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THE EFFECTS OF EXPECTATIONS ON TECHNOLOGY ADOPTION: SOME EMPIRICAL EVIDENCE*

ALLEN M. WEISS

Rosenberg [1976] argues that in many markets prospective buyers for an innovation are strongly influenced by expectations "... concerning the timing and significance of future improvements ..." The primary objectives of this article are to provide a model of the innovation decision process of user firms that expect improvements in current best technology and to offer an empirical study which tests the model's predictions. Among other results, we find empirical support for Rosenberg's argument and demonstrate theoretically that, compared to models without technological expectations and learning, the optimal decision process is non-monotonic.

I. INTRODUCTION

IN HIS REVIEW of the history of technological innovation, Rosenberg [1976] argues that prospective buyers for an innovation are strongly influenced by expectations "... concerning the timing and significance of future improvements ..." and that under these circumstances it may be sensible to delay until these improvements occur. Observers of "high-technology" markets often make a similar point. The process by which technological improvements are accepted seems to be affected quite closely by the *expectations of future improvements* in the current best technology. Apparently, a decision to buy now based on the superiority of the current best alternative over the incumbent technology may soon result in the buyer's owning an antiquated technology.

Despite its intuitive appeal and the support of informal analysis, there is no empirical evidence about this issue in the literature. The studies of technology improvement effects have only looked at substitution patterns at an aggregate level (e.g., Fisher and Pry [1971]; Norton and Bass [1987]) and thus do not reveal much insight into the firms' decision process.

Formal analysis of the issue is also quite scarce. Two papers that have examined the influence of future improvements provide mixed results. In Kamien and Schwartz's [1972] paper, uncertainty about future improvements tended to inhibit adoption of current best practice while Balcer and Lippman [1984] argue that such uncertainty can actually foster purchase. Importantly, neither of these papers models diffusion *per se*. User firms make their decisions simultaneously.

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The primary objective of the paper is to provide fresh insight into firms' decision processes when improvements are expected in currently available innovations. We contribute to the literature on technology adoption (e.g., Mansfield [1968]; Oster [1982]; Hannan and McDowell [1984]; Kamien and Schwartz [1982]) in at least two ways. First, from a theoretical standpoint, by explicitly assuming that firms do not have full information regarding the value of future improvements in a technology we demonstrate that the adoption decision in light of technological expectations is more complex than that identified in previous models (e.g., Balcer and Lippman [1984]). In particular, we show that expectations of earlier improvements do not always inhibit the adoption decision. This results from a lack of monotonicity in the optimal stopping rules. Second, our empirical evidence of the relationship between technological expectations and a firm's tendency to suspend the adoption decision process for a current technology is, based on the extant literature (Bridges, Coughlan and Kalish [1991]), the first of its kind and therefore provides a modest first step toward enhanced theory construction.

We proceed by first describing a simple analytic model of the firm's innovation decision process. Our approach draws on and extends the analytic literature on the adoption of innovations in uncertain environments (e.g., Jensen [1982]; Feder and O'Mara [1982]; Chatterjee and Eliashberg [1990]). In particular, we extend the method of analysis employed by McCardle [1985]. The model provides refutable predictions, which are tested in an empirical study of a set of printed circuit (PC) board manufacturers that are potential buyers of a new manufacturing technology called surface-mount technology.

II. A SIMPLE MODEL

To set the stage for the firm's decision problem, consider the following situation: a firm is currently using some technology to perform a task. We call this the firm's *incumbent* technology. At some point in time, $t = 0$, the firm is faced with news of a major technological innovation for performing the same task. This innovation is herein called the *current best* technology.

Denote x as the known benefits associated with its incumbent technology and y as the known benefits associated with the current best technology. The firm views the advantage of the current best technology over its incumbent technology as the *current technological lag*, $p = y - x$. By assuming a non-negative pace of technological change we have $p \geqslant 0$.

The cost of adopting the current best technology is c, which includes both puchase and installation costs as well as other disruption or "switching costs" (e.g., Jackson [1985]). The incremental profitability of the current best technology is thus $p - c$.

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Expectations are modeled in a simple manner. We assume that firms anticipate that technological improvements in the current technology will be forthcoming. Uncertain benefits and costs of sizes $\tilde{z}$ and $\tilde{c}_f$, respectively, and a launch date $\tilde{T}$ characterize these future improvements.

Analogous to the current best technology, the firm's position can be described by its *future technological lag*, $\tilde{q} = \tilde{z} - x$. The incremental profitability of the improved version of the technology is $\tilde{k} = \tilde{q} - \tilde{c}_f$. Let the firm's estimate of $\tilde{T}$ be T. We restrict our attention to the case where the incremental profitability of the future technology is expected to have non-negative net value; i.e., $E(\tilde{k}) = k \geqslant 0$.

Consider the firm's appraisal of suspending the adoption decision process for the current best technology in light of these expectations of future technological improvements. The suspension of the decision process essentially provides the firm with an *option* to purchase the improved technology when it becomes available. The value of this option is denoted in the model by the expected net present value of the future technology contingent on the firm's purchasing the technology when it becomes available; that is, $\beta^{T-t}k$ for any time $t \leqslant T-1$, where β is the one-period discount factor. However, since the firm is not committed to purchasing the future technology if it decides to suspend the decision process, the actual value of this option may be higher than $\beta^{T-t}k$.

We assume that by expending an amount s, the firm can obtain additional information regarding the size of the anticipated technological improvements in each period. This information is incorporated in a Bayesian fashion into its prior estimate of the incremental benefits of the future version of the technology, k.

