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Diffusion of New Products in Risk-sensitive Markets

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ABSTRACT

Diffusion of new products may be deterred by consumers' uncertainties about how they will perform. This paper introduces a decision-theoretic framework for modeling the diffusion of consumables, in which consumers choose between a current and new product so as to maximize expected utility. Consumers that are sufficiently risk-averse delay adoption, and change their prior uncertainties in a Bayesian fashion using information generated by early adopters. Under certain assumptions about the underlying consumer choice process and the market dynamics, the result is logistic growth in the share of consumers that choose the new product. The model can be generalized by allowing for consumer heterogeneity with respect to performance of the new product. The paper concludes with a discussion of applications for market forecasting, design of market trials and other extensions.

KEY WORDS Diffusion of innovation Logistic growth Consumer choice Risk-sensitive markets

INTRODUCTION

Growth in demand for innovative products may be hampered by potential adopters' uncertainties about how they will perform. Uncertainty about performance may stem from two sources: the 'newness' of the product, implying a lack of information about its effectiveness, and variation in the product's effectiveness for different consumers. For example, when a new drug is introduced doctors may be unsure how to extrapolate from clinical trials performed on selective groups of patients. More generally, the success, usefulness or profitability of technologically novel products or processes may be uncertain to the potential adopter; such products are the focus of our model. Given limited information from early tests or advertising claims, risk-averse consumers delay adoption and may benefit from additional information about performance.

The supplier of such products seeks to estimate how quickly and to what extent demand will grow, and insure rapid diffusion throughout the potential market. Existing market penetration

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models generally postulate that the time at which different consumers adopt depends upon the degree to which they are influenced by so-called 'internal' and 'external' information, such as word-of-mouth and advertising effects, respectively. Rogers and Shoemaker (1971), for example, characterize early adopters as 'innovators' or 'opinion leaders', since they are minimally affected by external influences. Given assumptions regarding these communication patterns, functional forms such as the exponential, logistic and modified-logistic curves can be derived. The sales growth model developed by Bass (1969) assumes a modified-logistic curve; the subsequent extensions by Robinson and Lakhani (1975), Mahajan and Peterson (1978), Bass (1980), Bass and Bultez (1982), Horsky and Simon (1983) and others incorporate the influence of pricing, advertising and a changing population on the rate of information diffusion and the ultimate saturation level. Easingwood *et al.* (1983) extend the Bass model by allowing the word-of-mouth effect to systematically vary over time. The well-known models of Fourt and Woodlock (1961) and Mansfield (1961) represent special cases of the Bass model under purely external influences and purely internal influences, respectively.

The logistic model has gained empirical support through its application to a variety of durable goods (Rogers, 1983). In these applications it is assumed that the population consists of a finite number of potential adopters, each of whom makes one purchase, and the model describes the share of adopters in this finite population as a function of time. Our paper focuses on a somewhat different situation, where there is a continuous flow of independent consumers or potential adoption decisions. The model describes the decisions to adopt the new product as a fraction of the flow. Thus, saturation is reached when the entire flow of purchase decisions is directed in favor of the new product. This type of application arises in dealing with consumables or, for example, in health care when the flow represents patients seeking treatment for a particular disease. Communication among consumers consists of the transfer of information between today's users and tomorrow's (or next year's) potential purchasers.

Despite its empirical support, the logistic model lacks a choice- or decision-theoretic foundation which would explain the basis for individual adoption decisions and their timing. This issue is crucial for modeling diffusion of consumables. Conventional models often assume that an innovative technology is good for all consumers, a bias recognized in Rogers' third revision of his classic text (1983). Adoption is seen as simply a matter of informing the potential adopter of the existence of the innovation (and perhaps also price); once the consumer is aware, adoption is immediate or delayed through an unspecified process. Another drawback of these models is a frequent assumption of a homogeneous and 'well-mixed' population; each individual has an equal likelihood of sending and receiving messages, and performance of the product is identical for all. However, when there is product uncertainty and risk-avoidance by potential consumers the market share may be less than the fraction of consumers who are aware of the product. In such an environment, learning involves finding out about how a product performs rather than just learning of the product's availability. Products which are revealed to be ineffective may have declining demand as consumers abandon them, a phenomenon not addressed by the classic diffusion models.

Some diffusion models incorporate uncertainty about product performance. Bernhardt and MacKenzie (1972), for example, postulate that potential adopters apply 'safety margins' to their estimates of the value of adoption. Value net of this safety margin must exceed pre-adoption value to induce adoption. The model developed by Kalish (1983) treats awareness of and adoption of the innovation as separate steps, each dependent on current uncertainty and product attributes. The adoption rate depends on the fraction of the potential population that is aware but has not adopted. Potential adopters are those whose risk-adjusted valuation of the innovation exceeds its price; the discount due to risk-aversion declines with the cumulative number of adopters. The change in fraction aware is a function of advertising, the fraction already aware and cumulative adopters. The model is fairly general and includes some earlier models as special cases.

