

Using the analytical logic underlying the classical adopter categorization approach proposed by Rogers, the authors suggest that adopter categories for a product innovation can also be developed by using other well-established diffusion models such as the Bass model. With data on 11 consumer durable products, they compare adopter categories generated by the classical approach and the Bass diffusion model, respectively. An application examining the diffusion of personal computers is documented to illustrate the usefulness of the adopter categorization based on the Bass diffusion model in studying differences among adopter categories.

Determination of Adopter Categories by Using Innovation Diffusion Models

All potential adopters of a new product do not adopt the new product at the same time. Consequently, on the basis of the degree to which an individual is relatively earlier in adopting the new product, adopters can be classified into adopter categories (Rogers 1983). Development of adopter categories is important because they can assist in (1) targeting prospects for a new product (i.e., potential innovators and laggards; Kotler and Zaltman 1976), (2) developing marketing strategies for penetrating various adopter categories (Engel, Blackwell, and Miniard 1986), and (3) predicting the continued acceptance of a new product (Bass 1969; Mahajan and Muller 1979).

Development of adopter categories requires determination of (1) the number of adopter categories, (2) the percentage of adopters to include in each category, and (3) a method to define categories (Rogers 1983, p. 245).

The most widely accepted method of adopter categorization is that proposed by Rogers (1983). One assumes that the noncumulative adopter distribution takes

the form of a bell-shaped curve. Consequently, using two basic statistical parameters of the normal adopter distribution—mean time of adoption (t) and its standard deviation (σ)—one obtains five adopter categories.

<i>Adopter category</i>	<i>% adopters</i>	<i>Area covered under normal curve</i>
Innovators	2.5	Beyond $t - 2\sigma$
Early Adopters	13.5	Between $t - \sigma$ and $t - 2\sigma$
Early Majority	34.0	Between t and $t - \sigma$
Late Majority	34.0	Between t and $t + \sigma$
Laggards	16.0	Beyond $t + \sigma$

The categorization scheme proposed by Rogers offers several advantages. First, it is easy to use. Second, because it offers mutually exclusive and exhaustive standardized categories, results can be compared, replicated, and generalized across studies. Third, because the underlying diffusion curve is assumed to be normal, continued acceptance of the product can be predicted and linked to the adopter categories.

Despite these advantages, Rogers' categorization has potential limitations. First, in spite of its theoretical appeal, the assumption that all new products follow a normal-distribution diffusion pattern is questionable. As argued by Peterson (1973), in most marketing situations, new product adoption patterns are likely to exhibit non-normal adopter distributions (for a review of other adopter distributions, see Mahajan and Peterson 1985). Second, in spite of the method's simplicity, Rogers provides no empirical or analytical justification of why the size of the adopter categories should be the same for all new

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products. That is, why should Innovators constitute the first 2.5% of adopters and why should Laggards be the last 16% of adopters?

To overcome these shortcomings, Peterson (1973) suggested an alternative approach for developing adopter categories. Because adoption dates can be considered a one-dimensional ordered vector, this approach involves partitioning these data into k mutually exclusively and contiguous groups such that the within-group sum of squares is minimized and, simultaneously, the among-groups sum of squares is maximized. To determine the optimal number of categories, the number of groups k can be varied until no significant incremental change in within-group sum of squares is observed. This approach has certain advantages over the approach proposed by Rogers. First, no assumption is made about an underlying adopter distribution. Second, the number and size of adopter categories are not fixed for all products. They are determined by available diffusion data.

The categorization procedure suggested by Peterson, however, is not without shortcomings. First, because the number and size of adopter categories are situation-specific, the potential for replications and comparisons across products is limited. Second, because determination of the number and size of adopter categories is data-dependent, different numbers and sizes of adopter categories might be obtained for the same innovation, depending on the length of adoption time-series data used to develop the categories. Third, because one does not assume any adopter distribution underlying the diffusion process, continued acceptance of the product cannot be predicted and linked to the adopter categories.

The purpose of our article is to suggest that adopter categories can be developed by using other established diffusion models such as the Bass model. Development of such categories subsumes advantageous features of the approaches suggested by Rogers and Peterson and offers several distinguishing features. First, unlike the approach suggested by Rogers, the categorization does not involve the assumption that the diffusion process follows a normal distribution. Second, instead of arbitrarily dividing the adopter distribution into a certain number of categories, the proposed approach exploits certain unique analytical properties of diffusion models to generate adopter categories. In fact, we show that, though not recognized by Rogers, the same analytical logic underlies the adopter categorization he proposed. Third, though the shape of the adopter distribution is data-specific (captured by the coefficients of diffusion models) and the determination of adopter categories is innovation-specific, one can make interstudy comparisons based on common values of diffusion model parameters describing the adopter distribution. Finally, because diffusion models have been used to describe and predict the growth of new products, continued acceptance of a new product can be linked to the adopter categories.

We first describe how innovation diffusion models can be used to develop adopter categories, then present analytical derivations needed to calculate the number and

size of adopter categories. Next we compare the adopter categories based on the Bass model with those based on the normal distribution. An application examining the diffusion of personal computers among professionals illustrates the linkage between diffusion models and profiles of adopter categories. We conclude with limitations and extensions of the suggested categorization scheme.

INNOVATION DIFFUSION MODELS AND ADOPTER CATEGORIES

The *diffusion effect* has been defined as the cumulatively increasing degree of influence on an individual to adopt or reject an innovation. In fact, Rogers' use of the normal distribution in developing adopter categories is based on the diffusion effect. Articulating the justification for normal adopter distribution, he writes (1983, p. 244):

... we expect normal adopter distributions because of the diffusion effect, defined . . . as the cumulatively increasing degree of influence upon an individual to adopt or reject an innovation, resulting from the activation of peer networks about the innovation in the social system. This influence results from the increasing rate of knowledge and adoption or rejection of the innovation in the system. Adoption of a new idea is the result of human interaction through interpersonal networks. If the first adopter of the innovation discusses it with two other members of a social system, and each of these two adopters passes the new idea along to two peers, the resulting distribution follows a binomial expansion, a mathematical function that follows a normal shape when plotted over a series of successive generations. The process is similar to that of an unchecked infectious epidemic.

The diffusion effect or interpersonal interaction (or the word-of-mouth effect) suggested by Rogers has also served as the underlying behavioral thesis for several other innovation diffusion models (for a review, see Mahajan and Peterson 1985). For example, one model that has provided the main impetus for examining the growth of a new product in marketing is the diffusion model proposed by Bass (1969). The Bass model describes the diffusion process by the following differential equation ($p, q \geq 0$):

$$(1) \quad f(t) = \frac{dF(t)}{dt} = [p + qF(t)][1 - F(t)]$$

where $F(t)$ is the cumulative fraction of adopters at time t and $f(t) = \frac{dF(t)}{dt}$ is the rate of diffusion at time t . Bass

(1969, p. 217) has referred to p as the coefficient of innovation and q as the coefficient of imitation. If m is the total population of potential adopters, the cumulative number of adopters at time t is $mF(t)$. Integration of equation 1 yields the S-shaped cumulative adopter distribution, $F(t)$, captured by the Bass model. Further differentiation of $F(t)$ gives the noncumulative adopter dis-

tribution representing the specified diffusion process. As derived by Bass (1969), these distributions are given by:

$$(2) \quad F(t) = \frac{1 - e^{-(p+q)t}}{1 + (q/p) e^{-(p+q)t}}$$

and

$$(3) \quad f(t) = \frac{p(p+q)^2 e^{-(p+q)t}}{(p + qe^{-(p+q)t})^2}$$

Figure 1A depicts the noncumulative adopter distribution, $f(t)$, underlying the Bass model. As derived by Bass (1969), its peak, $f(T^*)$ or $F(T^*)$, at time T^* occurs when

$$(4) \quad T^* = -\frac{1}{(p+q)} \ln(p/q),$$

$$(5) \quad F(T^*) = \frac{1}{2} - \frac{p}{2q},$$

and

$$(6) \quad f(T^*) = \frac{1}{4q} (p+q)^2.$$

Given equations 1 through 6, we can point out certain distinguishing features of the Bass model.