II(i). *Analysis of Decision Problem*

Following the analysis presented by McCardle [1985], we characterize the firm's situation as an optimal stopping problem.[1] Defining $V(t, k)$ as the

[1] One could alternatively model the firm's decision problem using option pricing methods (Pindyck [1991]). With option methods, the true value of the underlying asset is known today, but there is uncertainty over tomorrow's value. In the present model, a technology exists whose future value, by virtue of technological improvements, is also uncertain. Thus, the two approaches are similar, and indeed some of the results derived here are not inconsistent with the results from a traditional option model. However, in the traditional options model where Markov processes are assumed, having observed many periods of, say, price information is no better for assessing tomorrow's price than simply observing today's price. Thus, no learning takes place. This is a reasonable approach for situations where an assumption of fully informed markets is viable. However, a central feature of the present model is that more periods of information give the firm a better estimate of a future technology's true value. Given that the future technology does not yet exist, this is a reasonable assumption. Moreover, allowing the firm to learn about the value of a future technology by gathering costly information is consistent with the observed process that organizations use when buying improving technologies (e.g., Rosenthal [1984]).

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maximum expected value of the decision facing the firm, it can be described recursively by the following dynamic functional equation:

(1) For $t = 0, 1 \ldots T - 2$:

$$V(t,k) = \max[p - c, \beta^{T-t}k, -s + \beta EV(t+1, M(t,k))]$$

with terminal condition: $V(T-1,k) = \max[p - c, \beta k]$

In this formulation, $M(t,k)$ is the pre-posterior expected value of k at time $t + 1$ given the present estimate of k. In this decision model, the firm must decide at each point in time which is the greatest: (a) the net value of adopting latest technology ($p - c$), (b) the net value of suspending the adoption decision process for the current best technology ($\beta^{T-t}k$), or (c) gathering more information about the size of the anticipated technological improvements at a cost s and getting the discounted expected value of the decision for the next period ($\beta EV(t+1, M(t,k))$).[2]

Note that one period before the anticipated future technology is due to be launched ($t = T - 1$) the decision problem involves only the choice between adoption and suspending the adoption decision process because we assume that the current best technology becomes unavailable when the future version of the technology is launched.

It is possible that the incremental profitability associated with the expected future technological improvements is viewed as so far superior to that for the current best technology that $\beta^{T-t}k > \max[p - c, -s + \beta EV(t+1, M(t,k))]$ for all k. Of more interest is the situation where the option of gathering additional information is optimal for some values of k. To this end, we define a *continuous region*:

$$C_t = \{k\colon -s + \beta EV(t+1, M(t,k)) > \max[p - c, \beta^{T-t}k]\}$$

This continuation region is a set of values of k for which it is optimal that the firm gathers information rather than adopting or suspending the adoption decision process. Assuming that this continuation region exists and that the firm's initial value for k falls within this region guarantees that the firm begins its acquisition decision process by gathering information.

The following proposition demonstrates that two critical numbers k_t and k^t exist such that the firm's optimal decision policy is to:

adopt the latest technology if $k \leqslant k_t$

search for more information if $k_t < k < k^t$

suspend the adoption decision process if $k \geqslant k^t$.

[2] Assuming a conjugate pair of distributions such as beta-Bernoulli, we can write down the value of $M(t,k)$, which represents the updated estimate of $\bar{k}$.

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Lemma 1. $V(t, k)$ is nondecreasing and convex in k. (See Appendix for all Proofs)

Proposition 1. The critical numbers k_t and k^t exist.

From Figure 1, the hypothesis follows that the likelihood of suspending the adoption decision process (adopting) is directly (inversely) related to the size of the anticipated technological improvements.

Lemma 2. For any t, the probability of searching varies directly with a combination of an increase in k^t and a decrease in k_t, while the probability of suspending the adoption decision process at a given time t varies inversely with k^t and the probability of adoption at a given time t varies directly with k_t.

Proposition 2. k^t is nonincreasing in t, and k_t is nonmonotonic and convex in t.

Proposition 2 denotes a key theoretical result of this model. Unlike extant innovation models that are similar in approach but that do not incorporate technological expectations (e.g., McCardle [1985]; Bhattacharya, Chatterjee and Samuelson [1986]), similar hypothesis testing models in other contexts (e.g. Bertsekas [1976]), as well as previous decision models with technological expectations (e.g., Balcer and Lippman [1984]), the critical values *do not exhibit monotonic behavior with respect to time.* k_t first increases and then decreases in t. Hence, a firm that at some early point in time thought that an innovation was not worth adopting (i.e., $k > k_t$) may well adopt at some later time $t + n$ even if its own estimate of the incremental profitability associated with the technological improvements k is unchanged. In short, what was not good enough yesterday can be good enough today. This insight is consistent with that of Balcer and Lippman [1984]. As time goes on, however, this threshold decreases again as the future technological improvements draw nearer.

Recall that expectations were also described by the launch data parameter T. We now consider the effects of changing this parameter of the innovation decision. Assume that the decision problem is at time $T-2$, so the value of the optimal decision is $\bar{V}(T-2, k)$. Now, a shortening of the launch date by one period (holding k constant) results in $\bar{V}(T-1, k)$ as the optimal value of the decision problem. But, from Lemma 3 (see Appendix) we know that $\bar{V}(T-2, k) \geqslant \bar{V}(T-1, k)$. So decreasing T has the effect of decreasing $\bar{V}$. Since Lemma 3 holds for all t, it follows that $\bar{V}(t, k)$ is nondecreasing in T for all t. Thus, decreases in T have the effect of decreasing $\bar{V}(t, k)$. From Figure 2, it is evident that this has the effect of decreasing k_t,[3] using the

[3] This result is consistent with option theory in that the likelihood of suspending the decision process, and thereby giving the firm the option to purchase the improved technology when it becomes available, increases as the "expiration date" increases.