In an adoption model for innovations of uncertain profitability Jensen (1982) describes diffusion as the result of individual firms, with varying uncertainties about performance, waiting to obtain sufficient evidence that the technology will succeed. The probability of adoption is a function of the prior uncertainty and the number of observations, which are received simultaneously by all firms and are described by a Bernoulli process. Under certain assumptions regarding the initial distribution of beliefs and the information-generating process, the result is an S-shaped or concave diffusion curve. A similar model by Jensen (1983) addressing two competing uncertain innovations provides similar results.

Gilbert and Train (1981) propose a similar model in which potential consumers have identical initial uncertainties but vary in risk aversion. A Bernoulli process with Bayesian learning characterizes the success probability after a given number of trials. Firms rank alternative technologies according to their current expectation over uncertain cost savings. The model was used in an empirical application for the electric power industry to relate adoption timing to firms' risk-aversion; the dynamics were not considered.

Our model is similar to those of Gilbert and Train and of Jensen in that uncertainties are reduced according to a Bayesian learning model. Customers have varying risk aversion, and are modelled as expected utility maximizers. In our model, potential adopters update on the basis of actual results rather than simply becoming aware that a new technology exists. Finally, we model the dynamics explicitly, by relating the rate of adoptions to the rate of change in underlying uncertainty.

The remainder of this paper is organized as follows. In the next section we describe our basic diffusion model. The model includes a description of consumer choices and learning which together determine the dynamics of demand growth. The third section describes applications and extensions to the model. The model can be used by a supplier to formulate strategies for testing and trials prior to introducing a product on the market. We describe how the parameters of the model can be estimated. This section also discusses other applications and extensions. The paper concludes by contrasting our results with those of others and suggesting directions for further research.

THE DIFFUSION MODEL

The model takes the view that a manufacturer or supplier has perfect information about the performance (i.e. success rate) of his product or technology. Consumers, however, are uncertain about the product's performance and will make their decisions accordingly. Thus the supplier projects the diffusion of the new product by modeling the process by which consumers learn about its performance from the experience of prior adopters. Consumers must often choose from among several available products for filling a particular need. We focus on such choices where the decision is between an innovative product with uncertain performance and a currently available product with known performance. Figure 1 depicts these components of the diffusion model.

The model is based upon the following assumptions:

(1) A constant flow of consumers, denoted λ, face the product choice at each point in time. The flow may include repeat purchases. However, we do not account for serial correlation

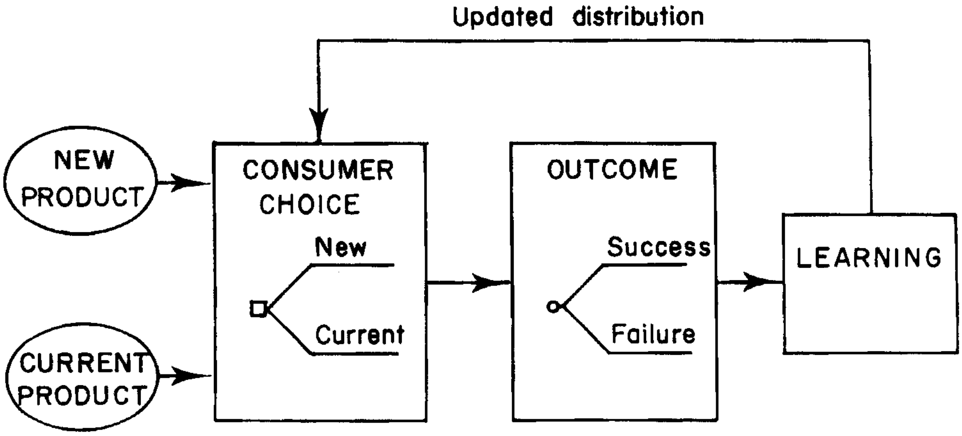

Figure 1. Diffusion model components

among purchases, i.e. we assume that the purchase decisions in every time period are independent.

