VENKATESH SHANKAR, GREGORY S. CARPENTER, and LAKSHMAN KRISHNAMURTHI*

Although pioneers outsell late movers in many markets, in some cases innovative late entry has produced some remarkably successful brands that outsell pioneers. The mechanisms through which innovative late movers outsell pioneers are unclear. To identify these mechanisms, the authors develop a brand-level model in which brand sales are decomposed into trials and repeat purchases. The model captures diffusion and marketing mix effects on brand trials and includes the differential impacts of innovative and noninnovative competitors' diffusion on these effects. The authors develop hypotheses on how the diffusion and marketing mix parameters of the brands differ by market entry strategy (pioneering, innovative late entry, and noninnovative late entry). The authors test these hypotheses using data from 13 brands in two pharmaceutical product categories. The results show that an innovative late mover can create a sustainable advantage by enjoying a higher market potential and a higher repeat purchase rate than either the pioneer or noninnovative late movers, growing faster than the pioneer, slowing the pioneer's diffusion, and reducing the pioneer's marketing spending effectiveness. Innovative late movers are advantaged asymmetrically in that their diffusion can hurt the sales of other brands, but their sales are not affected by competitors' diffusion. In contrast, noninnovative late movers face smaller potential markets, lower repeat rates, and less marketing effectiveness compared with the pioneer.

Late Mover Advantage: How Innovative Late Entrants Outsell Pioneers

Although pioneers outsell late movers in many markets (e.g., Kalyanaram and Urban 1992; Robinson 1988; Robinson and Fornell 1985; Urban et al. 1986), a growing body of evidence suggests that in some cases late movers outsell pioneers (e.g., Golder and Tellis 1993; Lieberman and Montgomery 1988; Lilien and Yoon 1990). The personal computer, wine cooler, and video game markets are examples in which pioneers were eclipsed by late movers. Lilien and Yoon (1990) find that success is lower for first and second entrants; higher for third and fourth; and again lower for fifth, sixth, and subsequent entrants in selected French markets for industrial goods. Golder and Tellis (1993) find that market share leadership for pioneers is supported in only 4 of the 50 product categories they studied.

Late movers can outsell pioneers in at least two ways. First, a late mover can beat a pioneer at the pioneer's own game. The pioneer plays a central role in defining the category concept (e.g., Kleenex) and buyer preferences for the category (Carpenter and Nakamoto 1989). These preferences are the foundation for competition between the pioneer and later entrants in a category (e.g., Carpenter and Nakamoto 1996). By understanding these preferences, a late mover can identify a superior but overlooked product position, undercut the pioneer on prices, or out-advertise or outdistribute the pioneer, thereby beating the pioneer at its own game. The freeze-dried coffee market offers one such example. Maxwell House's Maxim pioneered the category, but Nestle's Taster's Choice identified a superior position and overtook Maxim (Urban et al. 1986).

Second, a late mover can overtake a pioneer through innovation. Innovation in either product or strategy can re-

*Venkatesh Shankar is Assistant Professor of Marketing, College of Business and Management, University of Maryland (e-mail: vshankar@mbs.umd.edu). Gregory S. Carpenter is Associate Professor of Marketing, J. L. Kellogg Graduate School of Management, Northwestern University (e-mail: g-carpenter@nwu.edu). Lakshman Krishnamurthi is A. Montgomery Ward Professor of Marketing and Chairperson, Marketing Department, J. L. Kellogg Graduate School of Management, Northwestern University (e-mail: laksh@nwu.edu). The authors thank the editor, three anonymous *JMR* reviewers, and participants at the Wharton conference on Innovation in New Product Development for insightful comments and suggestions. The authors also thank IMS America for providing the data used in this research.

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shape the category and the competitive game between the pioneer and late entrants, enabling a late mover to overtake the pioneer (Berndt et al. 1995; Carpenter et al. 1997; Carpenter and Sawhney 1996; Yip 1982). For example, Gillette has built a powerful position in the razor market through a process of continuing innovation. Through these innovations, it has overtaken the pioneer, Star, and many others (Golder and Tellis 1993). The role of innovation is particularly vivid in evolving or so-called "high-technology" markets (Carpenter and Sawhney 1996; Golder and Tellis 1993), such as the video cassette recorder market, in which the pioneer Ampex was overtaken by Matsushita, and the microwave market, in which the pioneer Amana was eclipsed by Samsung. Innovation plays a role in so-called "low-technology" markets as well: Tide dominates the laundry detergent market pioneered by Dreft, and Eveready leads the flashlight battery market launched by Bright Star (Golder and Tellis 1993).