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numerical results for k_t, this also has the effect of increasing k_t for large values of $T - t$ or decreasing k_t for small values of $T - t$.

We now bring together the results for the size of anticipated future technological improvements (k) and the timing of these improvements (T). The results confirm the intuition that when a greater pace of technical change is anticipated (as indicated by larger anticipated improvements and/or sooner launch dates), firms are more prone to suspend their adoption decision processes for the current innovation. This suggests that the early versions of an innovation are handicapped by the expectations of improvements, and diffusion is delayed. These analytic results are consistent with Rosenberg's [1976] assertion that various innovations undergoing technological change (e.g., incandescent light bulbs, commercial jet airplanes, the oxygen steel-making process, the catalytic converter) were slowed by potential buyers' expectations of improvements in the technology.

Finally, it is straightforward to show (see the Appendix, Proposition 3) that the critical numbers are both nondecreasing in the current technological lag p and nonincreasing in the total switching costs c. Also, k_t is nondecreasing in the cost of search s, while k^t is nonincreasing in s. Hence, as total switching costs increase, firms will tend to suspend their adoption processes more and adopt less. Also, as information about the size of anticipated technological improvements is more difficult to acquire (i.e., the costs of search s increases), firms are more prone to shutting down the information acquisition process earlier. This appears counter-intuitive. It captures the idea that when searching is more costly, decisions are made without reducing as much uncertainty as otherwise. Notice that more costly search makes firms more prone to suspend their adoption processes as well.

III. EMPIRICAL STUDY

We now present data from a survey of firms in the potential market for an innovation that is expected to continue improving. We offer evidence that is relevant to issues addressed in our model as well as address some claims that have been made in the extant literature. To begin, we introduce the research context and then describe the data collection procedures and measures used. The results of the statistical models are then presented, and a discussion of the results closes the paper.

III(i). *Research Context*

The data presented here deal with user firms that currently possess some incumbent equipment for performing a task and are confronted with an innovation. Due to improving technology, even better innovations are anticipated.

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An industrial context that appears to match these requirements is the assembly of printed circuit boards. Here, firms with automated assembly lines generally use the "through-hole" process to affix electrical components (e.g., resistors, integrated circuits) to printed-circuit boards. With this process the components are machine-attached via holes in the circuit board. Such holes take up space and require that components are placed on only one side of the circuit board. "Surface-mount technology" (SMT) is a new method for automated assembly of these boards.[4] It does not use holes for attaching the leads of components; instead, the devices are soldered directly on the board. Accordingly, the major benefit afforded by this newer technology is higher printed-circuit board densities.

While SMT is generally considered to be an improvement over the "through-hole" process, it is not yet in widespread use by firms. Although precise numbers are unavailable, industry observers speculate that (as of 1993) about 10% of firms in the United States with automated printed-circuit assembly line currently use SMT. Interviews with equipment suppliers and a perusal of the trade press reveal that the diffusion of SMT has been handicapped by the "curse" of anticipated improvements.

To understand the content of these improvements, consider the machines involved in SMT. There are basically three machines that a firm must purchase in order to implement SMT. First, a pick and place machine places components on the circuit board. The performance of these machines has been improving steadily in terms of speed, accuracy of placement, and flexibility in types of components that can be handled.

Second, a soldering machine is used to affix the component permanently. The reliability of these machines has also been improving rapidly as their manufacturers become more familiar with the substantially different soldering technique used here as compared to "through-hole" technology. Third, testing equipment is necessary to assure components are affixed and connected properly. In SMT the components are so small that their leads require special handling methods to ensure connections are sound and reliable. Together, these machines have been improving in terms of performance and reliability.

III(ii). *Sample and Data Collection*

Firms in the potential market for SMT are those with automated assembly lines for manufacturing printed circuit boards. They may manufacture these boards for outside sales in the "merchant" market, or they may be "captive" producers that incorporate these boards in some equipment being produced for sale.

[4] Some firms use manual assembly techniques, but SMT is not a replacement for manual assembly, which is used only for very low volume work or specialized needs such as building prototypes.

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As we are interested in these firms' decision processes and this requires data about their perception of technology advances, traditional types of archival data on the diffusion of SMT and the arrival dates of improvements would not be very useful. Instead, we use the sociological methodology of "key informants" to gather the data. This methodology has been used in other studies of economic theory (e.g., Anderson and Schmittlein [1984]). Using Campbell's [1955] criteria of informant knowledgeability and ability to communicate, the principal technical production manager at the manufacturing plant at each firm was selected as the key informant. The principal technical production manager is a generic term for many specific organizational titles. These include principal production engineer, manufacturing manager, process engineer, manufacturing engineer, or vice-president of manufacturing. Such individuals are the most knowledgeable of the firm's current manufacturing technology and are responsible for keeping abreast of the newest technologies and practice. Consequently, they have a key role in all SMT related decision-making and can report on the decision regarding purchase of SMT at their plant.