(2) There is only one innovative product, and it is only available in one configuration. In general, there may be dosages or processes employing the new product in varying amounts or configurations; we treat these as the same product.
(3) Only one current product, with known performance, competes with the new one.
(4) Performance of both the current and new product is characterized by a Bernoulli trial. However, while the success rate of the current product, ϕ_c, is known, the success rate of the new product, ϕ_n, is uncertain.
(5) Consumers have a utility function over the success rate that is monotonically increasing in the rate (for example, a hospital has a utility function over the fraction of successes it would achieve with a procedure).
(6) Consumers select the product that maximizes their expected utility.
(7) Consumers exhibit constant proportional risk aversion (defined below), but are heterogeneous in the magnitude of that risk aversion, denoted ρ. The parameter ρ is exponentially distributed in the population and the distribution is known to the producer.
(8) All consumers share the same information, which consists of the prior distribution on the success rate experienced by previous users of the new technology, the number of previous adopters of this new technology and the number of successes experienced by these adopters. Consumers' prior over the success rate of the new technology is described by a Beta distribution.
(9) Consumers' adoption decisions are based on their posterior success rate, which is obtained by updating their prior in a Bayesian fashion, based on the number of successes and adoptions.
(10) Consumers' initial beliefs about the expected success rate with the new technology are correct in that the observed success rate is equal to the expected success rate.
(11) The supplier knows the true success rate of the new and current products. To forecast the diffusion of the new product induced by consumers' learning he assumes that the reported number of successes equals the expected number of successes, i.e. the true success rate times the number of adopters.

Assumptions (1)–(3) describe how many consumers face the product choice, and what choices they make, at any given time; (4)–(7) specify the basis by which consumers reach their decision; (8)–(10) describe the consumer's state of information about the products, and how that state of information changes with new information about the product. The assumption of a deterministic success rate (assumption (11)) is obviously restrictive, since the supplier may not know with certainty how the new product will perform in a large, heterogeneous population. However, assumptions (10) and (11) allow us to focus on consumer learning as the main cause of increasing market penetration.

Choice of product

The choice of each consumer is represented by an expected-utility maximization over the success rate with available products:

$$\max_{i \in I} \int \mathrm{d}\phi\, p(\phi_i) U(\phi, \rho) \tag{1}$$

where I refers to the set of available products, and we adopt the convention that $i = n$ denotes the new product and $i = c$ denotes the current product, and

$p(\phi_i)$ = consumers' subjective probability density function on success rate ϕ of product i,
ρ = risk-aversion parameter of utility function,
$U(\phi, \rho)$ = utility on success rate parametric on risk aversion.

The product choice depends on what outcomes will occur with the new and current products, respectively. The outcome may be defined with respect to one or more attributes such as success rate, productivity, profitability and price. These, however, will be collapsed to a single numeraire ϕ, that describes the success rate of the product. Hence, any price effect is collapsed in ϕ as well.

The risk-aversion parameter (ρ) is defined by the Arrow–Pratt measure of relative risk aversion: the ratio of the second and first derivatives of the utility function. In general, this ratio is not constant, i.e. $-U''(\phi)/U'(\phi)$ depends on ϕ. However, if the utility function displays constant proportional relative risk aversion, then $-\phi U''(\phi)/U'(\phi)$ is constant across all outcomes. In what follows, ρ is defined to be this constant.

Risk aversion decreases the expected utility when there is uncertainty concerning the outcome. Since there is uncertainty concerning the outcome with the new product but not with the current one the value of the new product to a consumer is discounted according to his risk aversion. The difference in expected utilities is monotonically decreasing in the risk-aversion parameter, i.e.

$$\frac{\partial}{\partial \rho} [EU_{\mathrm{n}}(\phi, \rho) - EU_{\mathrm{c}}(\phi, \rho)] < 0 \tag{2}$$

where E refers to the expectation over the uncertain outcome ϕ. Consumers for which the difference in expected utilities is zero are indifferent between the two products; from the monotonicity assumption there is, at most, one such value of the risk aversion parameter. Above this value, which we refer to as the 'indifference threshold', consumers choose the current product; for lower values of risk aversion the new product is preferred.

To simplify the analysis it is useful to approximate the expected utilities through use of the certain equivalent, or the outcome that has a utility equal to the expected utility of the uncertain outcome. For monotonically increasing utility functions, picking the alternative with the higher expected utility is equivalent to doing so with the higher certain equivalent. The certain equivalent can be approximated to second order by a function of the mean and variance:

$$\phi_{ce} = \bar{\phi} - 1/2\ \rho\ \mathrm{var}(\phi)/\bar{\phi} \tag{3}$$

where ϕ_{ce} is the certain equivalent of the random variable, $\bar{\phi}$ its mean and $\mathrm{var}(\phi)$ its variance (Howard, 1977). The approximation is exact for an exponential utility function and normally distributed random variable.