Existing empirical analyses of sequential entry have focused on explaining the advantages associated with pioneering. These analyses have produced important insights about the advantages of early entry and the strategies available to late movers (e.g., Bowman and Gatignon 1996; Carpenter and Nakamoto 1990; Kalyanaram and Urban 1992; Parker and Gatignon 1996; Urban et al. 1986). These studies show that pioneers enjoy substantial advantages relative to late movers and that late movers should identify superior positions and outspend pioneers to beat them at their own game. These analyses, however, have not examined the impact of innovative late entry on either the diffusion process or the responsiveness of brands' sales to marketing expenditures. That may suggest mechanisms of advantage for innovative late movers. For example, most previous analyses have assumed that diffusion of competitors leaves the focal brand's diffusion and marketing mix effects unaffected (e.g., Bowman and Gatignon 1996; Kalyanaram and Urban 1992; Urban et al. 1986). Other studies that examine the effect of competitor diffusion (Parker and Gatignon 1994, 1996) assume that this effect on the pioneer is the same regardless of whether the competitors are innovative or not. By not exploring innovation, many intriguing questions about its role remain open. For example, does innovative late entry lead to faster diffusion, greater potential markets, and higher repeat purchase rates compared with other entry strategies? Does the diffusion of an innovative late mover slow the pioneer's diffusion or reduce its marketing spending effectiveness in a way that noninnovative late movers do not?

In this article, we address these questions to identify mechanisms that enable an innovative late mover to outsell a pioneer. We analyze two markets comprising 13 brands. In each market, the pioneer was followed by innovative and noninnovative late entrants and was overtaken by an innovative late mover. We model the sales of each brand using a generalization of the Bass (1969) model that captures the impact of a brand's diffusion, its competitors' diffusion, its marketing spending, and repeat purchases on its sales. Unlike previous models of sequential entry, we model brand sales rather than trials (Parker and Gatignon 1994, 1996) or market share (Bowman and Gatignon 1996; Kalyanaram and Urban 1992; Urban et al. 1986), allow each brand to have unique parameters to reflect asymmetries in competition, and explicitly examine the differential impacts of diffusion of innovative and noninnovative competitors on brand sales. On the basis of the model, we develop hypotheses to explain how the diffusion and marketing spending parameters differ by entry strategy (pioneering and innovative and noninnovative late entry).

Estimating our model and testing our hypotheses produces fresh insights about the role of innovation in late entry strategy. Our results show that noninnovative late movers have less effective marketing spending and lower repeat purchase rates compared with pioneers and innovative late entrants, which is consistent with prior empirical studies examining pioneers and late movers (e.g., Bowman and Gatignon 1996; Kalyanaram and Urban 1992; Urban et al. 1986). In addition, we show that pioneers have higher potential markets than noninnovative late movers and that their diffusion and marketing mix effectiveness are unaffected by diffusion of noninnovative late entrants. Thus, compared with these weaker rivals, pioneers enjoy significant advantages that can be surmounted only at considerable expense.

Innovative late movers, however, face a dramatically different situation. Our results show that innovative late entry creates asymmetries in diffusion, response to marketing expenditures, market potential, and repeat rates. Compared with pioneers and noninnovative late entrants, innovative late movers diffuse faster, enjoy higher market potential, and have higher repeat rates. Moreover, innovation enables a late mover to have an impact on the pioneer's diffusion and market response that a noninnovative late mover does not. Greater diffusion of an innovative late mover slows the pioneer's diffusion and reduces the pioneer's marketing spending effectiveness. Greater diffusion of the pioneer and noninnovative later entrants, conversely, does not have any impact on the innovative late mover. Combined, these results suggest that innovative late movers can create a *late mover advantage*: Compared with a pioneer and noninnovative late movers, an innovative late mover will spend less on marketing and generate less trial to achieve the same level of unit sales. Moreover, innovative late movers are advantaged asymmetrically in that their diffusion can hurt the sales of other brands, but their sales are not affected by competitors' diffusion. We explore the implications of these results for late entry strategy, timing of entry, and the competitive process between pioneers and late entrants.