To obtain a sampling frame of these key informants we approached a trade journal (*Electronics Packaging and Production*) for their list of subscribers. Our interview with the editor revealed that our key informants would be subscribers to this journal, which reports on topics of interest to printed-circuit manufacturing. A contrast can be drawn between this approach and a SIC-based frame. Recall that we require a sample of firms from the potential market for SMT. Because this market is not homogeneous with respect to their SIC codes and includes firms that make these boards for sale as well as for internal use, it is very difficult to specify an SIC-based frame.

An immediate difficulty with the current frame is that it reaches well beyond the population of interest. The subscribers include many individuals and firms outside our population of interest (i.e., firms in the potential market for SMT). Consequently, such firms have to be screened out. Because firms in the potential market for SMT must possess automated printed-circuit assembly lines, all firms that did not currently have an automated printed-circuit assembly line were identified and deleted from the analysis.

The data collection effort was accomplished by first contacting subscribers by phone to solicit participation in the study and to identify whether the firm possessed automated printed-circuit assembly lines. A mail questionnaire packet was then sent to each informant. The packet contained two versions of the questionnaire. One version was tailored for firms that had already adopted SMT while the other was tailored for firms without SMT in place. They differed only in some wording and grammatical changes made in order to reflect the fact that the past tense is more appropriate when dealing with the adopter group. Informants completed only that version that was appropriate for the status of the firm (i.e., adopter or not). These questionnaires were developed with the aid of on-site visits and phone contacts with a dozen

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firms. These steps ensured that the specific wording used was appropriate and that confusing questions could be flagged and reworded as needed.

III(iii). *Dependent Variable*

We classify firms into categories representing their decision state (STATUS). Adopters were separated from non-adopters by asking the informants to report if SMT was currently in place in their firm. We asked the informants in non-adopting firms to assess the current status of SMT in their firm by checking one of the two responses below.

- It is *on hold* for the time being. We have looked into it and have decided not to get into it at this time. However, we may reconsider at a future point in time.
- We are still *seriously* looking at it. We are actively gathering information (for example, visiting SMT sites, etc.) and evaluating the possibility of getting into SMT.

In this way, firms are classifed (a) as having adopted, (b) as having suspended their adoption process, or (c) as continuing to search.

Given the subtlety of the difference between these two classes of non-adopters, we felt it prudent to include a validity check on their responses. We reasoned that firms that are still searching for information should be engaged in certain critical activities to a greater extent than those firms that have put the process on hold. Consequently, informants in the non-adopting firms were asked to rate the current extent of five activities (on 7-point scales, anchored with No Involvement/Very Much Involvement) that have been identified as critical indicators of an active adoption process at work (Ozanne and Churchill [1971]). These include contacting SMT vendors, identifying SMT system offerings, establishing SMT selection criteria, evaluating SMT system alternatives, and deciding on the purchase of a specific SMT system. As expected, firms responding in the search category reported a much higher level of these activities than those firms reporting having put the decision on hold. A statistical test of the mean differences is highly significant ($F = 11.39$, $(5, 39\ df)$, $p \leqslant 0.001$).

III(iv). *Independent Variables*

Incremental Benefits The technological lag parameter in the model was measured as the perceived superiority of the current innovation over their current equipment. Each informant was asked to rate SMT relative to their incumbent equipment (using a 7-point format with "Not at all Better" and "Very much Better" as the end points) on two aspects of the technology: PC board density (DENSITY) and equipment maintenance cost (MAINT).

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Expectations To measure expectations of improvements, we asked the informants to report their perception of the speed (PACE) at which SMT technology was improving with respect to performance and reliability. Informants used a 7-point format with "Very Slow Pace of Improvement" and "Very Fast Pace of Improvement" as the anchor points.

Certainty of Expectations This variable (CERTAIN) measures the certainty of the expectations of potential users regarding the timing of future improvements to SMT. While our model does not consider the uncertainty in these expectations, it is included in the empirical study since conflicting predictions have been made in the literature about its possible effects (e.g., Kamien and Schwartz [1972]; Balcer and Lippman [1984]). To measure this variable, we first asked the informants to forecast the arrival date for an SMT system that represents a significant overall improvement over existing systems. This provided a benchmark for which they were asked to assess the certainty attached to their forecast. Informants used a 7-point format with "Very Uncertain" and "Very Certain" as the anchor points.

Adoption Cost We measure two aspects of costs. First, the informants were asked to estimate the equipment costs (EQUIPCOST) associated with installing SMT. These costs are assessed relative to the size of their firm's printed circuit board manufacturing assets using a 7-point scale with "Very Small" and "Very Large" as the anchor points. The second measure (SWITCHCOST) deals with the costs of switching from their current method to SMT. It captures those sunk costs that are associated with their existing technology. These costs were measured on two rating scales. Specifically, informants used a 7-point format with "Strongly Disagree" and "Strongly Agree" as the endpoints when responding to the following questions: (a) With SMT, our way of doing things would have to change a great deal; and (b) It would be easy to replace our current employees with new personnel specifically trained in SMT (reverse-coded). Since these two items are intended to represent the same variable, an analysis was run that revealed a suspected high correlation between the two items ($r = 0.61$). Accordingly, a composite index capable of representing the variable was constructed using the first principal component of the two items (Kennedy [1993]).

Search Costs We use the skills and knowledge of the participants in the innovation decision within a firm as a surrogate for cost of search. When skill levels are higher, and a greater diversity of skills are present, the cost of search is lowered. This is the approach taken in sociologically oriented work on organizational activities (e.g., John and Martin [1984]). Accordingly, informants were asked to what extent decision participants possessed a variety of skills and specialized knowledge. A 7-point scale format with "Strongly Disagree" and "Strongly Agree" as the anchor points was used.

