of competition among technologies within a market (see Table 2). We identified these important attributes based on articles collected through the historical method. We recorded the maximum performance for any commercialized product based on the technology at each time period. Our sample includes technologies introduced more than a hundred years ago and those introduced only in the last decade. It also includes markets from basic utilities, medical therapeutics, and the digital industry. Figure 1 shows the performance of all technologies in three of the six markets.

We define a step as an improvement in performance *however small,* of *any product in the market* based on a technology. We make the following assumptions: (1) The performance of a technology in the market is based on the best performance of any commercialized product based on that technology. Because of constraints in production, competitive agreements, or regulation, the performance of products in the market often does not change at all in some years. Hence the performance curve is flat in these years. (2) We have identified all products in the market based on all technologies. (3) The performance of these products is correctly reported by manufacturers.

We used the following rules to ensure reliable and consistent data. First, we measure the performance of a technology based only on commercialized products of that technology. Second, if two sources provide conflicting performance for a technology in a period, we choose the one whose values are more consistent with the rest of the series. Third, if no record is available for a certain year, but a later record confirms that performance has not changed since the last available record, we assume that the performance has not changed in the intervening years. Fourth, if no record is available for a certain year, but a later record confirms that performance has changed since the last available record, we treat the intervening years as

Figure 1 Performance of Technologies in the (a) Desktop Memory, (b) Automotive Battery, and (c) Display Monitor Markets by Year



missing data. Using these rules, we were able to collect data on only 804 technology years compared with the total of 901 technology years in our original sample (89%).

Method of Prediction

A direct comparison of statistical models across markets on all these technologies is not possible unless the performance plots are modified to convert absolute performance to some sort of relative performance. Because we want to analyze how a technology improves over time, we calculate the ratio of current performance to its performance in the first year of introduction. We fit all methods after transforming the data onto a log scale. This transformation reduces skewness in the data and generally gave lower prediction errors for all methods. We explain the specific procedure for carrying out the prediction in two parts: partitioning of sample and evaluation of predictive accuracy.

Partitioning of Sample. To test the accuracy of predictions for future technology innovation using SAW and the six alternative models, we divided the technologies into training (in-sample) and testing (out-of-sample) time periods. We could use data on only 25 technologies because the ESL technology had only one observation by 2009. For each technology, we aimed to predict the performance for the most recent five years. The training period consisted of the remaining data (see Figure A2a in Online Appendix A). For the SAW approach, we fitted the model using the training observations for all technologies except the one for which we wished to make predictions. We then used the training observations from the curve for which we were forming predictions to make predictions using Equations (7) and (8). This approach guaranteed a fair comparison with the other models by ensuring that the out of sample data for a particular curve was never used, directly or indirectly, to form estimates for a given technology.

Evaluation of Predictive Accuracy. We compare the predictions on the test time period with the actual evolution of the technology using two measures. The first is the average absolute deviation (AAD):

$$AAD_i = \frac{1}{Z}\sum_{t=1}^{Z} |P_{it} - \hat{P}_{\iota t}|, \tag{12}$$

where Z is the length of the testing period, P_{it} is the performance level at time t of the testing period for technology i, and $\hat{P}_{\iota t}$ is the corresponding estimate using a given model.

The second approach standardizes the curves according to the absolute values of the technology (Percentage AAD). This method scales the error relative to the level of performance in the technology. Specifically we compute

$$Percentage\_AAD_i = \frac{1}{Z}\sum_{t=1}^{Z} \frac{|P_{it} - \hat{P}_{\iota t}|}{P_{it}}. \tag{13}$$

We report the median values of *AAD* and *Percentage_AAD averaged* over all the technologies.

Results

We first present the results on the drivers of technological change. Next, we compare the performance of SAW with alternative models in predicting technology evolution. We then present the findings on the step size, wait time, and growth rate for all technologies. Finally, we present plots of the patterns of technology evolution for all markets combined.