MODEL FORMULATION

Consider a market in which the pioneer is followed by other brands that enter sequentially, including innovative and noninnovative late movers. Brands expend resources on marketing to generate trials, some of which lead to repeat purchases. They diffuse over time, affected by word of mouth, innovative purchases, and competitors' sales. Our interest in this setting is to explain the sales of each brand in terms of the diffusion process, its marketing efforts, and the competitors' diffusion. This will help reveal the impact of innovation on brand diffusion and market response and examine possible sources or mechanisms of advantage for the brands. In such a setting, we decompose brand sales into trials and repeat purchases as follows:

$$S_{it} = T_{it} + \rho_i CT_{i(t-1)}, \quad (1)$$

where

S_{it} = sales of brand i at time t,

T_{it} = trials of brand i at time t,
ρ_i = the repeat purchase rate of brand i,[1] and
$CT_{i(t-1)}$ = cumulative trials of brand i at the end of time t − 1.

Brand trials are affected by both diffusion and marketing mix effects. We model the diffusion effect as consisting of both innovative and imitative factors, as has been done extensively at the product category level (e.g., Bass 1969). Brand-level diffusion, however, also can be influenced by diffusion of competitors (e.g., Mahajan, Sharma, and Buzzell 1993; Parker and Gatignon 1994, 1996; Peterson and Mahajan 1978). To account for these effects, we model the impact of competitors' diffusion on a brand's trials. To examine the differential impact of innovative and noninnovative competitors on a brand's diffusion process, we include separate variables for the diffusion of innovative and noninnovative competitors.[2]

A brand's trial depends on its marketing spending (e.g., Chatterjee and Eliashberg 1990; Kalish 1983; Parker and Gatignon 1994, 1996). Marketing mix effects at the brand level have been shown to be asymmetric (Bowman and Gatignon 1996; Carpenter et al. 1988; Carpenter and Nakamoto 1989; Parker and Gatignon 1994) and can be affected by increased competition (Gatignon, Anderson, and Helsen 1989). To capture these, we specify unique marketing spending parameters for each brand and allow these parameters to differ depending on the diffusion of competitors. Competitor diffusion reflects competitor dominance, which influences a brand's marketing effects (Schmalensee 1987). As a competitor brand diffuses over time, its pool of adopters expands. Greater numbers of adopters increase the competitor brand's dominance in the market and this can affect significantly the effectiveness of a brand's marketing activities. The impact of competitor diffusion may differ depending on whether the competitors are innovative or not. To examine the differential impacts of innovative and noninnovative competitors on a brand's marketing effects, we include separate variables for the diffusion of innovative and noninnovative competitors.

Specifically, we model brand trials as

$$(2)\quad T_{it} = \left[a_i + b_i CT_{i(t-1)} + c_{iI} CS_{iI(t-1)} + c_{iN} CS_{iN(t-1)}\right] \left[M_i - CT_{i(t-1)}\right] TM_{it}^{\beta_{i0} + \beta_{iI}CS_{iI(t-1)} + \beta_{iN}CS_{iN(t-1)}},$$

where i, t, I, and N represent brand, time, innovative competitors, and noninnovative competitors, respectively,

a_i = coefficient of external influence of brand i,
b_i = word-of-mouth coefficient of brand i,
c_{iI} = coefficient of influence of innovative competitors on brand i's diffusion,
$CS_{iI(t-1)}$ = total cumulative sales of innovative competitors of brand i at the end of time t − 1,
c_{iN} = coefficient of influence of noninnovative competitors on brand i's diffusion,
$CS_{iN(t-1)}$ = total cumulative sales of noninnovative competitors of brand i at the end of time t − 1,
M_i = market potential for brand i,
TM_{it} = total marketing mix expenditures of brand i at time t,
β_{i0} = brand i's marketing mix parameter,