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User Market Structure We asked the informants to assess competition in their market (USERMARKET) on a 7-point rating scale that asked the informant how competitive the environment is in their industry compared to industries in general (the scale endpoints were Not Competitive/Very Competitive). This specifically relates to the effects of buyer-side market power on the innovation purchase decision. The effect of user industry structure has been examined in analytical models with somewhat conflicting results depending on assumptions of cooperative behavior among firms. For example, Reinganum [1981] assumes non-cooperative behavior and finds that user market power accelerates diffusion, while Quirmbach [1986] finds the opposite effect under conditions of cooperative behavior. Empirical evidence is quite scarce on this topic.

Control Variables Finally, included in our analysis are two variables that control for two important sources of heterogeneity across firms in our sample. To the extent that the central benefit of SMT (i.e., increased board density) is an important dimension of the firm's production output (denoted BDIMPORT), we might anticipate increased likelihood of adoption and decreased likelihood of suspending the adoption decision process, holding expectations of future improvements constant, because this may be central to the firm's current product strategy. BDIMPORT was measured on a 7-point scale (anchored with Not at all Important/Very Important). It is also possible that anticipated growth in board production (GROWTH) influences SMT adoption. Previous research (e.g., Oster [1982]; Hannan and McDowell 1984]) have found inconsistent results on this variable. GROWTH was measured as the anticipated percentage increase in the volume of PC boards produced over the next two years.

III(v). *Findings*

The sample used for the estimation includes 85 firms (24 adopters, 29 searchers, 23 firms that had suspended their adoption decision process). While the 85 firms do not constitute a very large sample, it is comparable in size to previous studies relying on a questionnaire methodology. Notice that we might have over-sampled adopters (industry speculation held that roughly 10% of firms had adopted SMT at the time of this study). While this does not jeopardize the theoretically relevant comparisons across the three groups, it does caution us to be careful about projecting parameter estimates to the SMT market.

Using a maximum likelihood approach, we estimated a multinomial logit model, with STATUS as a three-category dependent variable and the previously described independent variables as predictors. The model can be

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expressed as:

$$Pr(y = i) = \frac{e^{\bar{x}\bar{\theta}_i}}{\sum_{j=1}^{J=3} e^{\bar{x}\bar{\theta}_j}} \qquad \text{for } i = 1, 2, 3$$

To estimate the coefficients we set $\bar{\theta}_3 = 0$, where $J = 3$ is the search category. A positive coefficient in $\bar{\theta}_1$ then represents an increase in the probability of suspending the adoption decision process contrasted with searching, with respect to an increase in the relevant independent variable, and vice versa. Likewise, each coefficient in $\bar{\theta}_2$ contrasts the probability of adoption with searching, with respect to changes in the relevant independent variable.

Table I displays the results of the estimation. As the χ^2 statistic shows, we can easily reject the null hypothesis that the explanatory variables are jointly insignificant ($\chi^2(20\ df) = 41.67$; $p < 0.001$).

TABLE I
MULTINOMIAL MODEL
DEPENDENT VARIABLE: STATUS

Independent Variable	*Coefficient*	*Estimate*	*Standard Error*
CONSTANT	θ_{11}	−1.20	2.43
	θ_{21}	−5.03	2.97**
DENSITY	θ_{12}	−0.13	0.25
	θ_{22}	0.23	0.29
MAINT	θ_{12}	−0.34	0.23
	θ_{22}	0.40	0.24**
PACE	θ_{12}	0.59	0.31**
	θ_{22}	−0.10	0.29
CERTAIN	θ_{13}	0.16	0.22
	θ_{23}	0.57	0.25**
SEARCHSKILL	θ_{14}	−0.41	0.22**
	θ_{24}	−0.38	0.19**
EQUIPCOST	θ_{15}	0.01	0.18
	θ_{25}	−0.20	0.19
SWITCHCOST	θ_{16}	−0.18	0.28
	θ_{26}	−0.54	0.28**
USERMARKET	θ_{17}	−0.48	0.28**
	θ_{27}	−0.28	0.32
BDIMPORT	θ_{18}	−0.30	0.19
	θ_{28}	0.14	0.21
GROWTH	θ_{19}	0.01	0.01
	θ_{29}	0.01	0.01

$\chi^2(20\ df) = 41.67$**
* significant at $p \leqslant 0.10$ (1-tail)
** significant at $p \leqslant 0.05$ (1-tail)

Consistent with our model, we see that firms that perceive greater incremental equipment maintenance benefits to SMT (MAINT) are more

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likely to adopt ($\theta = 0.404$) and are less prone to suspend the adoption decision process ($\theta = -0.342$). The effects for incremental density benefits (DENSITY), however, are insignificant. Looking at the expectations measures we see that the forms that anticipate a greater pace of improvements (PACE) are more prone to suspend their adoption decision process for the current innovation ($\theta = 0.590$). This is also consistent with the prediction from the model. However, PACE has no significant effect on adoption of the current SMT equipment.

The coefficients for CERTAIN show that firms that hold more certain expectations of improvements are more prone to adopting ($\theta = 0.572$) and also to suspending the adoption decision process ($\theta = 0.166$). However, this latter effect is not significant.

Looking at the cost of search surrogate, we find that a greater ability to search (SEARCHSKILL) results in a lowered tendency to suspend the adoption decision process ($\theta = 0.410$) as well as a lowered tendency to adopt earlier ($\theta = -0.380$). Plainly, these firms can afford to search longer, as would be expected intuitively.