The consumer will be indifferent between choosing the new product and the current product when the certain equivalents of the two products are equal. Using the certain equivalent approximation above, this occurs when

$$\phi_c = \bar{\phi}_n - 1/2\ \rho\ \mathrm{var}(\phi_n)/\bar{\phi}_n \tag{4}$$

From this, we obtain the threshold risk-aversion level at which a consumer is indifferent between the two products:

$$\rho^* = \frac{2(\bar{\phi}_n - \phi_c)\bar{\phi}_n}{\mathrm{var}(\phi_n)} \tag{5}$$

This result is the same as that obtained by Gilbert and Train (1987).

Equation (5) shows that the greater the expected performance advantage with the new product, $(\bar{\phi}_n - \phi_c)$, or the smaller its variance, the larger is the threshold level of risk aversion. Since all consumers with risk aversion less than this threshold prefer the new product, a larger threshold implies greater market share for the product. In the following section we are concerned with how the threshold changes over time as uncertainty declines.

Reduction of uncertainty

As consumers learn about how the new product has performed for earlier adopters they change their uncertainty about its performance. Consumers are Bayesian in that they update their uncertainties by combining the observed outcomes with their prior uncertainty according to Bayes' Rule:

$$p(\phi_n \mid D) = \varkappa p(\phi_n) p(D \mid \phi_n) \tag{6}$$

where $\varkappa$ is a normalization constant, $p(\phi_n)$ the prior density function and D the data observed. We can think of D as the information obtained by an experimental sample from a random process, or sufficient statistics of this sample; $p(D \mid \phi_n)$ is the likelihood of such a sample conditional on ϕ_n. We have assumed that the prior density and observations are the same for all consumers.

Condition (5) showed how the change in the risk-aversion threshold after updating depends on the change in the mean and variance. When the outcome is a success rate, and the prior density is described by a Beta distribution, the sample-generating process can be described by a binomial distribution over the number of successes. The posterior mean and variance can be written in terms of the prior moments and the observed outcomes:

$$\bar{\phi}_n' = \bar{\phi}_0 \frac{N_0}{N_0 + N} + \bar{\phi}_1 \frac{N}{N_0 + N} \tag{7}$$

$$\mathrm{var}(\phi_n') = \frac{\bar{\phi}_n'(1 - \bar{\phi}_n')}{N_0 + N + 1}$$

where the prime denotes the posterior statistic, $\bar{\phi}_0$ and N_0 are parameters of the prior density and $\bar{\phi}_1$ and N are the observed success rate and the cumulative number of samples. The parameter N_0, referred to as the 'precision', is related to the prior variance on the success rate.

In equation (7) it is clear that as the number of observations (N) increases, the weight attached to the observed success rate increases and the mean approaches the 'true' success rate known to the supplier or manufacturer. The variance declines with the number of samples and approaches zero in the limit. Thus, so long as the underlying success rate is no worse with the new product than with the current one the risk-aversion threshold (5) increases, and an increasing share of consumers, with increasing risk aversion, choose the new product. In what follows we are concerned with the dynamics of this process of demand growth.

Dynamics

The supplier or manufacturer of the new product may be concerned with decisions affecting how quickly demand grows following the time of introduction. These dynamics are defined by three components: the market share for the new product given the number of samples generated and the outcomes obtained (i.e. the risk-aversion threshold defined by equation (7)), the number of samples generated given the market share and the outcomes obtained given the number of samples generated.

If the population distribution is expressed as a cumulative frequency $F(\rho)$ over their risk-aversion parameters then the rate of change in the cumulative number of purchases, denoted $\dot{N}(t)$, is given by

$$\dot{N}(t) = \lambda F(\overset{*}{\rho}) \tag{8}$$

where λ is the constant 'birth' rate of new consumers. Cumulative purchases increase so long as λ is positive and some portion of the population distribution falls below the current risk-aversion threshold.

The outcomes that will be obtained from each period's new adoptions depend on the underlying 'true' process parameters. While these parameters may in general be uncertain, we have made the simplifying assumption that they are known to the manufacturer, and the analysis proceeds on the basis of what the decision maker believes to be the true performance of the new product. Nevertheless, there is uncertainty as to the growth curves that will occur. The probability distribution over the number of successes in a given number of samples is described by a binomial distribution. Thus the sample outcome is a random variable and the market share is stochastic after market introduction, because of the dependence of the market share on the outcomes obtained. In general, this system has no closed form solution.

To simplify, we have assumed that the outcomes obtained are the expected outcomes that would result from the given number of samples, given a known success rate. In other words, the successes occurring each period are assumed to be a fixed proportion of the adoptions.