Table 3 Drivers of Step Size and Wait Time

Covariate	Step size Est.	Step size t-value	Wait time Est.	Wait time t-value
Year of introduction (H1)	0.19	39.7	−0.12	−247.3
Order of entry (H2)	−0.31	−8.0	−0.05	−1.3
No. of competing technologies (H3)	−0.11	−3.0	0.42	12.4
No. of prior steps (H4)	−0.01	−1.3	−0.06	−6.4
Average prior wait time (H5)	0.08	3.4	−0.003	−0.1
Last step size (r – Equation (3))	0.02	2.9	0.002	0.3
Last wait time (s – Equation (6))	−0.04	−2.8	−0.01	−0.8

Drivers of Technological Change

Table 3 presents the parameter estimates for the Step and Wait submodels. The year of introduction covariate has a positive sign for the Step submodel but a negative sign for the Wait submodel. The results support H1, that products introduced in later years tend to have shorter waits and larger steps.

The order of entry covariate has negative signs for both the Step and Wait submodels. The results indicate that, after controlling for year of entry, later entrants to a market tend to have a shorter wait but smaller steps. The negative coefficient for the step size is highly statistically significant and is consistent with the preferential attraction theory (H2B).

The number of competing technologies covariate has a negative sign for the Step submodel and a positive sign for the Wait submodel. The results suggest that after controlling for the effects above, our results support H3A and reject H3B.

The number of prior steps covariate has a negative sign for both the Step and Wait submodels. The results support H4 and suggest that technologies that have a number of prior steps continue to have small steps that happen at frequent intervals.

The average prior wait time covariate has a positive sign for the Step submodel but a slightly negative sign for the Wait submodel. The results partially support H5, suggesting that, after conditioning on the other covariates, technologies with long average prior wait times also have larger step sizes but may not continue to have long wait times.

Finally, the last step size and the last wait time covariates are statistically significant in the Step submodel, providing evidence that there is a correlation between step sizes and wait times, even after adjusting for the other covariates.

Comparison with Alternative Models

Table 4 presents the median errors over all technologies, comparing SAW with the alternative models. We use the final five years for each technology as the testing period; i.e., $Z = 5$. We found that all of the alternative models generally gave superior results using the log transformed data, so we report only these results. We also adjusted the competing methods so that their predicted curve passed through the final training data point (see Figures A2b and A2c in Online Appendix A). This generally gave superior results and made the models comparable to SAW, which forms its predictions in the holdout period starting from the final training data point.

Table 4 Comparison with Alternative Models: Median of Test Errors ($Z = 5$ Years)

Model	Path of tech. change	No covariates AAD	No covariates % AAD	Hypothesized covariates AAD	Hypothesized covariates % AAD
Moore/Kryder	Exponential	0.45	0.12	0.30	0.07
Logistic	S-shaped	0.27	0.08	0.31	0.07
Bass	S-shaped	0.28	0.08	0.56	0.21
Gompertz	S-shaped	0.31	0.09	0.32	0.07
Gupta	Irregular	0.26	0.07	0.31	0.08
Tobit II	Irregular	0.41	0.14	0.34	0.16
SAW	Irregular	0.20	0.05	0.13	0.07
Naïve	No change	0.24	0.06	N/A	
Diff Reg		N/A		0.55	0.13

Notes. Refer to Table 3 for hypothesized covariates. N/A, not applicable.

Table 4 contains two sets of results for each method. The first is the random effects fit with no covariates, and the second is the fit that incorporates the covariates from Table 3 using (11). Among the models without covariates, SAW is significantly superior on both metrics. When incorporating covariates, SAW improves further on the AAD metric, in absolute terms and relative to the competing methods. SAW is the best in AAD and tied for the best in Percentage AAD. Figure 2 plots the median AAD by year for models with covariates and demonstrates that SAW outperforms most models in every year during the testing period. The only exceptions are 2005 and 2006, where the SAW and Gupta models both have zero AAD. In all other years, and for all other methods, SAW is superior. We also compare the per-technology performance of SAW relative to the competing methods (see Table 5). The SAW model is first,