First, note from equation 3 that $f(t=0) = f(t=2T^*) = p$. That is, as shown in Figure 1A, the noncumulative adopter distribution is symmetric with respect to time

around the peak time T^* up to $2T^*$. In fact, in the Bass model one assumes that the diffusion process is initiated by pm number of adopters. Second, according to Bass (1969), the term $p[1 - F(t)]$ in equation 1 represents adoptions by persons who are not influenced in the timing of their adoption by the number of people who already have bought the product. Bass refers to these adoptors as "Innovators" (1969, p. 218). In contrast, the term $qF(t)[1 - F(t)]$ in equation 1 represents adoptions by persons who are influenced by the number of previous adoptors. These adoptors are called "Imitators" by Bass (1969, p. 217). That is, as depicted in Figure 1B, throughout the diffusion process, one assumes the presence of two types of adoptors, "Innovators" and "Imitators." However, unlike the categorization suggested by Rogers, adoptors, who are labeled "Innovators" in the Bass model, are *not* simply the first 2.5% of the adoptors. Rather, they are present at any stage of the diffusion process. The distinction between an "Innovator" and an "Imitator" in the Bass model is based on interpersonal influence, not the time of adoption. Bass (1969, p. 216) has hypothesized, however, that "we might ordinarily expect the first adoptors to be innovators." In a strict sense, one could argue that Innovators defined by the Bass model should not be called "innovators" because they are not necessarily the first adoptors of an innovation as defined by Rogers. As noted by Lekvall and Wahlbin (1973) (and also by Mahajan and Muller 1979 and Mahajan and Peterson 1985), because the Bass model captures the spread of an innovation due to the mass media (external sources of information) and interpersonal (internal source of information) communication channels, the Bass model coefficients p and q should be referred to as the coefficient of external influence and the coefficient of internal influence, respectively. Moreover, one can show that for an innovation, the proportion of adoptions due to external influence, $F_1(t)$, is given by¹

¹From equation 1, because $p[1 - F(t)]$ gives the fraction of adoptions due to external influence at time t , the total fraction of adoptions due to external influence, $F_1(t)$, between any two time periods, say t_0 and t_f where $t_f > t_0$, is given by

$$F_1(t) = p \int_{t_0}^{t_f} [1 - F(t)] dt.$$

Because $F(t)$ is given by equation 2,

$$F_1(t) = p \int_{t_0}^{t_f} \left[1 - \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \right] dt.$$

Let $Z = e^{-(p+q)t}$ or $dZ = -(p+q) e^{-(p+q)t} dt$. Therefore,

$$F_1(t) = -p \int_{Z_0}^{Z_f} \frac{dZ}{p + qZ}.$$

This gives

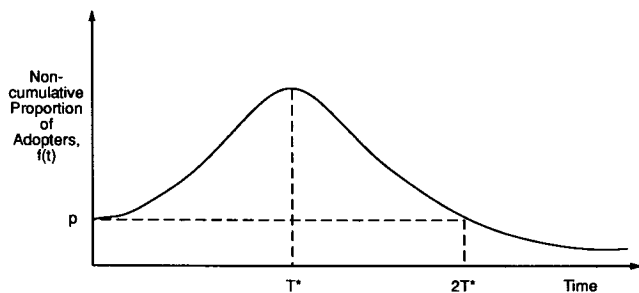
$$F_1(t) = \frac{p}{q} \ln \left[\frac{p + q e^{-(p+q)t_0}}{p + q e^{-(p+q)t_f}} \right]$$

Substitution of $t_0 = 0$ in this equation yields equation 7.

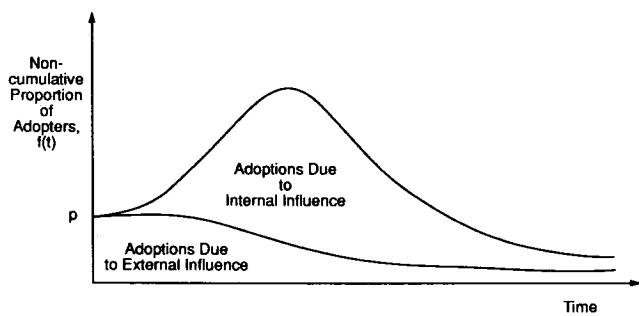
Figure 1

DISTRIBUTION OF ADOPTERS—THE BASS MODEL

A. The Adopter Distribution



B. Adoptions Due to External and Internal Influences



$$(7) \quad F_1(t) = \frac{p}{q} \ln \left[\frac{1 + \frac{q}{p}}{1 + \frac{q}{p} e^{-(p+q)t}} \right]$$

and, hence, the proportion of adoptions due to internal influence is $F_2(t) = 1 - F_1(t)$. From equation 7, and for any innovation, the total fraction of adoptions due to external influence during its entire life cycle is given by