With a constant flow of consumers, λ, and an exponential distribution on risk aversion in the population,

$$F(\rho) = 1 - \exp(-\gamma\rho); \; 0 \leqslant \rho < \infty \tag{9}$$

where γ is a shape parameter equal to the reciprocal of the mean risk aversion in the population. We can rewrite the risk-aversion threshold expressed by equation (5) in terms of the mean and the number of samples. Specifically, substituting from equation (7) for the variance

$$\overset{*}{\rho}(t) = \frac{2(\bar{\phi}_{\mathrm{n}}(t) - \phi_{\mathrm{c}})}{1 - \bar{\phi}_{\mathrm{n}}(t)} \, (N(t) + N_0 + 1) \tag{10}$$

where the terms that are changing in time are indexed by t.

By assumption, consumers' prior over the success rate is unbiased, so the mean of the prior equals the true success rate known to the supplier or manufacturer. Thus only the variance changes. Since the prior and observed mean are the same, we see from equation (7) that the posterior mean is equal to the prior. Then substituting $\bar{\phi}_0$ for $\bar{\phi}_n(t)$ in equation (10), the growth in adoptions (equation (8)) is given by

$$\dot{N}(t) = \lambda[1 - \exp(-\gamma k(N + N_0 + 1))] \tag{11}$$

where

$$k = \frac{2(\bar{\phi}_0 - \phi_c)}{1 - \bar{\phi}_0}$$

and λ is the flow rate of consumers. Noting that the market share is given by the expression within the outer brackets in equation (11), the market share, denoted w, is described by

$$\dot{w}(t) = \gamma k \lambda (1 - w) w \tag{12}$$

The solution to (12) is a Logistic curve:

$$w(t) = \frac{1}{(1 + b \exp(-at))} \tag{13}$$

where $a = \gamma k \lambda$ defines the steepness of growth and is positively related to the flow rate of consumers and the difference in the success rates with the two products. The coefficient b in equation (13) is solved by the initial conditions. The market share in the limit is 1.

Equation (13) describes a diffusion curve conditional on the supplier's expectations. As we noted earlier, diffusion in a market for consumable goods is described by the growth in market share, not by the cumulative penetration of a fixed population, as in the markets for durable goods. Thus the Logistic curve applies to the market share, not cumulative adoptions or sales, as it is most often used.

The preceding results show that market share growth curves can be derived using micro-level assumptions regarding consumer choice behavior. The model can be extended to cases in which the initial and observed success rates are different from the supplier's success rate. The Logistic curve corresponds to the case in which the new product is more effective than the current one, and is perceived as such by potential consumers, but uncertainty—expressed by the variance—leads risk-averse consumers to delay adoption until more evidence is obtained.

APPLICATIONS AND EXTENSIONS

The model can be used for market forecasting by estimating the values of the underlying parameters. This section describes how this can be done, and describes an application for designing market tests or trials prior to market introduction. Finally, some extensions are discussed.

Market forecasting

To estimate future market share growth for a new product, several parameters are required:

γ: the parameter of the distribution on risk aversion in the population,
λ: the flow rate of consumers (also the long-run saturation point),
ϕ_c: the success rate with the current technology,
ϕ_0 and N_0: the initial conditions on the uncertain success rate with the new technology,
ϕ_n: the true success rate with the new technology.

Some of these parameters can be observed directly or estimated from market research, specifically λ, ϕ_c and ϕ_n. The remaining parameters can be estimated through observation of the actual number of cumulative adoptions (N) and successes (N_s). Starting with an initial estimate for the unknown parameters of the model, the estimate can be improved recursively as N and N_s are observed. This approach differs from the conventional methods, which are based on fitting the curve to historical market share observations and attributing the error in the observations to additive random noise.

In developing the forecasting procedure based on the approach described in this paper one might attribute the error in the observed adoptions to deviations in the observed success rate from the mean, resulting from finite realizations of the underlying Bernoulli process. Such a model of the observation noise is more appealing, since it is tied directly to the underlying model driving the Logistic curve. However, developing such a forecasting procedure is outside the scope of this paper.

Pre-market trials

The model addresses products whose adoption is delayed by risk-averse consumers' uncertainty about whether the new product is actually superior to a current one. In such an environment it may be important for the supplier to generate information through trials or tests prior to market introduction. Through the provision of such information, the supplier may alter the initial state of information (ϕ_0 and N_0), thereby altering the market share trajectory.