Figure 2 Median AAD for Models with Covariates

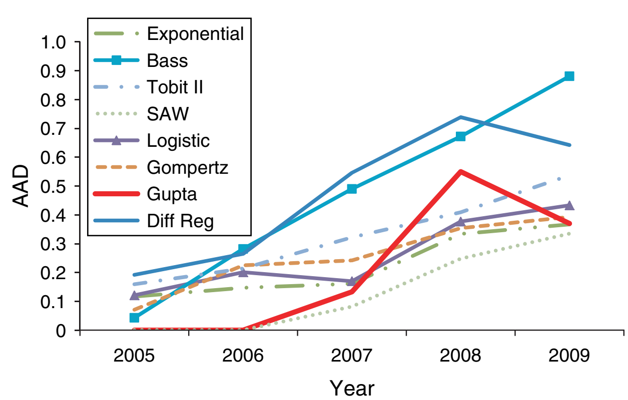


Table 5 **Average AAD in Testing Period for All Models and Technologies**

Technology	Exp	Logistic	Bass	Gompertz	Gupta	Tobit II	SAW	Diff Reg
Incandescent	0.10	0.22	0.72	0.28	0.08	0.06	0.05[a]	1.16
Arc discharge	0.12	0.20	1.47	0.24	0.00	0.02	0.00[a]	0.05
Gas discharge	0.09	0.11	0.85	0.11	0.12	0.04	0.11	0.03
LED	1.32	1.37	1.47	1.47	1.47	1.26	1.39	1.13
MED	0.05	0.03	0.00	0.00	0.00	0.24	0.07	0.01
Magnetic	0.32	0.32	0.62	0.62	0.25	0.23	0.26	0.74
Optical	0.22	0.25	0.02	0.00	0.46	0.72	0.00[a]	0.21
Magneto-optical	1.30	1.30	1.71	1.61	1.09	0.88	1.61	1.30
Holographic	0.28	0.12	0.39	0.31	0.30	0.29	0.37	0.15
Semiconductor	0.78	0.65	0.86	0.75	0.76	0.72	0.86	0.74
CRT	0.35	0.01	0.03	0.01	0.42	0.32	0.13	0.72
LCD	0.24	0.10	0.23	0.18	0.25	0.45	0.10[a]	0.37
OLED	0.16	0.05	0.58	0.07	0.31	0.22	0.08	0.55
PDP	0.30	0.31	0.37	0.37	0.37	0.30	0.26[a]	0.32
LCOS	0.09	0.32	0.05	0.33	0.06	0.14	0.04[a]	0.04
Dot matrix	0.47	0.48	0.52	0.48	0.29	0.34	0.48	0.50
Inkjet	0.32	0.55	0.69	0.47	0.31	0.46	0.58	0.68
Laser	0.96	1.11	1.42	1.35	1.13	0.83	1.39	1.08
Thermal	0.63	0.71	1.16	1.07	1.01	0.82	0.87	0.60
Copper/aluminum	0.93	0.63	0.00	0.62	1.27	1.06	0.00[a]	2.07
Fiber optics	0.77	0.76	0.51	0.66	0.45	1.84	1.21	1.00
Wireless	0.50	0.50	1.38	0.32	0.32	0.47	0.05[a]	0.85
Galvanic cell	0.13	0.05	0.56	0.07	0.00	0.13	0.00[a]	0.39
Fuel cell	0.08	0.16	0.07	0.17	0.25	0.61	0.30	0.25
Flow cell	0.03	0.01	0.03	0.00	0.00	0.12	0.00[a]	0.08
No. of times best	1	5	2	2	4	2	10	3
Median	0.30	0.31	0.56	0.32	0.31	0.34	0.13	0.55

Note. MED, microwave electrodeless discharge; LCOS, liquid crystal on silicon.
[a]Lowest AAD across all models.

equal in performance on 40% of technologies, and has the lowest median AAD across all technologies for the five holdout (most recent) years.