Neither of the two cost measures, EQUIPCOST and SWITCHCOST, have any significant effect on the tendency to suspend the adoption decision process. Looking at their effects on adoption, we find that EQUIPCOST is insignificant, while greater switching costs reduce the probability of early adoption ($\theta = -0.543$). This is consistent with the comparative statics from our model.

The level of competition in the user firms' industry (USERMARKET) appears to reduce the tendency to suspend the adoption decision process ($\theta = -0.484$). Its effect on adoption is insignificant. Finally, the two control variables (BDIMPORT and GROWTH) have insignificant effects.

IV. DISCUSSION AND CONCLUSIONS

The principal result of interest from the model concerned the effects of expectations. We saw that greater expectations of improvements reduced the market for the current innovation because firms tend to suspend their adoption decision process for the current innovation. Other results concerning adoption costs as well as the ability to search were also obtained from the model.

The empirical results above tend to support these expectations derived from the formal model. We found that a greater expected pace of improvements led to an increased tendency to suspend the adoption decision process for the current innovation. Evidently, the "curse" of anticipated improvements is stalling the diffusion of SMT in the printed-circuit board assembly market. To the best of our knowledge this is the first study to demonstrate an expectations effect on diffusion of an innovative technology. It supports the more informal analysis of Rosenberg [1976] that contended that technology

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expectations were of critical importance in understanding diffusion patterns of innovative technology.

The results involving uncertainty are interesting as they shed light on some conflicting results in the literature. Kamien and Schwartz [1972] concluded that uncertainty about the timing of improvements inhibited purchases of current innovations, whereas Balcer and Lippman [1984] contend that such uncertainty is more likely to encourage purchase of current innovations. According to our data, uncertainty discourages firms from adopting the current innovation, and thus is more supportive of the Kamien and Schwartz position.

With respect to the cost of search results, it should be noted that while search models have figured prominently in modeling diffusion (e.g., Jensen [1982]; Feder and O'Mara [1984]), there is virtually no empirical evidence about the ability of such models to describe firm decision processes. The data indicate quite clearly that firms behave in the fashion predicted by search process model. Those firms that face a higher cost of search tend to shut down the process quicker. The basic model of optimal search appears to be a robust description of firm behavior.

Finally, our data shed further light on the effects of user market structure. We find that more perceived competition in user industries tends to make firms less prone to suspending the adoption decision process for the current innovation. Since this reduces the handicap faced by the early versions of a new techology, it would appear to speed up the diffusion process. It provides some support for Quirmbach's [1986] conclusion that user market competition can speed diffusion, but is apparently not consistent with Reinganum's [1981] interpretation. Our data are consistent with Mansfield's data [1968] but not with the data reported by Hannan and McDowell [1984]. Clearly, more empirical work is needed to sort these discrepancies in market structure effects.

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APPENDIX

Proof of Lemma 1

Observe that $V(T-1,k)=\max[p-c,\beta k]$ is nondecreasing and convex in k. Using an induction argument, assume that for some $t<T-1$, $V(t+1,k)$ is nondecreasing and convex in k. Then $V(t,k)=\max[p-c,\beta^{T-t}k,\ -s+\beta EV(t+1,M(t,k))]$ is convex and nondecreasing in k. Since t was chosen arbitrarily, it follows that $V(t,k)$ is nondecreasing and convex in k for all $t=0,1,\ldots,T-1$.

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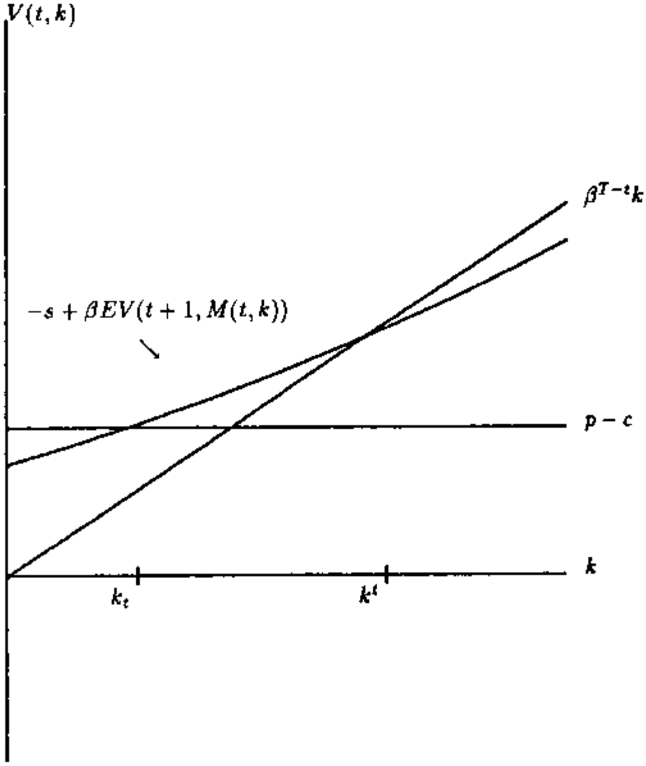

Figure 1

Proof of Proposition 1

In $(V \times k)$ space we depict the three arguments of the maximum function defined for $V(t, k)$. $p - c$ is a horizontal line in this space and is positive by assumption. Next, note that as k approaches 1, $-s + \beta EV(t, M(t, k))$ is less than $\beta^{T-t}k$ by an amount approaching s. As k approaches 0, $-s + \beta EV(t + 1, M(t, k))$ is less than $p - c$, also by an amount approaching s. Finally, assuming that the continuation set C_t is nonempty implies Figure 1.