β_{iI} and β_{iN} are coefficients of influence of innovative and noninnovative competitors' diffusion, respectively, on brand i's marketing mix parameter, and the other terms are defined as previously. The multiplicative form of Equation 2 has been found to describe new product growth well (Bass, Krishnan, and Jain 1994; Jain and Rao 1990). It enables us to examine separately diffusion and marketing mix effects on brand trials. Diffusion effects are captured in five parameters, namely, a_i, b_i, c_{iI}, c_{iN}, and M_i. As in the original Bass (1969) model, a_i and b_i capture the impacts of innovative and imitative purchases, respectively, on brand i's trials. We capture the impact of competitors' diffusion on a brand's diffusion by decomposing competitors into two groups, namely, innovative and noninnovative brands. Separate parameters c_{iI} and c_{iN} capture the impacts of the diffusion of innovative and noninnovative competitors, respectively.[3] Brand i's market potential is captured by M_i. We allow each brand to have its separate market potential. Differences in M_i reflect differences in brand positioning created by differences in each brand's physical attributes. The model can be extended to capture the impact of marketing mix on market potential (e.g., Kalish 1985; Parker and Gatignon 1994).

We capture the impact of marketing mix activities through the term TM_{it} and its coefficients β_{i0}, β_{iI}, and β_{iN}. β_{i0} reflects the impact of brand i's marketing activities on its trial. β_{iI} and β_{iN} capture the impacts of the diffusion of innovative and noninnovative competitors, respectively, on the effectiveness of brand i's marketing efforts. We assume the exponent of TM_{it} is less than one, which is consistent with empirical evidence (Bass, Krishnan, and Jain 1994). For a similar modeling approach, see Jain and Rao (1990) and Parker and Gatignon (1994, 1996).

Combining the brand trial and repeat purchase components, we specify brand sales as

$$(3)\quad S_{it} = \left[a_i + b_i CT_{i(t-1)} + c_{iI} CS_{iI(t-1)} + c_{iN} CS_{iN(t-1)}\right] \left[M_i - CT_{i(t-1)}\right] TM_{it}^{\beta_{i0} + \beta_{iI}CS_{iI(t-1)} + \beta_{iN}CS_{iN(t-1)}} + \rho_i CT_{i(t-1)} + \varepsilon_{it},$$

where ε_{it} is an error term assumed to have a mean of 0. All other terms are defined as previously.[4]

Equation 3 is a generalization of the Bass (1969) model. If competitors' diffusion, marketing spending, and repeat purchase variables are excluded from Equation 3, it reduces to Bass' (1969) original model. We extend it in ways con-

[1]We assume a brand's repeat purchase rate to be constant for two reasons. First, it enables tractability of model estimation. Second, prior research has found this assumption to be appropriate (e.g., Hahn et al. 1994). It should be noted that this assumption is more valid in contexts in which the extent of brand switching and competitive effects on repeat purchases are lower, for example, ethical drug and computer software markets.

[2]The noninnovative competitors of each late mover brand include the pioneer.

[3]We represent diffusion of competitive brands by an observable variable, namely, competitor cumulative sales, because unlike own cumulative trials, trials of competitor brands cannot be estimated using the iterative estimation method that we propose subsequently.

[4]We subsequently test for the assumption of normality of residuals.

sistent with previous approaches in the diffusion literature. We include the marketing efforts in a manner similar to Jain and Rao's (1990) and Parker and Gatignon's (1994, 1996) extensions of the Bass (1969) model. We include the impact of competitor diffusion on brand trials in a manner similar to Parker and Gatignon (1996) and include repeat purchases similar to Hahn and colleagues (1994). In this formulation, marketing effort principally affects brand trials, whereas the market potential and repeat purchase rates are determined by other factors, such as the product attributes. Unlike these models, however, we capture the impact of competitor diffusion on both diffusion effects (through $c_{iI}CS_{I(t-1)} + c_{iN}CS_{N(t-1)}$) and marketing mix effects (through $\beta_{iI}CS_{I(t-1)} + \beta_{iN}CS_{N(t-1)}$). Furthermore, we capture the effects of innovative and noninnovative competitors on a brand's sales separately. Table 1 summarizes how our model compares with prior models in the literature.