To design a pre-market trial, the supplier wishes to find the recruitment rate (λ_s) and trial length (t_1) that maximize future profits. We make the simplifying assumptions that these parameters are fixed in advance. The supplier's objective is

$$\max_{\lambda_s, t_1} - \int_0^{t_1} \mathrm{d}t\, e^{-\delta t} c(\lambda_s) + \int_{t_1}^{T} \mathrm{d}t\, e^{-\delta t} \pi\lambda\, F(\overset{*}{\rho}(t;\, \lambda_s t_1)) \tag{14}$$

where T is the product lifetime or decision horizon, δ the discount rate, $c(\cdot)$ the trial costs for a given rate of recruitment, π the per-sale profits and F the cumulative distribution on risk aversion. In equation (14) price and cost (hence π) are fixed. The first term represents the discounted cost of the trial and the second term the discounted profit stream given by the product of per-sale profits (π), the flow rate of consumers (λ) and the market share (F). The indifference threshold $\overset{*}{\rho}(t)$ depends on the total number of samples prior to introduction, $\lambda_s t_1$, as described by our learning model.

The first-order conditions for the solution are:

$$\int_0^{t_1} \mathrm{d}t\, e^{-\delta t}\, c_1'(\lambda_s) = \int_{t_1}^{T} \mathrm{d}t\, e^{-\delta t}\, \pi\, \lambda F' \frac{\partial \overset{*}{\rho}}{\partial \lambda_s} \tag{15}$$

and

$$e^{-\delta t_1}[c(\lambda_s) + \pi\lambda F(\overset{*}{\rho}(t_1))] = \int_{t_1}^{T} \mathrm{d}t e^{-\delta t}\, \pi\lambda F' \frac{\partial \overset{*}{\rho}}{\partial t_1} \tag{16}$$

Condition (15) specifies that the discounted marginal trial costs equal the discounted marginal future value; $\partial\overset{*}{\rho}/\partial\lambda_s$ is positive if additional samples increase market share by resolving uncertainty. Similarly, condition (16) states that the discounted marginal trial cost and foregone profits at t_1 equal the discounted marginal future value. As before, $\partial\overset{*}{\rho}/\partial t_1$ is positive if additional samples increase the expected utility for the new product. Since λ_s and t_1 together determine the sample size of the trial, conditions (15) and (16) specify an optimal testing plan prior to market introduction. This differs from conventional test-marketing strategies since there is learning by consumers (as well as by the producer). This strategy also offers an alternative to pricing and advertising strategies.

Extension to a quality-heterogeneous population

In the logistic model derived above, performance is identical for all consumers and only risk aversion differentiates their choices. More generally, the outcome for each product may depend on characteristics of the consumer. For example, the performance of a medical technology may depend on the severity of a patient's illness; this may influence the attractiveness of the new product to patients less sick than the early adopters. (For other medical products the opposite may be true.) Many existing diffusion models fail to account for consumer heterogeneity, which may result in overly optimistic forecasts.

The model can be extended by allowing for heterogeneity with respect to the performance obtained with each product. This influence can be treated as a shift parameter on the subjective outcome density. This extension is reported in detail elsewhere (Schwartz, 1985); this section summarizes the basic approach and results.

While several consumer attributes may influence this shift in the outcome density, and the relevant combination of attributes may depend on the type of product, we assume that a single parameter, denoted z, captures these influences for a given product. We can think of this parameter as a quality ranking, so that a lower z represents higher-ranking consumers who have better relative outcomes, as formalized below.

Before, a single risk-aversion threshold ρ^* defined the point at which consumers are indifferent between the two products and represented a boundary between adopters and non-adopters. In this extension the indifference threshold depends also on the quality index, and is denoted $\rho^*(z)$. Thus $\rho^*(z)$ is a mapping for each quality level, of the risk-aversion threshold which equates the expected utilities. As before, the indifference threshold represents a boundary between adopters and non-adopters. As Figure 2 shows, the risk-aversion threshold is decreasing in the quality ranking; its specific shape depends on the specific functional forms.

As before, the market share grows if the expected utility for the new product increases after updating and shrinks if the converse is true. The change in expected utility is determined by the change in the probability distribution on the outcome; this is determined by the quality levels of adopters for which outcomes are reported and by the flow rate of new consumers.

Critical mass and short-run stalling

A particular concern is 'stalling' or zero market growth and how marketing policies may be used to overcome this possibility. In the logistic model without quality variation, so long as the market share is positive, additional samples will be generated, since there is a constant flow of consumers. Ultimately, the uncertainty is eliminated (i.e. the variance declines toward zero), and the market share approaches 100% of the flow of consumers. A critical assumption underlying this model is that the success rate with the new product is greater than with the current one. If we remove this assumption then there is a possibility that market growth is zero at some point in time. Any of the following conditions may in general result in zero growth:

(1) The indifference threshold or population distribution of risk aversion is such that the market share is zero initially.
(2) There is no uncertainty about the underlying process parameters, hence additional samples do not change the perceived performance distribution.
(3) The outcomes of early adopters result in no increase (or a decrease) in the expected utility for the new product.