We also implemented the Exponential, Logistic, Bass, and Gompertz models using fixed effects for the parameters, i.e., fitting the models separately to each curve. The results (not shown here) were generally inferior to those reported in Table 4, suggesting that building strength by fitting all curves simultaneously using random effects improves prediction accuracy. However, because the alternative models were still inferior to SAW, we can conclude that SAW is performing well not only because of its ability to build strength across technologies but also because of its functional form, which more accurately matches the observed data.

Step Size, Wait Time, and Growth Rate

Equations (7) and (8) provide predicted step size and wait times that can be used to predict the future evolution of a technology. Table 6 presents the average predicted step size (on a log scale) and wait time (in years) for each technology (see columns 4 and 5). By taking the ratio of predicted step size and wait time, we can also assess the average long run growth rate for each technology (column 6). Column 7 of Table 6 contains the estimates for τ_2, the exponent used in a fixed-effects model to fit an exponential curve to each technology, along with the associated standard error, σ_{τ_2}. Kryder's law predicts that $\tau_2 = (12/13)\log 2 = 0.64$, whereas Moore's law implies $\tau_2 = (12/18)\log 2 = 0.46$. Almost all technologies exhibited rates of growth considerably slower than these values. The lone exceptions were the fiber optics and wireless technologies, which had estimated coefficients of $\tau_2 = 0.44$ and $\tau_2 = 0.60$, respectively. Thus, contrary to claims in the literature, Kryder's law and Moore's law appear to be neither applicable to the magnetic storage technology nor generalizable across markets.

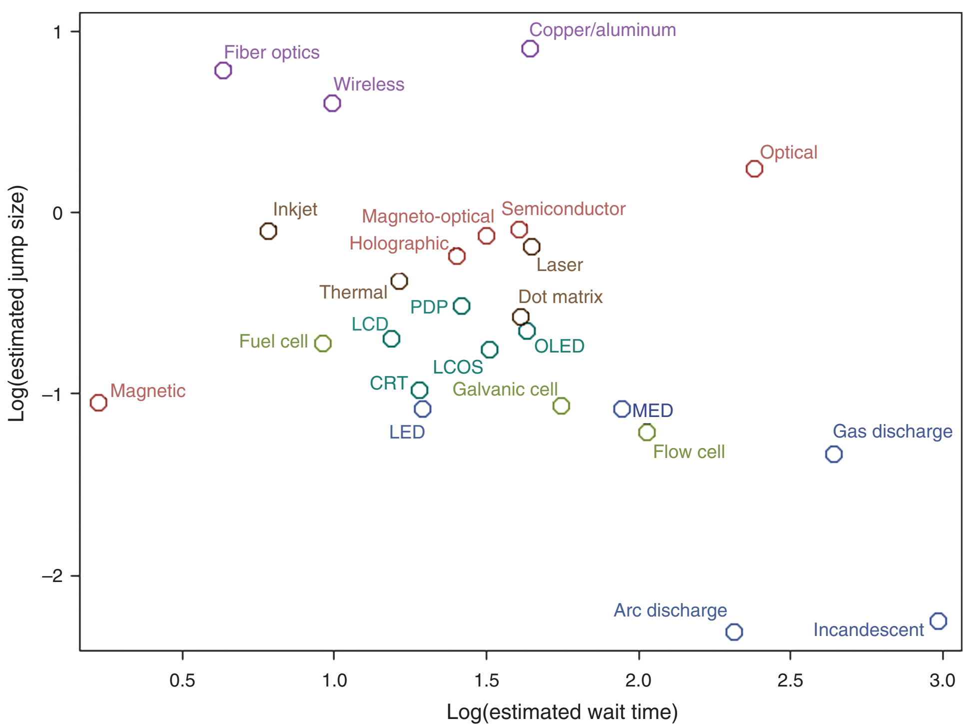
Figure 3 provides a plot of the predicted step sizes and wait times for each of the 25 technologies on a two-dimensional graph. Two aspects stand out: First, there is clear clustering, with technologies from the same markets generally showing similar predicted step sizes and wait times. We might expect this form of clustering, because technologies within the same market will tend to have similar properties. Second, the unconditional correlation between step size and wait time is negative (−0.32).