Proof of Lemma 2

This lemma follows directly from Proposition 1 which implies that when a firm has estimate k at time t, the probability of adoption at time t can be written as $\Pr(k \leqslant k_t)$, the probability of gathering more information is $\Pr(k_t < k < k^t)$, and the probability of suspending the adoption decision process is $\Pr(k \geqslant k^t)$.

Proof of Proposition 2

Consider the following transformation:

(A-1) $\quad \bar{V}(t, k) = V(t, k) - \beta^{T-t}k$

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Note that while this transformation of the firm's decision problem alters the optimal value of the decision,[5] the critical numbers, and thus the firm's policy decision, are unaffected. Using equations (1) and (A-1) and the fact that $\beta EV(t+1, M(t,k)) = \beta\{E\bar{V}(t+1, M(t,k)) - \beta^{T-t-1}k\}$, upon rearrangement we can write the following functional equation for $\bar{V}(t,k)$.

$$\bar{V}(t,k) = \max[0, p - c - \beta^{T-t}k, -s + \beta E\bar{V}(t+1, M(t,k))]$$
$$\text{with terminal condition:} \quad \bar{V}(T-1,k) = \max[0, p - c - \beta k]$$

Using the model in Proposition 1, two critical numbers can be shown to exist for this transformed problem. The following lemma can then be used to depict their behavior over time.

Proof of Lemma 3 $\bar{V}(t,k)$ is nonincreasing in t.

Observe that

$$\begin{aligned}\bar{V}(T-2,k) &= \max[p - c - \beta^2 k, 0, -s + \beta E\bar{V}(T-1, M(t,k))] \\ &\geqslant \max[p - c - \beta k, 0] = \bar{V}(T-1,k)\end{aligned}$$

Using an induction argument, assume that $\bar{V}(t,k) \geqslant \bar{V}(t+1,k)$ for some $t < T-2$. To show that $\bar{V}(t-1,k) \geqslant \bar{V}(t,k)$ it suffices to show that

$$\begin{aligned}E\bar{V}(t, M(t,k)) &\geqslant E\bar{V}(t+1, M(t+1,k)) \colon E\bar{V}(t, M(t,k)) \\ &\geqslant E\bar{V}(t, M(t+1,k)) \geqslant E\bar{V}(t+1, M(t+1,k))\end{aligned}$$

The first inequality follows from the convexity of $\bar{V}(t,k)$, and the fact that $M(t+1,k)$ is less risky than $M(t,k)$ in the sense of second order stochastic dominance (see McCardle [1985]). The second inequality follows from the induction hypothesis.

Returning to the behavior of the critical numbers, we can see from Figure 2 that k^t is increasing in t since $-s + \beta E\bar{V}(t, M(t,k))$ is nonincreasing in t.

The pattern for k_t is more complex both $p - c - \beta^{T-t}$ and $\bar{V}(t,k)$ are decreasing over time. Thus, k_t may be increasing or decreasing with time. Since β^{T-t} increases the fastest as $t \rightarrow T$ and slowest as $t \rightarrow 0$, we might expect that monotonicity will fail to hold.

In an effort to understand the movement of k_t, the critical numbers were numerically calculated for numerous values for the parameters. The behavior of the critical numbers appear to be robust over this large range of values since not one simulated run deviated from the general pattern exhibited in Figure 3, which displays the critical numbers for one calculation. It shows that k_t first increases and then decreases with t. Consistent with the analytic result, k^t decreases monotonically with t.

Proof of Lemma 4

Define the critical numbers given by equation (1) implicitly as:

(A-2) $\quad k_t = \max[k \colon V(t,k) = p - c]$

(A-3) $\quad k^t = \min[k \colon V(t,k) = \beta^{T-t}k]$

[5] One needs to add back the value β^{T-t} in the transformed problem to calculate the value of the original problem.

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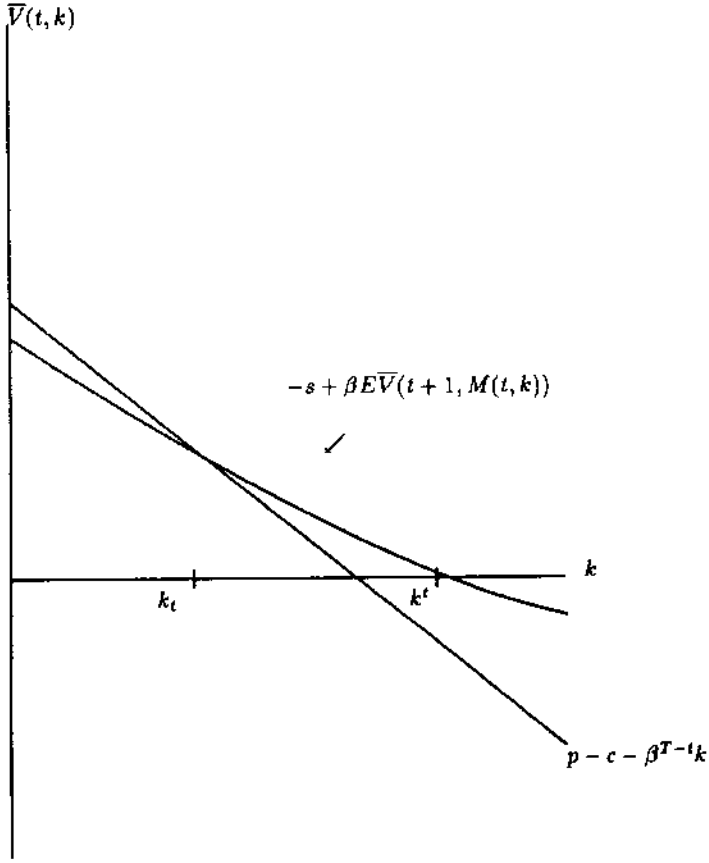