Compared with previous models of sequential entry, Equation 3 offers two principal advantages. First, by modeling total brand sales rather than brand trials or market share, we can estimate diffusion parameters, market potential, and repeat rates for each brand using a single model. Previous models of market shares estimate diffusion parameters for all brands but the pioneer and provide no estimates of market potential (e.g., Bowman and Gatignon 1996; Kalyanaram and Urban 1992; Urban et al. 1986). Analyses of brand trials alone provide estimates of market potential but not repeat purchase rates (e.g., Parker and Gatignon 1994, 1996). In contrast, Equation 3 provides estimates of both market potential and repeat rates for each brand.

Second, by allowing each brand to have unique parameters, Equation 3 captures asymmetries in both diffusion and market response. Asymmetries in market response have been shown to exist (Bowman and Gatignon 1996; Parker and Gatignon 1994, 1996), but the role of innovation in creating these asymmetries has not been addressed. Equation 3 captures two sources of asymmetry due to innovative late entry. One is the different diffusion, marketing mix, and repeat purchase parameters for each brand (a_i, b_i, β_{i0}, and ρ_i). The other is the differential competitive influence related to brand diffusion and market response (c_{iI}, c_{iN}, β_{iI}, and β_{iN}). Significant differences in these parameters indicate potentially important asymmetries in diffusion and market response. By separating the late entrants into innovative and noninnovative late entrants, we are able to assess the difference in the competitive impact of innovative late entrants relative to noninnovative late entrants on the pioneer's diffusion and market response.

Equation 3 captures the impact of innovation in two ways. First, innovation will be reflected in differences in trial and repeat purchase parameters. All brands in Equation 3 have unique parameters; differences between innovative and noninnovative late entrants will reflect the impact of innovation on trial and repeat rates. Second, innovation will be reflected in the impact of the diffusion of innovative late movers on the trials of competitors' brands. Equation 3 can be generalized as well to account for other roles of innovation.[5]

HYPOTHESES

The form of Equation 3 enables us to develop hypotheses about how the parameters differ by different market entry strategies, namely, pioneering and innovative and noninnovative late entry. Testing these hypotheses reveals how innovative late entry can create a competitive advantage over pioneers or noninnovative late entrants.

Brand Growth

Consider first the variation in growth rates of brands by entry strategy. Kalyanaram and Urban (1992) find that later entrants grow faster than early entrants in market share relative to the pioneer, which implies that later entrants will diffuse faster in sales than early entrants. Kalyanaram and Urban (1992), however, do not consider the role of innovation. The pioneer is faced with the task of creating awareness for the product category and its brand. Late movers, however, only need to develop brand awareness and can rely on the pioneer's efforts to establish the category. After a category is established, innovativeness may provide relative advantage over other brands that in turn can lead to faster adoption (Rogers 1995). Clearly, an innovative late mover does not need to develop category awareness, and given that consumers know about the category, it might be easier for it to develop awareness for its brand relative to its rivals.[6] Therefore, innovative late movers will grow faster than non-

[5]Equation 3 also could be used for forecasting brand sales. That, however, is not the purpose in constructing it. As a result, other models, designed primarily for forecasting (e.g., Hahn et al. 1994; Kalish 1985), may be more suitable for that task.

[6]We thank an anonymous reviewer for this explanation.

Table 1

COMPARISON OF OUR MODEL WITH RELEVANT LITERATURE

Model	*Dependent Variable*	*Asymmetric Competition*	*Estimation of Market Potential*	*Estimation of Repeat Rate*	*Competitor Diffusion*	*Separate Impacts of Innovative and Noninnovative Competitors*
Bass (1969)	Trials	No	Yes	No	No	No
Bowman and Gatignon (1996)	Market share	Yes	No	No	No	No
Hahn and colleagues (1994)	Sales	Yes	Yes	Yes	No	No
Jain and Rao (1990)	Trials	No	Yes	No	No	No
Kalish (1985)	Trials	No	Yes	No	No	No
Kalyanaram and Urban (1992)	Relative market share	No	No	Yes	No	No
Parker and Gatignon (1994, 1996)	Trials	Yes	Yes	No	Yes	No
Urban and colleagues (1986)	Relative market share	No	No	No	No	No
Our research (1997)	Sales	Yes	Yes	Yes	Yes	Yes

innovative late movers that in turn will grow faster than the pioneer. We formalize this as

H_{1a}: Noninnovative late entrants grow faster than the pioneer.
H_{1b}: Innovative late entrants grow faster than the pioneer.
H_{1c}: Innovative late entrants grow faster than noninnovative late movers.