Figures A3a and A3b in Online Appendix A plot the step size and wait times, respectively, for each technology as a function of calendar year. The positive slope of the trend line in Figure A3a suggests that the step size is increasing over time, and the negative

Table 6 Step Size, Wait Times, and Growth Rates

(1) Category	(2) Technology	(3) Year of introduction	(4) Mean step size	(5) Mean wait time	(6) Growth rate from SAW (Equations (7) and (8))	(7) Growth rate from exponential model (SE)
External lighting	Incandescent	1879	0.11	19.73	0.01	0.02 (0.001)
	Arc discharge	1908	0.10	10.11	0.01	0.03 (0.001)
	Gas discharge	1932	0.27	14.02	0.02	0.02 (0.001)
	LED	1965	0.34	3.63	0.09	0.13 (0.005)
	MED	1989	0.34	6.98	0.05	0.01 (0.002)
Desktop memory	Magnetic	1937	0.35	1.25	0.28	0.31 (0.007)
	Optical	1982	1.28	10.83	0.12	0.12 (0.011)
	Magneto-optical	1986	0.88	4.47	0.20	0.24 (0.011)
	Holographic	2002	0.79	4.06	0.19	0.12 (0.017)
	Semiconductor	2002	0.91	5.00	0.18	0.26 (0.066)
Display monitor	CRT	1929	0.38	3.59	0.10	0.19 (0.016)
	LCD	1967	0.50	3.29	0.15	0.21 (0.011)
	OLED	1971	0.52	5.13	0.10	0.11 (0.011)
	PDP	1984	0.60	4.13	0.15	0.20 (0.018)
	LCOS	2004	0.47	4.52	0.10	0.02 (0.007)
Data transfer	Dot matrix	1953	0.56	5.02	0.11	0.07 (0.005)
	Inkjet	1975	0.91	2.19	0.41	0.32 (0.013)
	Laser	1976	0.83	5.21	0.16	0.19 (0.014)
	Thermal	1979	0.69	3.37	0.20	0.29 (0.018)
Desktop printer	Copper/aluminum	1962	2.47	5.17	0.48	0.38 (0.021)
	Fiber optics	1977	2.19	1.88	1.16	0.44 (0.016)
	Wireless	1982	1.83	2.69	0.68	0.60 (0.051)
Automotive battery	Galvanic cell	1780	0.34	5.74	0.06	0.06 (0.008)
	Fuel cell	1838	0.49	2.62	0.19	0.10 (0.008)
	Flow cell	1980	0.30	7.60	0.04	0.02 (0.002)

Figure 3 Plot of Step Sizes and Wait Times for 25 Technologies



slope in Figure A3b suggests that the wait time is decreasing over time. Figure A3c plots the growth rate (on a log scale) over calendar time and shows a very clear trend of exponentially increasing growth rates over calendar time, with a correlation of over 0.6 with a p-value below 1%. These results suggest that technology evolution is occurring at a faster pace with calendar time.

Discussion

This section summarizes the findings and discusses the implications and limitations.

Summary of Findings

The current research leads to four major findings:

1. The traditional laws of technology evolution such as Moore's law and Kryder's law do not generalize across markets; none holds for all technologies even in a single market.
2. SAW produces superior predictions over traditional methods, such as the Bass model or Gompertz's law, and can form predictions for a completely new technology by incorporating information from other categories on time-varying covariates.
3. The signs of the significant drivers of technology evolution suggest that
    a. recent technologies improve at a faster rate than old technologies;
    b. as the number of competitors increases, the performance of technologies increases in smaller steps and longer waits;
    c. later entrants to a market and technologies that have a number of prior steps tend to have smaller steps and shorter waits; and
    d. technologies with long average prior wait times continue to have large step sizes.
4. Technologies cluster in their performance by market.