Figure 2

Using equations (A-2) and (A-3), we first specify the effects of the critical numbers on $V(t,k)$. Observe that $V(T-1,k) = \max[p-c, \beta k]$ is nondecreasing in p and nonincreasing in c. Also, $V(T-2,k) = \max[p-c, \beta^2 k, -s+\beta EV(T-1,k)]$ is nonincreasing in c and s and nondecreasing in p. Assume that $V(t+1,k)$ is nondecreasing in p and nonincreasing in c and s for some $t < T-2$. Then, $V(t,k)$ is also nondecreasing in p and nonincreasing in c and s. For the purposes of Proposition 3, it is also usful to show that $\frac{\partial V}{\partial p} \leqslant 1$. Consider that $V(T-1,k) = \max[\beta k, p-c]$, which implies that $\frac{\partial V}{\partial p} \leqslant 1$. Assume that $\frac{\partial V(t+1,k)}{\partial p} \leqslant 1$ for some $t < T-2$. Then $\frac{\partial V(t,k)}{\partial p} = \frac{\partial}{\partial p}\max[p-c, \beta^{T-t}, -s+\beta EV(t+1,k)] \leqslant 1$. Since t was arbitrarily chosen, it follows that $\frac{\partial V}{\partial p} \leqslant 1$ for all t.

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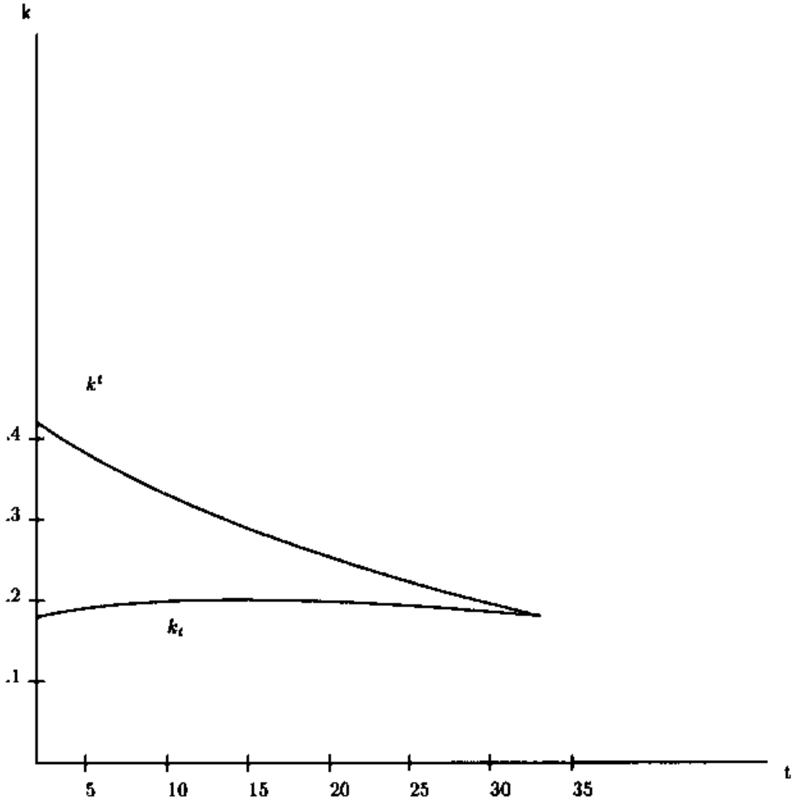

Parameter Values for simulation:

$\alpha = 1\ \delta = 2\ c = 0.3\ p = 0.5\ T = 50\ \beta = 0.9\ s = 0.002$

Figure 3
Non-monotonic behavior of critical values

Proof of Proposition 3

To establish the effect of p on the critical numbers,[6] we assert based on (A-2), that there exists a k_t such that $V(t, k_t) = p - c$.

Since k_t is a function of p, we can write $V(t, p, k_t(p)) = p - c$.

Differentiating with respect to p and rearranging, we have: $\dfrac{\partial k_t}{\partial p} = \dfrac{1 - \partial V/\partial p}{\partial V/\partial p}$.

[6] A similar method can be used to investigate the behavior of adoption costs, c, and search costs, s.

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Since $\frac{\partial V}{\partial p} \leqslant 1$ (Lemma 4) and $\frac{\partial V}{\partial k_t} \geqslant 0$ (Lemma 1), it follows that $\frac{\partial k_t}{\partial p} \geqslant 0$. Hence, k_t is nondecreasing in p.

From (A-3), we can assert that there exists a k^t such that, $V(t, k^t) = \beta^{T-t}k$ and since k^t is a function of p, we can write, $V(t, p, k^t(p)) = \beta^{T-t}k^t(p)$.

Differentiating with respect to p and rearranging we have, $\frac{\partial k^t}{\partial p} = \frac{\partial V/\partial p}{\beta^{T-t} - \partial V/\partial k^t}$.

Since $\frac{\partial V}{\partial p} \geqslant 0$ (Lemma 4) and $\frac{\partial V}{\partial k^t} \leqslant \beta^{T-t}$ for all t since the maximum slope for $V(t, k)$ is β^{T-t}, k^t is nondecreasing in p.

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