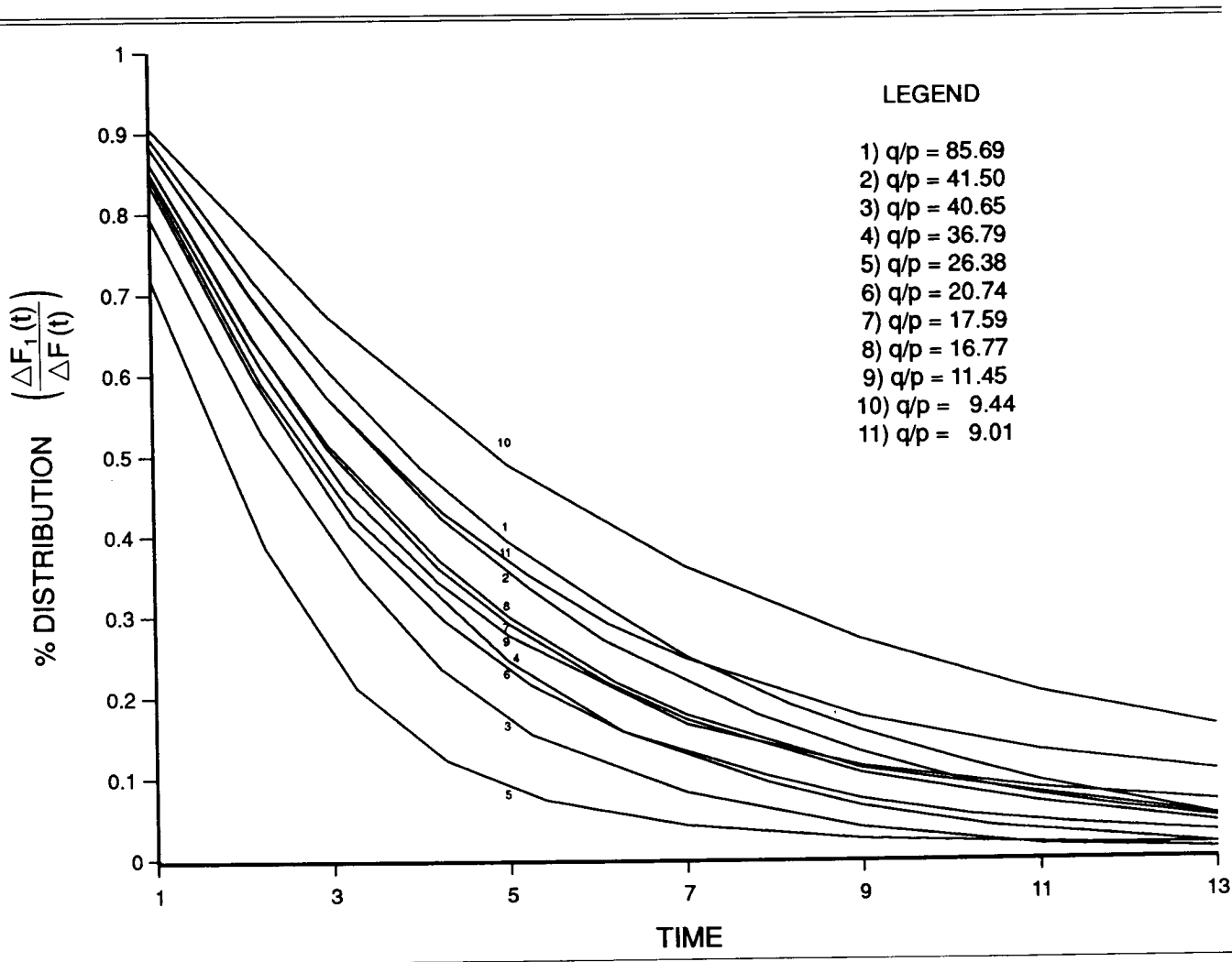
$$(8) \quad F_1(t = \infty) = \frac{p}{q} \ln \left(1 + \frac{q}{p} \right).$$

Figure 2 is a plot of the ratio of adoptions due to external influence at time t to the total adoptions due to external and internal influences at time t (i.e., $\frac{\Delta F_1(t)}{\Delta F(t)}$) from

equations 2 and 7) for the 11 consumer durable products analyzed by Bass (1969). For these products, the value of q/p ranges from 9.0 (for black and white television sets) to 85.7 (for electric refrigerators). As is evident in Figure 2, though adoptions due to external influence tend to be clustered at the earlier stages of the diffusion process (i.e., the ratio of adoptions due to external influence to total adoptions at any time t is high in the initial time periods and decreases monotonically over time), they can be present throughout the diffusion process. In short, "innovators" defined in the Bass model are not necessarily the first adopters of an innovation.²

²In a recent article, Tanny and Derzko (1988) suggest an extension of the Bass model that considers Innovators and Imitators as two distinct groups. As in the Bass model, however, in their extension the Innovators can be present at any stage of the diffusion process.

Figure 2
DISTRIBUTION OF EXTERNALLY INFLUENCED ADOPTIONS FOR CONSUMER DURABLE GOODS



Development of Adopter Categories

Given these observations on the Bass model, an important question remains. How can the Bass adopter distribution be used for developing adopter categories based on the *time of adoption* as suggested by Rogers?

To answer this question, we follow Ziemer (1985) who, in his investigation of diffusion models for forecasting technological innovations, has suggested that further insights into diffusion models can be obtained by examining trends in both the noncumulative adopter distribution $f(t)$ and its rate of change $\left(\frac{df(t)}{dt}\right)$. These trends

indicate any changes in the adoption pattern that the population of potential adopters may exhibit in its acceptance of the innovation. Such trends for the Bass model are depicted in Figure 3 and summarized in the following table.

Time interval	Trend in $f(t)$ (i.e., $\frac{df(t)}{dt}$)	Trend in rate of change of $f(t)$ (i.e., $\frac{d^2f(t)}{dt^2}$)
Zero to T_1	Increasing faster	Increasing rate
T_1 to T^*	Increasing slowly	Decreasing rate
T^* to T_2	Decreasing slowly and then faster	Increasing rate
Beyond T_2 (T_2 to ∞)	Decreasing fast and then slowly	Decreasing rate

Using these trends, one can categorize adopters into four groups based on the time of adoption as shown in Figure 4A. In addition to Innovators (following Rogers), this categorization suggests four groups: Early Adopters, Early Majority, Late Majority, and Laggards.³ Note from Figure 4A that $f(t = 0) = p$ is the fraction of adopters who initiate the diffusion process and are referred to as Innovators.

Figure 4A proposes an adopter categorization scheme based on the Bass diffusion model. Clearly, the implementation of this categorization scheme depends on the existence of times T_1 and T_2 . T_1 and T_2 are the inflection points of $f(t)$ and can be obtained analytically.

In the next section, we present the analytical expressions for estimating the time duration and size of adopter categories based on the Bass model. It is important, however, to point out that the adopter categorization suggested by Rogers is based on the same analytical logic that is suggested here to develop the adopter categories based on the Bass model. In fact, as summarized by

³Because the Bass adopter distribution is symmetric around T^* up to time $2T^*$, it is possible to divide the Laggards into two groups from T_2 to $2T^*$ and beyond $2T^*$. However, following Rogers, as Laggards generally form a homogeneous group, we group them into one category.

Johnson and Kotz (1970), the points of inflection, T_1 and T_2 , for the normal distribution occur at one standard deviation away from the mean of the distribution, thus providing the same analytical reasoning underlying the categorization advanced by Rogers. The same analytical reasoning can be used to develop categories based on any diffusion model, provided that T_1 and T_2 exist.

NUMBER AND SIZE OF ADOPTER CATEGORIES

To implement the proposed approach for developing adopter categories, we must find expressions for (1) the points of inflection of the Bass adopter distribution and (2) the size of adopter categories.

The points of inflection can be found by taking the second derivative of $f(t)$, equation 3, with respect to time and equating it to zero. This step yields the following expressions for T_1 and T_2 .⁴

$$(9) \quad T_1 = -\frac{1}{(p+q)} \ln \left[(2 + \sqrt{3}) \frac{p}{q} \right]$$

and

$$(10) \quad T_2 = -\frac{1}{p+q} \ln \left[\frac{1}{(2 + \sqrt{3})} \frac{p}{q} \right]$$

To find the proportion of individuals included in each of the adopter categories, we must derive $F(T_2)$, the cumulative proportion of adopters at time T_2 , and $F(T_1)$, the cumulative proportion of adopters at time T_1 . Be-

⁴From equation 3,

$$\frac{df(t)}{dt} = \frac{-p(p+q)^3 e^{-(p+q)t}}{(p+q e^{-(p+q)t})^3} [p - q e^{-(p+q)t}]$$

and as shown in Figure 3,

$$\frac{df(t=0)}{dt} = p(q-p).$$

Similarly,

$$\frac{d^2f(t)}{dt^2} = -\frac{p(p+q)^4 e^{-(p+q)t}}{(p+q e^{-(p+q)t})^4} [(p+q e^{-(p+q)t})(-p+2q e^{-(p+q)t}) + 3q e^{-(p+q)t}(p-q e^{-(p+q)t})] = 0$$

Let $Z = e^{-(p+q)t}$. Then, $(p+qZ)(2qZ-p) + 3qZ(p-qZ) = 0$ or $q^2Z^2 - 4pqZ + p^2 = 0$.