The diffusion parameters a_i and b_i determine brand i's growth rate. Brand i will grow faster than brand j if at least one of the coefficients a_i or b_i is greater than a_j or b_j, respectively, and the other coefficient is at least equal (Bass 1969). Therefore, H_{1a} predicts that $a_N \geq a_P$ and $b_N \geq b_P$ (N = noninnovative late mover, P = pioneer), with at least one of these being a strict inequality. H_{1b} and H_{1c} predict that $a_I \geq a_i$ or $b_I \geq b_i$, with at least one of these being a strict inequality for $i \in \{P, N\}$, respectively (I = innovative late mover).

Competitor Diffusion

Consider next the impact of competitors' diffusion on the pioneer's diffusion. The impact of competitors' diffusion may differ depending on whether the competitors are innovative or noninnovative late entrants. Greater diffusion of a late entrant might not hurt the pioneer and in some cases will lend greater credibility to the category, which aids the diffusion of the pioneer (Carpenter and Nakamoto 1989). This is more likely to be the case for noninnovative late entrants. In contrast, greater diffusion of an innovative late mover is likely to have the opposite effect, challenging the pioneer's dominance and slowing its diffusion. This suggests the following:

H_{2a}: Greater diffusion of innovative late movers slows the pioneer's diffusion.
H_{2b}: Greater diffusion of noninnovative late movers has a nonnegative influence on the pioneer's diffusion.

Competitor diffusion effects are captured by c_{iI} and c_{iN}. A positive coefficient indicates that greater cumulative sales of competitors will increase brand i's sales. A negative coefficient suggests the opposite impact. H_{2a} predicts $c_{PI} < 0$, and H_{2b} predicts $c_{PN} \geq 0$.

Market Potential

Market potential is likely to differ for the pioneer and late movers. Pioneers initially face the prospect of a small market potential. Awareness is low, the cost of gaining trial is high, and the risk associated with market entry is high (Kalish and Lilien 1986a, b). Successful pioneers, however, might retain a larger share of buyers but need not have larger potential markets than all late entrants. In contrast, an innovative late entrant can free-ride on the category awareness and buyer education created by the pioneer and appeal to a greater pool of adopters than the pioneer if it offers greater value through superior positioning (Lieberman and Montgomery 1988). Therefore, market potential for innovative late movers may be at least as high as that for the pioneer. Noninnovative late movers, conversely, might suffer from perceptual disadvantage relative to the pioneer (Carpenter and Nakamoto 1989) and therefore will face a potentially smaller market. In addition, brands that enter a category late are likely to have a smaller potential pool of adopters (Parker and Gatignon 1996). This suggests the following:

H_{3a}: Market potential for an innovative late mover is as high as that for the pioneer.
H_{3b}: Market potential of the pioneer is higher than that for a noninnovative late mover.

H_{3a} and H_{3b} imply that $M_I \geq M_P > M_N$.

Marketing Expenditures

Consider next the impact of brand i's marketing expenditures on its sales, which is captured by β_{i0}. Bowman and Gatignon (1996) find that marketing effectiveness of late entrants is not as high as that of the pioneer. Other studies, for example Gatignon, Weitz, and Bansal (1990); Hahn and colleagues (1994); and Shankar (1997), however, find that superior brands have higher marketing spending effectiveness. We argue that the first result is likely to hold for noninnovative late entrants, whereas the second result should hold for innovative late entrants. Innovative products substantially enhance credibility, beliefs, and attitudes for communication messages, making marketing communications more effective (Rogers 1995). It is easier to promote a superior brand than one that is similar to all the other brands (Gatignon, Weitz, and Bansal 1990). These arguments lead to the following hypotheses:

H_{4a}: Noninnovative late movers have lower marketing spending effectiveness than pioneers.
H_{4b}: Noninnovative late movers have lower marketing spending effectiveness than innovative late movers.