Implications

This study has several implications for managers. First, our results suggest that popular laws and models such as Moore's law, Kryder's law, Gompertz's law, and the logistic model are naïve generalizations of what seems to be a complex phenomenon. Such theories make simplistic assumptions about the path of technology evolution (e.g., exponential or S-shaped) and thus are inadequate in predicting technology change well. Surprisingly, over the period covered in our analysis, it took 28 months for magnetic storage technology to double in performance, which is much longer than the commonly espoused versions of Moore's law claiming that performance doubles every 18 months (recent) or 12 months (original). Hence, although such laws may serve as long-term guideposts for industry evolution, using them to predict the performance of a technology is quite risky and potentially misleading. On the other hand, SAW explicitly models the discontinuous nature of the technology evolution curves observed empirically.

Second, SAW can help managers to reduce the nature and extent of uncertainty regarding the future path of technology evolution. SAW can be easily fit by a simple maximum likelihood approach and incorporates time-varying covariates for each technology. Thus, managers can use it to assess the nature of the threat posed by a competing technology by classifying it as one that is a long-wait/small-step technology, or vice versa. As an example, consider the competition between LCD and CRT monitors (see Figure 1c). Sony kept investing in CRT technology even after LCD first crossed CRT in performance in 1996. Instead of considering LCD, Sony introduced the FD Trinitron/WEGA series, a flat-screen version of the CRT. CRT crossed LCD for a few years, but ultimately lost decisively to LCD in 2001. In contrast, by backing LCD technology, Samsung grew to be the world's largest manufacturer of LCD monitors, whereas the former leader Sony had to seek a joint venture with Samsung in 2006 to manufacture LCD monitors. Prediction of the next step size and wait time using SAW could have helped Sony's managers make a timely investment in LCD technology.

Third, SAW overcomes limitations of prior models of depending on only environmental scanning (e.g., survey or the Delphi method) or extrapolation (e.g., trend analysis). SAW incorporates both environmental scanning by incorporating data from multiple technologies and extrapolation by incorporating past data from the target technology in making predictions. Further, SAW is flexible enough to allow for large periods of no change punctuated by big steps or small periods of small changes, approximating a smooth curve. As such, it partially resolves the controversy in the literature between technology evolution via a smooth curve (Basalla 1988, Dosi 1982) or via stable periods punctuated with big steps (Eldredge and Gould 1972, Tushman and Anderson 1986). For example, inkjet printers became the dominant technology in the market even though they had the lowest performance at its introduction through a series of small but frequent steps.

Fourth, our results suggest that the competitive landscape is becoming more intense. An increasing number of new technologies is entering the market. The rate of technology evolution is increasing at a faster pace. Thus, managers need a method and model to predict technology evolution to guide their multimillion dollar investments. SAW serves such a purpose. SAW can easily make predictions for a new technology with no prior data. This discussion brings us back to the key question that managers face: Which technology to back? In GM's case, it turned out to be a billion-dollar question. GM spent over a billion dollars on the hydrogen fuel cell. Yet the technology that leapt ahead in the 2000s was lithium-ion. Tesla based its battery on lithium-ion technology and had a car on the market in 2006. GM saw the need for lithium-ion only after the Tesla car was launched, and it launched a car using a lithium-ion battery only in December 2010. Many firms were taken by surprise by the sudden dominance of lithium-ion. Managers might have presaged the improvements in lithium-ion technology before 2006 by using our model.

Limitations
This study has five limitations. First, we had to limit our analysis to only six markets because of the time and difficulty of data collection. Second, our analysis does not include the impact of investments in R&D on technology evolution. This is a limitation of the data, rather than of SAW, as it could certainly include R&D budgets as a covariate, which should increase its predictive accuracy even more. Third, our analysis does not include the cost of the technology to buyers. Fourth, it is not possible to exactly estimate the step size and wait times for the years with missing data. However, given the small percentage of such data, this is unlikely to have a significant effect on the results. Fifth, we assume that firms announce all improvements in performance and that there are no minor improvements between steps. A possible extension may relax this assumption and allow for a low level of growth during the wait period. All of these limitations are potential opportunities for future research.

Electronic Companion
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