Therefore,

$$Z = e^{-(p+q)t} = \frac{4pq \pm \sqrt{16p^2q^2 - 4p^2q^2}}{2q^2} = \frac{p}{q} (2 \pm \sqrt{3})$$

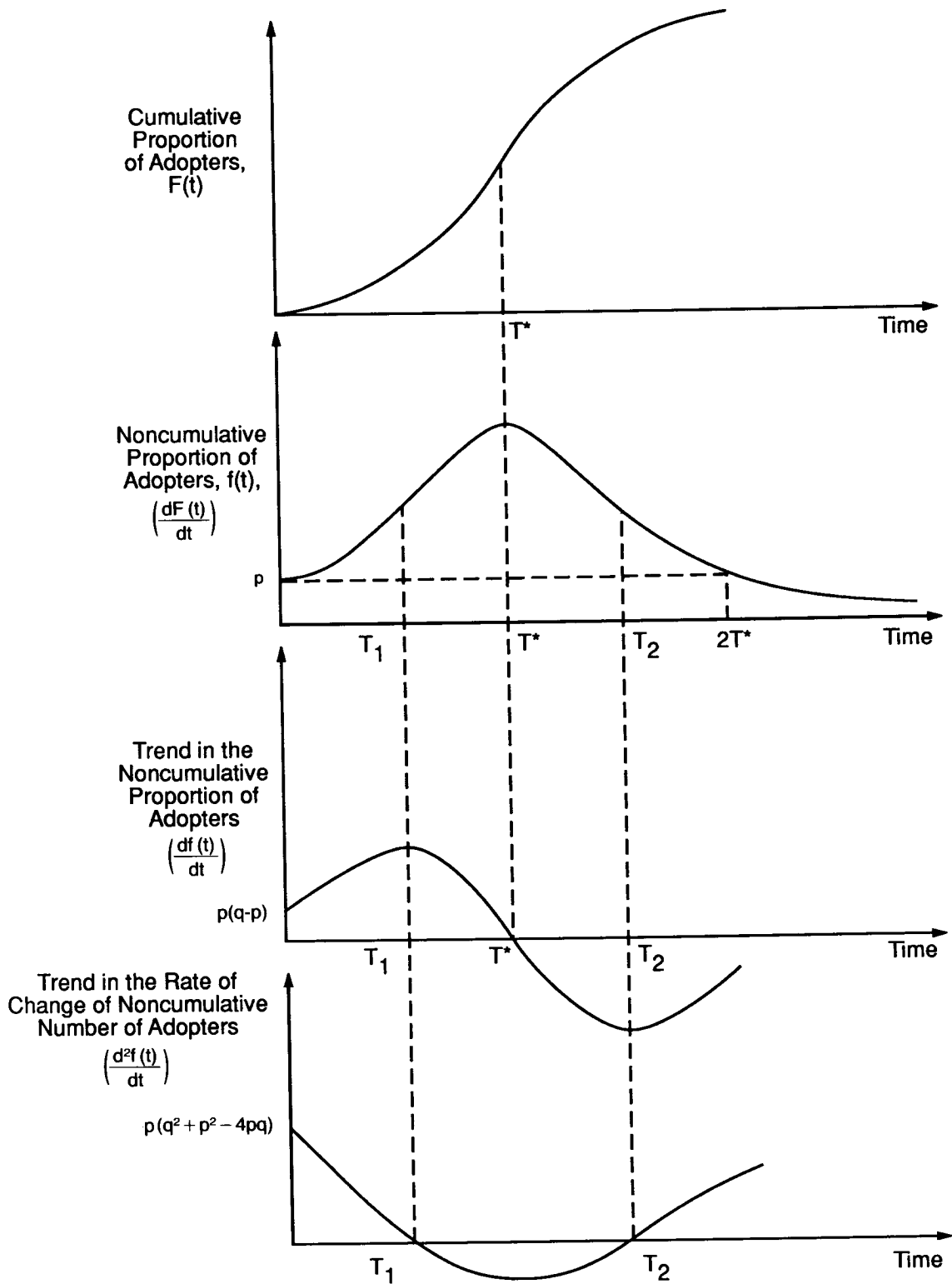
or

$$t = -\frac{1}{p+q} \ln \left((2 \pm \sqrt{3}) \frac{p}{q} \right).$$

This gives equations 9 and 10. As plotted in Figure 2,

$$\frac{d^2f(t)}{dt^2} (t=0) = p(q^2 + p^2 - 4pq).$$

Figure 3
ANALYTICAL PROPERTIES OF THE BASS DIFFUSION MODEL



cause $F(T^*)$ is known (i.e., equation 5), the sizes of various adopter categories can be found by noting that Early Adopters = $F(T_1) - p$, Early Majority = $F(T^*) - F(T_1)$, Late Majority = $F(T_2) - F(T^*)$, and Laggards = $1 - F(T_2)$. We can show that⁵

$$(11) \quad F(T_1) = F(T^*) - \frac{1}{\sqrt{12}} \left(1 + \frac{p}{q} \right)$$

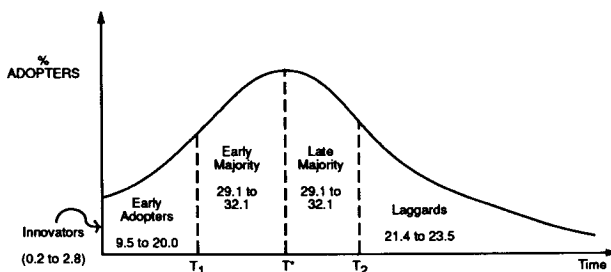
and

$$(12) \quad F(T_2) = F(T^*) + \frac{1}{\sqrt{12}} \left(1 + \frac{p}{q} \right).$$

The time durations and the sizes of the adopter categories based on the Bass diffusion model now can be estimated given equations 8 through 12. The expressions needed to estimate these items are summarized in Figure 4B. As we note from the figure, the time interval and the size of each adopter category depend on the two parameters of the Bass model—the coefficient of external influence (p) and the coefficient of internal influence (q). Consequently, both the time durations and the sizes of adopter categories are innovation-specific and their estimates respond to the penetration pattern of the product being considered. However, knowing p/q and/or $(p + q)$ values, we can compare the time duration and size of adopter categories across products. Also note in Figure 4B that, as in the categorization based on the normal distribution, the time intervals and the category sizes for Early Majority and Late Majority adopters are identical.