Therefore, H_{4a} implies $\beta_{N0} < \beta_{P0}$, and H_{4b} implies $\beta_{N0} < \beta_{I0}$.

Competitor Impact on Marketing Expenditures Effectiveness

Consider next the impact of competitors' diffusion on the pioneer's marketing mix response. Prior research suggests that the marketing effectiveness of incumbents can be affected by subsequent brands (Gatignon, Anderson, and Helsen 1989) and competitive brand dominance, which is reflected by the extent of competitors' diffusion (Schmalensee 1987). Greater diffusion of an innovative late entrant enhances its brand dominance, which in turn will cast doubt on the pioneer's dominance and thus reduce the pioneer's marketing effectiveness. As the innovative brand diffuses over time, it gains momentum that effectively can diminish the marketing spending effectiveness of the pioneer. In contrast, greater diffusion of noninnovative late movers is not likely to hurt the pioneer. In some cases, it can bring greater credibility to the pioneer (Carpenter and Nakamoto 1989), which may increase the pioneer's marketing effectiveness. This implies the following hypotheses:

H_{5a}: Innovative late movers' diffusion has a negative effect on the pioneer's marketing spending effectiveness.
H_{5b}: Noninnovative late movers' diffusion has a non-negative influence on the pioneer's marketing spending effectiveness.

The impact of competitor diffusion on a brand's marketing mix is captured by β_{iI} and β_{iN}. Thus, H_{5a} implies $\beta_{PI} < 0$, and H_{5b} implies $\beta_{PN} \geq 0$.

Repeat Purchase

Finally, consider the repeat purchase rate ρ_i. Consider first pioneers versus noninnovative later entrants. The pioneer can define the category or preempt superior perceptual positions (Carpenter and Nakamoto 1989; Lane 1980), which makes noninnovative later entrants less attractive and therefore produces lower repurchase rates. Kalyanaram and Urban (1992), for example, find that repeat purchase rates fall with later entry. Consider next innovative late movers versus other brands. Innovative late entry might not conform to the pattern of repeat rates associated with noninnovative late entry. An innovative later entrant might be perceived as superior to all other brands and can reshape the category and thus eliminate the pioneer's hold on either a strong association with the definitions of the category or the "best" position (Carpenter and Nakamoto 1996). This may produce higher repeat purchase rates, which have been shown to be higher for superior products (Hahn et al. 1994). This suggests the following:

H_{6a}: Repeat purchase rate is higher for a pioneer than for a noninnovative late mover.

H_{6b}: Repeat purchase rate is higher for an innovative late mover than for all other types of entrants.

On the basis of H_{6a} and H_{6b}, we expect $\rho_I > \rho_P > \rho_N$. Our hypotheses are summarized in Table 2.

DATA

We estimate Equation 3 using data on 13 brands from two categories of ethical drugs in the U.S. market during the 1970s and 1980s that are characterized by innovative late entries. The drugs were used primarily to treat chronic ailments. Data from both categories include sales, detailing (sales force), and journal advertising expenditures for the brands. The number of total prescriptions by physicians is used as a measure of unit sales.

In both markets, physicians can adopt more than one brand. Physicians are likely to be aware of multiple brands and the side effects of each. Trial is influenced by product characteristics and marketing activity. Not all trials will be successful in the treatment of patients. Successful trials, however, typically lead to repeat purchases with a low probability of brand switching.

Data from the first ethical drug category comprise 157 months of aggregate sales information starting from the introduction of the pioneering brand.[7] An innovative late mover entered after 71 months.[8] Three noninnovative late movers entered this category during months 112, 130, and 139. The pioneer created the market and remained a dominant brand until the innovative late mover entered the market with a new formulation. Data from the second category consist of aggregate sales information in a different prescription drug category for 124 months starting from the introduction of the pioneering brand. An innovative late mover entered the market after 37 months. Two noninnovative brands entered this category in month 61. Four other noninnovative late mover brands entered between months 102 and 108.

[7]According to our agreement with IMS America to preserve confidentiality, the names and product details of the brands cannot be disclosed.