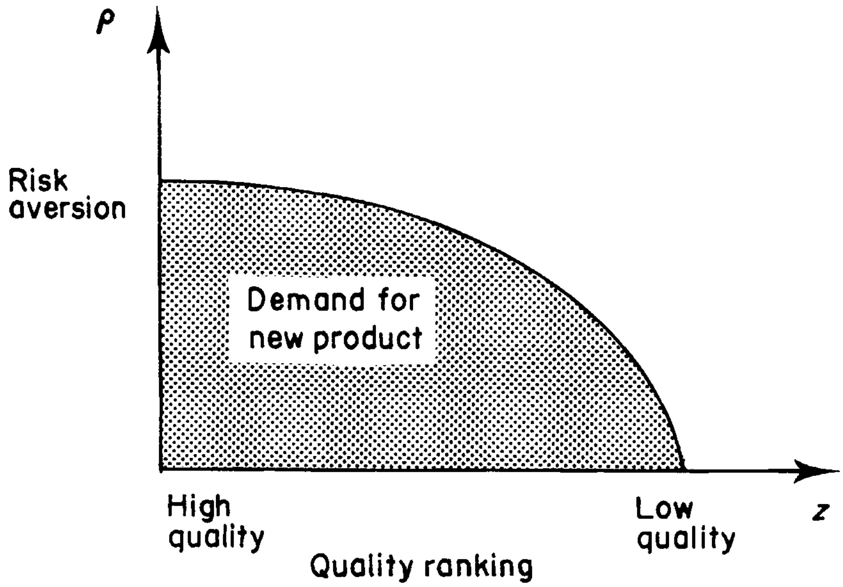

Figure 2. Indifference threshold with quality variation

The first case is a 'critical mass' condition: if the prior uncertainties and expectations are such that no consumers prefer the new product, then none will adopt and, unless exogenous information is provided, there will be no learning within the market. If consumers are highly risk averse, this condition may constitute a significant barrier to growth.

The second condition relates to the long-run indifference threshold; when uncertainty has been eliminated, the saturation point is reached. This stopping point can be overcome only by modifying the product to attract a new segment of consumers.

The third condition is of some concern to the supplier, since it may occur prior to the saturation point, after the system has moved past the critical mass. Such stalling can occur if the performance is revealed in the long run to be worse than expected (for example, a drug that displays unforeseen side effects). Alternatively, in the *short run* the product may appear worse than expected, due to a string of bad outcomes. What may in fact be a superior product could, on the basis of limited samples and a string of bad outcomes, experience a period of slow diffusion or abandonment.

SUMMARY AND DISCUSSION

We have shown that diffusion patterns that are commonly assumed in market penetration models and that have empirical support can be derived by aggregating the choices of individual consumers. In particular, the Logistic curve was obtained in a simplified model in which consumers face identical uncertainties but learn from the outcomes of earlier, less risk-averse adopters. Allowing for consumer heterogeneity in performance extends the model and provides a decision-theoretic basis for a wider range of trajectories than the logistic form provides.

The results obtained with this approach reinforce the sociological basis for the Logistic and related curves. According to our model, the early adopters are those who are less averse to risk and (when there is quality variation) whose outcomes are expected to be better. These early adopters rely mainly on information from outside the market (for example, producers' advertising claims) and may be thought of as Rogers' 'opinion leaders' or 'innovators'; later adopters are his 'imitators' and delay until enough information is generated by the market to overcome their uncertainty and convince them that the new product performs better even at lower quality levels.

Accounting for risk aversion and quality as an influence on product choices moves us beyond the assumptions that all consumers are alike and adopt as soon as they become aware of the innovation (assuming the price is right). While the growth curves resulting from such assumptions sometimes fit well with what is observed they afford limited analysis of marketing policies, primarily relating to advertising and to pricing or designing the product so as to expand the potential market share. With risky products it is clear that awareness and low price may not be sufficient for adoption.

Our model helps to explain observed exceptions to the often-assumed growth patterns. Three examples from the health care field are depicted in Figure 3 (OTA, 1976, pp. 75–6). The diffusion of intensive care units (ICUs) as a percentage of community hospitals between 1955 and 1974 sustained a four-year period of flat growth, followed by a 15-year period of linear growth. The flat portion of the curve can be explained as an information-generating period, while other hospitals waited to determine whether the performance of ICUs merited their costs. Hospitals adopting later differ from early adopters in their desire to avoid risk (perhaps due to their financial positions or the attitude of trustees) and their perception that they had less to gain from the innovation (perhaps due to small size or poorer-quality staff and facilities).