Figure 4
DURATION AND SIZE OF ADOPTER CATEGORIES BASED ON THE BASS DIFFUSION MODEL

A. The Adopter Categories^a



B. Analytical Expressions for the Adopter Categories

Adopter Category	Time Interval Covered on the Bass Adopter Distribution	Expression for the Time Interval	Expression for the Adopter Category Size
Innovators	Initiation of the Diffusion Process	-	p
Early Adopters	up to T_1	$\frac{1}{(p+q)} \ln \left[(2 + \sqrt{3}) \frac{p}{q} \right]$	$\frac{1}{2} \left(1 - \frac{p}{q} \right) - \frac{1}{\sqrt{12}} \left(1 + \frac{p}{q} \right) - p$
Early Majority	T_1 to T^*	$\frac{1}{(p+q)} \ln(2 + \sqrt{3})$	$\frac{1}{\sqrt{12}} \left(1 + \frac{p}{q} \right)$
Late Majority	T^* to T_2	$\frac{1}{(p+q)} \ln(2 + \sqrt{3})$	$\frac{1}{\sqrt{12}} \left(1 + \frac{p}{q} \right)$
Laggards	T_2 to ∞	-	$\frac{1}{2} \left(1 + \frac{p}{q} \right) - \frac{1}{\sqrt{12}} \left(1 + \frac{p}{q} \right)$

^aThe percentage range reported for each category is based on the parameter estimates reported by Bass (1969).

⁵The cumulative proportion of adopters at T_1 and T_2 can be found by expressing the second derivative of $f(t)$ as a function of $F(t)$, putting it equal to zero, and solving the resultant equation for $F(t)$. Ignoring the symbol t for simplicity, let

$$f = \frac{dF}{dt} = Z(F) = (p + qF)(1 - F).$$

Therefore, $\frac{dZ(F)}{dF} = (q - p) - 2qF$. Now

$$\begin{aligned} \frac{d^2f}{dt^2} &= \frac{d}{dt} \left[\frac{df}{dt} \right] = \frac{d}{dt} \left[\frac{dZ(F)}{dF} \cdot \frac{dF}{dt} \right] = \frac{d}{dt} \left[\frac{dZ(F)}{dF} \cdot f \right] \\ &= \frac{d}{dt} [(q - p - 2qF)f] \\ &= -2qf^2 + (q - p - 2qF)^2 f. \end{aligned}$$

That is, $\frac{d^2f}{dt^2} = 0$ implies that $-2qf + (q - p - 2qF)^2 = 0$. Substitution of f in terms of F and further simplification yields $6q^2F^2 - 6q(q - p)F + (q - p)^2 - 2pq = 0$. The solutions of this equation are given by

$$F = \frac{1}{2} \left(1 - \frac{p}{q} \right) \pm \frac{1}{\sqrt{12}} \left(1 + \frac{p}{q} \right).$$

These solutions give equations 11 and 12 by noting the value of $F(T^*)$ from equation 5.

COMPARISON OF ADOPTER CATEGORIES BASED ON THE BASS MODEL AND THE NORMAL DISTRIBUTION

To compare the adopter categories based on the Bass model with those based on the normal distribution, parameter estimates reported by Bass (1969) were used to gauge the range of the size of the adopter categories for the 11 consumer durable products he analyzed. As indicated before, for these products, the value of q/p ranges from 9.0 to 85.7. The essential results are reported in Table 1 and are summarized in Figures 4 and 5. Four observations emerge from these results.

1. As reported in Table 1, the percentage of innovators among the 11 products ranges from .2 to 2.9%; the highest percentage corresponds to $q/p = 11.4$ (steam irons) and the lowest percentage corresponds to $q/p = 85.7$ (electric refrigerators).
2. From Table 1, as q/p increases, the percentage of adopters in two groups (Early Adopters and Laggards) also increases. The percentage of adopters for the other two groups (Early Majority and Late Majority), however, decreases as q/p increases. That is, $q/p = 9.0$ (for black and white television sets) and $q/p = 85.7$ (for electric

Table 1
TIME, DURATION, AND SIZE OF ADOPTER CATEGORIES FOR CONSUMER DURABLE PRODUCTS

Product	No. of years covered	q/p	Adopter category								
			Innovators	Early Adopters		Early Majority		Late Majority		Laggards	
			% adopters	Years	% adopters	Years	% adopters	Years	% adopters	Years	% adopters
Black and white TV sets	16	9.0	2.8	3.1	9.5	4.7	32.1	4.7	32.1	12.5	23.5
Home freezers	16	9.4	1.8	4.8	10.9	7.0	32.0	7.0	32.0	18.8	23.3
Steam irons	12	11.4	2.9	3.1	11.3	3.7	31.4	3.7	31.4	10.5	23.0
Water softeners	12	16.8	1.8	4.8	14.6	4.2	30.6	4.2	30.6	13.2	22.4
Automatic coffee makers	14	17.6	1.7	4.9	15.0	4.1	30.5	4.1	30.5	13.1	22.3
Clothes dryers	14	20.7	1.7	4.6	15.6	3.5	30.3	3.5	30.3	11.6	22.1
Record players	10	26.4	2.5	2.9	15.6	1.9	30.0	1.9	30.0	6.7	21.9
Power lawnmowers	14	36.8	.9	6.6	18.1	3.8	29.65	3.8	29.65	14.2	21.7
Room airconditioners	16	40.6	1.0	5.6	18.2	3.0	29.6	3.0	29.6	11.6	21.6
Electric bed coverings	13	41.5	.6	9.6	18.64	5.3	29.56	5.3	29.56	20.2	21.64
Electric refrigerators	21	85.7	.2	14.3	20.0	6.0	29.1	6.0	29.1	26.3	21.4

refrigerators) set the range of sizes for these four adopter groups. Figure 4A summarizes the range of the sizes for the various adopter categories across the 11 consumer durable products. It is apparent from Figure 4A that, unlike the approach suggested by Rogers, the Bass model does not yield constant sizes of adopter categories. With the data from Table 1, Figure 5A is a plot of the percentage of adopters in each adopter category for the various values of q/p . The percentage distribution of adopters across the adopter categories tends to stabilize around $q/p = 40$.

- From Table 1, comparisons can be made between the sizes of adopter categories provided by the Bass model and the normal distribution.

Adopter category	Bass adopter distribution		
	Normal adopter distribution (%)	Range (%)	Approximate stable value after $q/p = 40$ (%)
Innovators	2.5	.2 to 2.8	1.0
Early Adopters	13.5	12.3 to 20.2	18.0
Early Majority	34	29.1 to 32.1	29.5
Late Majority	34	29.1 to 32.1	29.5
Laggards	16	21.4 to 23.5	22.0

These comparisons suggest that (1) the sizes of Innovators and Early Adopters groups provided by the normal distribution are in the range of sizes for the same two groups given by the Bass model and (2) the categorization based on the Bass model tends to generate a lower percentage of adopters in two groups (Early Majority and Late Majority) and a higher percentage in one group (Laggards). In spite of these differences, the similarity between the two approaches is noteworthy.

- Figure 5B is a plot of the adoptions due to external influence in the four categories of Early Adopters, Early

Majority, Late Majority, and Laggards.⁶ Figure 5B again confirms that adoptions due to external influence tend to occur among the earlier adopter groups. For example, for $q/p = 85.7$, of all the adoptions due to external influence, the percentage distribution across the four groups is 65.4, 19.2, 9.6, and 5.8, respectively. That is, adoptions due to external influence cluster among Early Adopters. In fact, as the value of q/p increases, adoptions due to external influence tend to cluster relatively

⁶Across the 11 products, the total number of adoptions due to external influence (i.e., equation 8) monotonically decreases as the value of q/p increases. It is 25.91% for $q/p = 9.0$ (black and white television sets) and 5.2% for $q/p = 85.97$ (electric refrigerators). From equation 7, one can easily derive that the adoptions due to external influence among the four groups are given by:

$$F_{11} \text{ (Early Adopters)} = \frac{p}{q} \ln \left[\frac{1 + q/p}{3 + \sqrt{3}} \right],$$

$$F_{12} \text{ (Early Majority)} = \frac{p}{q} \ln \left[\frac{3 + \sqrt{3}}{2} \right],$$

$$F_{13} \text{ (Late Majority)} = \frac{p}{q} \ln \left[\frac{2(2 + \sqrt{3})}{3 + \sqrt{3}} \right],$$

$$F_{14} \text{ (Laggards)} = \frac{p}{q} \ln \left[\frac{3 + \sqrt{3}}{2 + \sqrt{3}} \right].$$

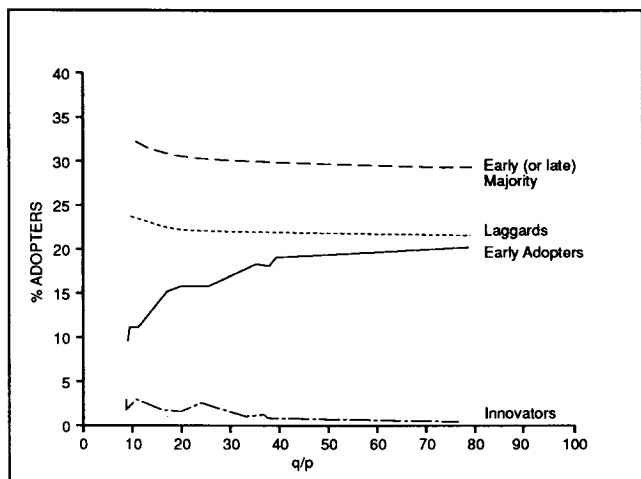
From these equations, one can easily check that $F_{12} > F_{13} > F_{14}$ for all values of q/p . However, $F_{11} > F_{12}$ when $q/p \geq 10$. Note that because $F_{11} - F_{12} = \frac{p}{q} \left[\ln \left(1 + \frac{q}{p} \right) - 2.4115 \right]$, for $F_{11} - F_{12} > 0$,

we must have $\ln \left(1 + \frac{q}{p} \right) > 2.4155$ or $q/p > 10.1961$. Hence, $F_{11} >$

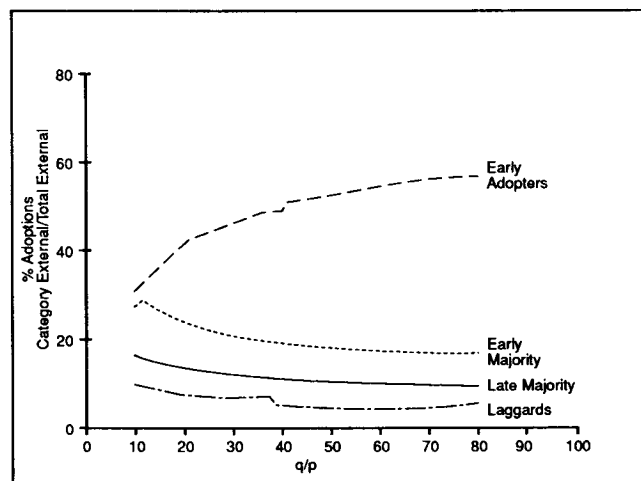
F_{12} when the ratio q/p is approximately greater than 10. That is, in general, the number of adoptions due to external influence decreases across the adopter categories (because the value of q/p generally has been observed to be greater than 10 for consumer durable products; see Bass 1969).

Figure 5
 VARIATION IN ADOPTER CATEGORY SIZES FOR THE
 VARIOUS VALUES OF q/p

A. Percentage of Adopters in Each Adopter Category



B. Percentage of Adoptions Due to External Influence in Each Adopter Category



higher in the earlier time periods. For example, for $q/p = 9.0$, the ratio of adoptions due to external influence to total adoptions due to external influence for Early Adopters is 32.2%; the same ratio for $q/p = 85.7$ is 65.4%.

AN APPLICATION

We examined the diffusion of personal computers among the subscribers of personal-computer-oriented magazines to demonstrate the potential usefulness of the adopter categorization scheme based on diffusion models and to assess the validity of the groupings. First, groups

based on the Bass model were formed. Then group differences were compared with those hypothesized and tested in the diffusion literature.

Expected Group Differences

Dickerson and Gentry (1983) report that adopters of personal computers (in comparison with nonadopters) tend to be older and have higher income, more education, and higher status (professional, technical, and managerial) occupations. These findings are consistent with those of most empirical studies in the diffusion theory literature (Gatignon and Robertson 1985).

Dickerson and Gentry (1983) also observe that adopters of personal computers have greater experience with other technical products. Similarly, Gatignon and Robertson (1985), on the basis of their review of adoption research, note that new product innovators are likely to be drawn from heavy users of other products within the product category. Adopters who adopt earlier than others are likely to have more to gain from the use of the product and hence have a greater usage propensity. Additionally, adoption of complex products such as personal computers depends on buyers' ability to develop new knowledge and new patterns of experience. Their ability can be enhanced by the knowledge and experience gained from related products. Thus, adopters of personal computers who adopt earlier than others can be expected to use a more diverse set of software (because of greater product need and higher creativity) and therefore should have greater expertise in the use of personal computers.

Consumers who are highly dependent on normative influence are slower to adopt innovations (Burt 1973). Adopters who adopt earlier than others are likely to have a greater propensity to use information from mass media than to use interpersonal advice (Midgley and Dowling 1978) and can be expected to use a greater number of publications as information sources. Feick and Price (1987) note that market mavens, individuals who assimilate and disseminate information on products (and therefore influence others), tend to be more receptive to advertising and rely on both print and broadcast media as information sources.

Finally, earlier adopters have been found to have higher levels of opinion leadership (Rogers 1983). Because the ability to render advice is based on knowledge and experience, earlier adopters of personal computers can be expected to be more involved in the evaluation process and in the purchase decision.

Survey Details and Results

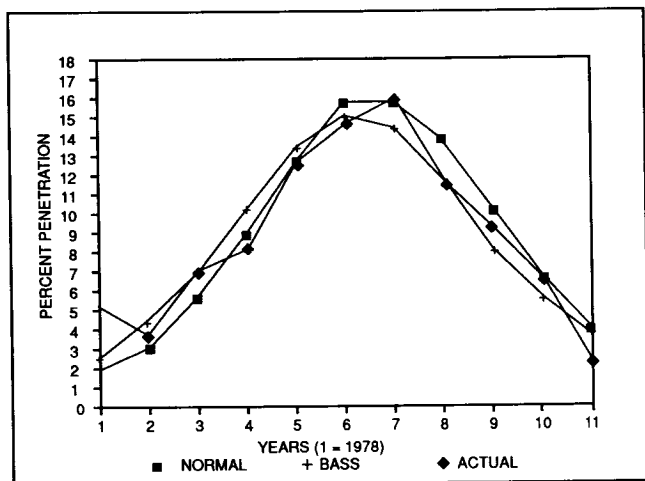
The data for our study were extracted from a larger advertising effectiveness study for 23 personal-computer-oriented publications. The sample frame consisted of subscribers to those publications. In general, these subscribers can be expected to be more interested in computers (than the general population) and, hence, earlier adopters of the product. Consequently, this sample

represents a more challenging test of the adopter categorization scheme based on the diffusion models than a sample from the population at large.