A very different example is provided by chemotherapy for leukemia, where very steep growth occurred in the first four years following introduction, by which time 80% of patients were treated using the new product. In this case of 'desperation-reaction' (Warner, 1975), aversion to the risk of the new technology did not hamper adoption since no efficacious alternative existed. As predicted by our model, rapid diffusion results when the advantage of the new product is apparent to a large share of the market. At the opposite extreme, exemplified by the diffusion of leucotomy operations (Figure 3(c)), it may be revealed that prior perceptions were overly optimistic and the actual performance is inferior to that of the current product. These operations were widely adopted in the early 1950s and subsequently abandoned after their safety and efficacy were challenged.

A limitation of our model is that awareness is not specifically accounted for. A discrete-time model, or a separate awareness component, may overcome this limitation. In our model the current product has no change in uncertainty over time; extending our approach to two competing uncertain products may allow for wider application. Finally, it may be useful to account for differences in the kinds of information engendered by external and internal sources; we assume that all such information concerns the outcomes of early adopters.

Other marketing strategies deserve further attention. Consumer heterogeneity with respect to performance presents an additional dimension over which pre-market trials may be designed. We showed that, in the absence of information, a smaller fraction of consumers will adopt at the lower-quality levels. Thus a trial targeted at these levels may be more effective than one aimed at the higher-quality ones. Another strategy is price discounting during the period just after market introduction so as to induce high rates of adoption and allow the market to generate information to potential adopters.

Advertising may be used in concert with trials or market surveillance to reinforce their effect. These strategies are particularly applicable in the context of clinical trials for new medical interventions. The research described in this paper was motivated by exploring ways to enhance

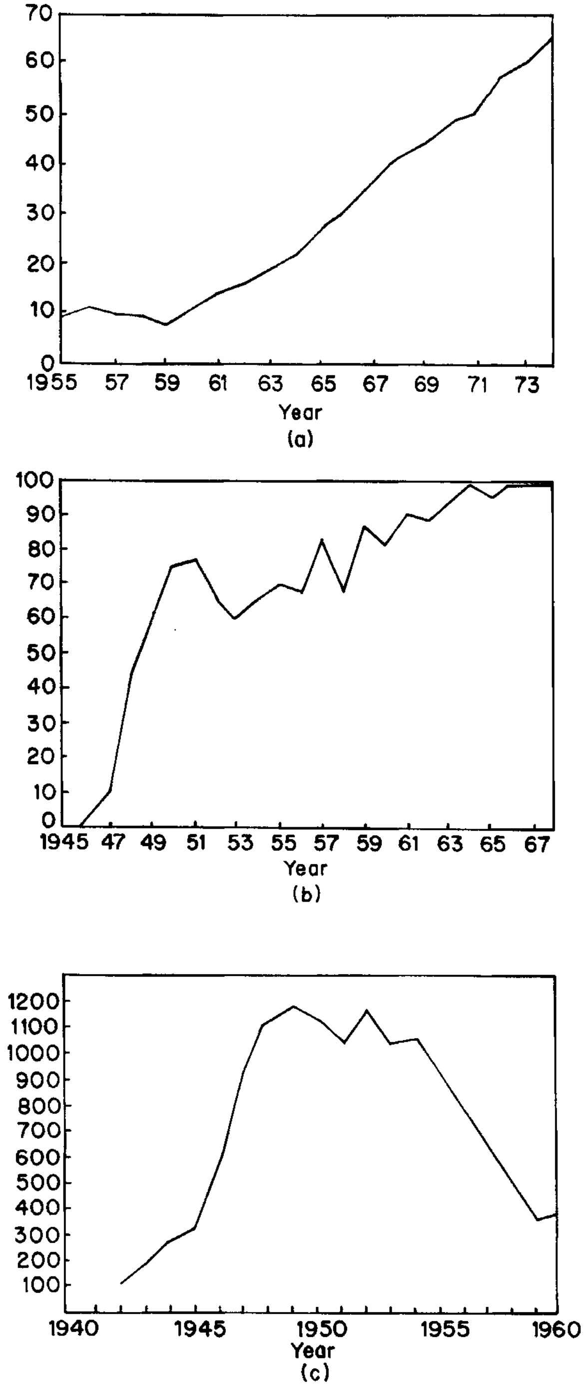

Figure 3. Diffusion of some medical technologies (from OTA, 1977, pp. 75–6). (a) Intensive care units; (b) chemotherapy for leukemia; (c) leucotomy operations (England and Wales)

such a trial to promote diffusion of new medical treatments for heart attack patients. Our approach has provided a useful adjunct to conventional clinical trials, with applicability to marketing strategies in general.

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