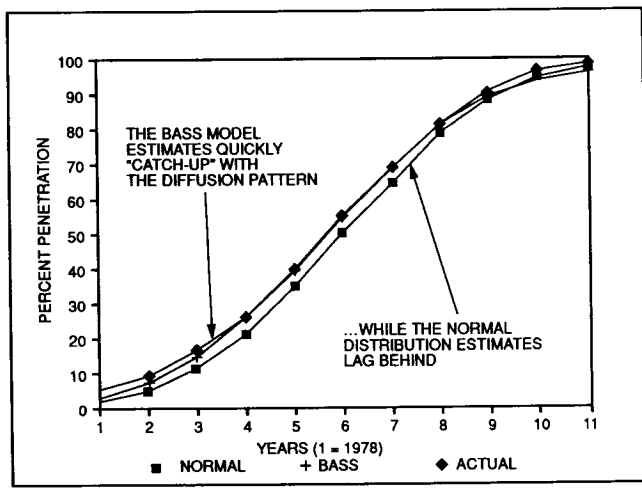
A seven-page survey was mailed in fall 1988 to potential respondents chosen randomly from the subscriber lists of the 23 publications after elimination of duplications. A response rate of slightly over 50% was obtained from two mailings. For proprietary reasons, a random subsample of 860 respondents was made available for our research. Within this group were 834 personal computer adopters (97%) covering the time period from 1978 to 1988. Figure 6 is a plot of the raw data depicting percentages for noncumulative and cumulative penetration of personal computers in this sample.

Figure 6
DIFFUSION PATTERNS FOR MICROCOMPUTERS

A. Noncumulative Diffusion Pattern



B. Cumulative Diffusion Pattern



To estimate the Bass model and to develop adopter categories, we used the maximum likelihood estimation procedure suggested by Schmittlein and Mahajan (1982) to obtain estimates for the coefficients of external influence (p) and internal influence (q). The estimation procedure provided a good fit to the data with the following fit statistics: $p = .02$, $q = .58$, $r^2 = .99$, mean square error = .0002 for the noncumulative distribution and .0003 for the cumulative distribution. To compare the adopter categories based on the Bass model with the adopter categories based on the normal distribution, we also fitted the normal distribution to the data, obtaining the following fit statistics: mean time of adoption = 6.1 years, standard deviation (years) = 2.48, $r^2 = .99$, mean square error = .0002 for the noncumulative distribution and .0014 for the cumulative distribution. Cumulative and noncumulative penetration curves provided by the Bass model and the normal distribution, respectively, are shown in Figure 6.

The Bass model and the normal distribution provide comparable fit statistics. Inspection of Figure 6B, however, reveals that the normal distribution consistently underestimates the diffusion pattern and lags the actual penetration curve. It eventually catches up with the penetration curve in year 9 (1986). In comparison with the Bass model, the normal distribution curve is unable to capture the flatter tail at the beginning of the cumulative penetration curve. The Kolmogorov-Smirnov test reveals that the cumulative normal distribution curve is significantly different from the Bass model and the actual penetration curve at $\alpha = .10$.

On the basis of the parameter estimates for the Bass model and the necessary equations summarized in Table 1, the following statistics were obtained for the adopter categories.

Adopter category	Time duration (years)	% adopters
Innovators	—	1.9
Early Adopters	3.6	16.6
Early Majority	2.1	29.8
Late Majority	2.1	29.8
Laggards	Beyond 7.8	21.9
		100.0

It is noteworthy that 1.9% of all adopters were classified as Innovators by the Bass model. Given their smaller number, Innovators were not separated but combined with Early Adopters to study differences across the adopter categories.

Tables 2 through 5 summarize the group differences on a variety of demographic, product usage, media access, and purchase involvement variables. These tables include the following statistics for each of the adopter categories on group description variables: group means (or proportions for nominal variables), F -ratios (or the chi square value for nominal variables where indicated) measuring overall differences across adopter categories,

Table 2
AGE, EDUCATION, INCOME, AND OCCUPATION DIFFERENCES AMONG ADOPTER CATEGORIES^a

Variable	Group means/proportions				Overall difference of proportions (χ^2)	Significant pairwise comparisons (adopter categories compared)					
	Early Adopters (1)	Early Majority (2)	Late Majority (3)	Laggards (4)		1-2	1-3	1-4	2-3	2-4	3-4
Age ^b	3.09	2.97	2.90	3.06	25.03**		*		**		*
Education ^c	4.12	4.06	3.96	3.78	20.88***		*	*		***	
Household income ^d	4.97	4.73	4.42	4.19	49.84*		*	*		*	*
Occupation ^e	.60	.58	.48	.44	13.80*		**	*	**	*	

^aOccupation is reported as a nominal variable. Because of the large number of categories used for the other three variables, their group means are reported to indicate the nature of trends. The significance results for all the variables are based on the chi square test.

^bIn years: 1 = <25, 2 = 25-34, 3 = 35-44, 4 = 45-54, 5 = >55.

^c1 = <high school, 2 = high school, 3 = some college, 4 = college graduate, 5 = master's, 6 = PhD.

^dIn \$'000: 1 = <15, 2 = 15-24, 3 = 25-34, 4 = 35-49, 5 = 50-74, 6 = 75-99, 7 = 100-149, 8 = 150+.

^e1 = professional, 0 = nonprofessional.

*Significant at $p = .01$.

**Significant at $p = .05$.

***Significant at $p = .10$.

and significant contrasts comparing two adopter categories at a time. The questions used in the survey to elicit information on the variables studied are included also.

Summary statistics reported in Table 2 indicate that the adopter categories are overall significantly different from each other on age, education, household income, and occupation. Group means (and group proportions for nominal variables where indicated) across the adopter categories suggest that the earlier adopters tend to have higher income, more education, and professional occupations. On the age dimension, however, the relationship is nonlinear, with the third group (Late Majority) having younger members. The contrasts indicate the differences between two adopter groups at a time. For example, adopters in Late Majority and Laggards categories are not significantly different from each other on the occupation dimension.

Table 3 reports group differences on the usage of personal computers and software and on expertise. Significant results for the overall differences across the adopter categories suggest that adopters of personal computers who adopt earlier than others tend to use them more often, use a greater amount of software, and have greater expertise in the use of personal computers. The contrasts again indicate the differences between adopter categories on these dimensions. For example, the results for the contrasts suggest that though the differences between Early Adopters and Early Majority categories are also in the expected direction, they are not statistically significant.

Findings related to magazine readership and advertising susceptibility are reported in Table 4. These results suggest that adopters of personal computers who adopt sooner than others are likely to read a larger number of computer and business magazines and are more likely to examine advertising related to personal computers. Though

Table 3
FREQUENCY OF USAGE, SOFTWARE USAGE, AND EXPERTISE DIFFERENCES AMONG ADOPTER CATEGORIES

Variable	Group means				Overall difference of means (F-ratio)	Significant pairwise comparisons (adopter categories compared)					
	Early Adopters (1)	Early Majority (2)	Late Majority (3)	Laggards (4)		1-2	1-3	1-4	2-3	2-4	3-4
Hours/week on PC ^a	2.73	2.58	2.42	2.18	10.03*		*	*		*	**
Number of software used ^b	4.57	4.29	3.69	2.50	31.74*		*	*	*	*	*
Expertise ^c	3.11	3.00	2.65	2.21	42.85*		*	*	*	*	*

^a1 = <5, 2 = 6-15, 3 = 16-30, 4 = >30.

^bTotal across 10 types: word processing, spreadsheet, database management, file management, multifunction, graphics, communication, utilities, programming, language, compiler.

^c1 = novice, 2 = intermediate, 3 = advanced, 4 = expert.

*Significant at $p = .01$.

**Significant at $p = .05$.

Table 4
COMPUTER AND BUSINESS MAGAZINE READERSHIP AND ADVERTISING FOCUS DIFFERENCES
AMONG ADOPTER CATEGORIES

Variable	Group means				Overall difference of means (F-ratio)	Significant pairwise comparisons (adopter categories compared)					
	Early Adopters (1)	Early Majority (2)	Late Majority (3)	Laggards (4)		1-2	1-3	1-4	2-3	2-4	3-4
Number of computer magazines read ^a	4.32	3.75	3.31	2.79	12.63*	**	*	*	***	*	**
Number of business magazines read ^b	2.99	2.88	2.52	2.11	4.59*		***	*		*	
Advertising focus ^c	1.53	1.48	1.34	1.20	2.86**		**	*		*	

^aIn last six months (max = 23).

^bIn last six months (max = 18).

^cHow closely do you read or examine PC-related advertising in this publication? (1 = not at all, 2 = not too closely, 3 = moderately, 4 = very closely).

*Significant at $p = .01$.

**Significant at $p = .05$.

***Significant at $p = .10$.

all of the group means on each of the variables are in the expected direction, the results for the contrast again indicate that on two variables (i.e., number of business magazines read and attention paid to personal-computer-related advertising), only Early Adopters and Early Majority categories are significantly different from Laggards. Additionally, the Early Adopters category is also different from the Late Majority.

Finally, Table 5 reports findings related to involvement in the purchase process as well as influence on others. These findings suggest that in spite of some insignificant differences between the first two adopter categories (i.e., Early Adopters and Early Majority), adopters of personal computers who adopt earlier than

others are more likely to be involved in personal computer decisions, in evaluation of personal computers, and in advising others about personal computers.

Overall, the results reported in Tables 2-5 clearly support the expected differences across the adopter categories. The application clearly demonstrates how the adopter categories based on other well-established diffusion models such as the Bass model can be used to study differences among adopter categories.

SUMMARY AND DISCUSSION

Following the analytical logic underlying the classical adopter categorization scheme suggested by Rogers, we propose that adopter categories can be developed by us-

Table 5
DIFFERENCES AMONG ADOPTER CATEGORIES ON INVOLVEMENT IN PURCHASING AND EVALUATING PERSONAL COMPUTERS FOR ORGANIZATION AND ADVISING OTHERS ABOUT PERSONAL COMPUTERS

Variable	Group proportions				Overall difference of proportions (χ^2)	Significant pairwise comparisons (adopter categories compared)					
	Early Adopters (1)	Early Majority (2)	Late Majority (3)	Laggards (4)		1-2	1-3	1-4	2-3	2-4	3-4
Purchasing personal computers for organization ^a	.67	.67	.56	.47	20.58*			*		*	
Evaluating personal computers for organization ^b	.57	.58	.45	.38	22.26*		*	*	*	*	
Advising others ^c	.44	.41	.26	.10	60.38*		*	*	*	*	*

^aInvolvement in purchase decisions (product need) for personal computers for organization (1 = yes, 0 = no).

^bInvolvement in evaluating personal computers for organization (1 = yes, 0 = no).

^cInvolvement in recommending personal computers (brands) to others (1 = frequently, 0 = never/occasionally).

*Significant at $p = .01$.

ing other well-established diffusion models such as the Bass diffusion model. Development of such categories overcomes several shortcomings of Rogers' categorization scheme. It also avoids some fairly arbitrary time-based definitions (Midgley and Dowling 1978, p. 230). It yields a category structure in which the size of adopter categories is not assumed to be identical for all innovations. That is, categories reflect the groupings of adopters that are unique to a particular innovation and are not based on the amount of time-series diffusion data available for clustering the adopters. Moreover, inter-study comparisons across the various products can be based on the basic parameters of the diffusion models.

Our development of the adopter categories is based on the Bass diffusion model. There is no reason to believe that such schemes cannot be developed with other diffusion models, provided adopter distributions of those models have the points of inflection (i.e., T_1 and T_2 in Figure 3). Our choice of the Bass model is based on the fact that, among all the diffusion models used in marketing, it is the only one that explicitly considers the communication process for innovation diffusion proposed by Rogers. In this respect, it provides an alternative to the classical approach based on normal adopter distribution pioneered by Rogers.⁷

The proposed categorization, however, is not without shortcomings. First, as summarized in Figure 4, the duration and the size of adopter categories depend only on the parameters p and q . Consequently, the proposed approach will not be applicable to situations in which the Bass model does not capture the diffusion process (i.e., it yields wrong signs for p and q). In such situations, however, if an alternative diffusion model is used to describe the diffusion process (e.g., flexible models described by Mahajan and Peterson 1985), adopter categories still can be developed provided that the adopter distribution of the alternative diffusion model has the points of inflection. The size of adopter categories may vary depending on the specific model used to describe the diffusion process.

Second, as demonstrated by Heeler and Hustad (1980) and Srinivasan and Mason (1986), stable and robust estimates of p and q can be obtained only if the data under consideration include the peak of the adopter distribution. Furthermore, estimates of p and q may also differ depending on the particular estimation procedure used to derive them (Mahajan, Mason, and Srinivasan 1986). Though the nonlinear estimation procedure suggested by

Srinivasan and Mason (1986) is conceptually and empirically appealing (Bass 1986; Mahajan, Mason, and Srinivasan 1986), we endorse the recommendation by Heeler and Hustad (1980) that these estimation procedures be used in conjunction with management judgments to derive parameter estimates. Parameter estimates also may be developed as a function of actionable marketing variables, and "what-if" analyses could be performed to determine their impact on the adoption curve and resulting adopter categories (Gatignon, Eliashberg, and Robertson 1989; Rao and Yamada 1988; Srivastava et al. 1985). Because the size of adopter categories depends on the coefficient values, sensitivity of the categories to these values should be assessed.

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⁷Olshavsky (1980) has hypothesized that because product life cycles are becoming shorter, it is questionable whether meaningful categories that distinguish adopters by their time of adoption can be developed. Irrespective of the length of the product life cycle, the proposed approach does provide a systematic way to group adopters by the time of adoption. For a particular innovation, the variables that characterize the differences across groups can only be determined empirically.

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