[8]In each category, an innovative late mover provided more functional benefits to the consumer than the pioneer, which is consistent with the definition of an innovative late mover proposed by Banbury and Mitchell (1995).

Table 2
SUMMARY OF HYPOTHESES

Hypotheses	*Description*	*Parameter Condition*
Growth		
H_{1a}	Noninnovative late movers grow faster than the pioneer.	$a_N \geq a_P$, $b_N \geq b_P$
H_{1b}	Innovative late movers grow faster than the pioneer.	$a_N > a_P$ and/or $b_N > b_P$
H_{1c}	Innovative late movers grow faster than noninnovative late movers.	$a_I \geq a_P$, $b_I \geq b_P$
		$a_I > a_P$ and/or $b_I > b_P$
		$a_I \geq a_N$, $b_I \geq b_N$
		$a_I > a_N$ and/or $b_I > b_N$
Competitor Diffusion		
H_{2a}	Greater diffusion of innovative late movers has a negative competitive influence on the pioneer's diffusion.	$c_{PI} < 0$
H_{2b}	Greater diffusion of noninnovative late movers has a non-negative competitive influence on the pioneer's diffusion.	$c_{PN} \geq 0$
Market Potential		
H_{3a}	Market potential for an innovative late mover is as high as that for the pioneer.	$M_I \geq M_P$
H_{3b}	Market potential of the pioneer is higher than that for a noninnovative late mover.	$M_P > M_N$
Marketing Expenditures		
H_{4a}	Noninnovative late movers have lower marketing spending effectiveness than pioneers.	$\beta_N0 < \beta_P0$
H_{4b}	Noninnovative late movers have lower marketing mix effectiveness than innovative late movers.	$\beta_N0 < \beta_I0$
Competitive Impact on Marketing		
H_{5a}	Innovative late movers' diffusion has a negative effect on the pioneer's marketing spending effectiveness.	$\beta_{PI} < 0$
H_{5b}	Noninnovative late movers' diffusion has a non-negative effect on the pioneer's marketing spending effectiveness.	$\beta_{PN} \geq 0$
Repeat Rate		
H_{6a}	Repeat purchase rate for the pioneer is higher than it is for a noninnovative late mover.	$\rho_P > \rho_N$
H_{6b}	Repeat purchase rate for an innovative late mover is higher than it is for the pioneer.	$\rho_I > \rho_P$

The data for categories I and II are summarized in Table 3, which shows that the innovative late mover in each category has higher average monthly sales than either the pioneer or the noninnovative late movers. Although the innovative late mover's average spending is higher than the pioneer's and the noninnovative late movers' in category I, it is lower in category II. The innovative late movers in both categories, however, overtook the pioneers in monthly sales as reflected by the average sales in the last month of the data in Table 3. The key question is, How?

We exogenously determined the innovativeness of the brands through a survey of 32 physicians who prescribe drugs in these categories. We measured innovativeness along four primary dimensions: dosage, efficacy, side effects, and range of indications. These dimensions are consistent with those used in previous studies of ethical drugs (e.g., Gatignon, Weitz, and Bansal 1990; Hahn et al. 1994). On each dimension, physicians rated the innovativeness of each brand on a five-point scale ranging from "very poor" to "very good."[9] We computed an overall measure of innovativeness by averaging across the four dimensions. We found the overall innovativeness of the second entrant in each category to be significantly higher than the pioneer's, whereas we found the innovativeness of the other late entrants in each category to be either significantly lower than or equal to that of the pioneer, which is consistent with an accepted perception among physicians about these brands.[10] In addition, the innovative late entrant in each category was perceived to be higher than all the other brands on one dimension of innovativeness and at least as high as the other brands in the remaining dimensions.

We exclude price and distribution from our analysis for several reasons. During the period of the data, there was not much pressure on physicians, the decision makers in this market, to pay attention to prices. No generic products entered during the period of data, so there was no price competition, which is consistent with other studies on ethical drugs (e.g., Gatignon, Weitz, and Bansal 1990; Hahn et al. 1994). We do not have data on distribution. The companies that produced and marketed the brands in the data sets, however, employ essentially the same distribution channels, so distribution is not a differentiating factor.

MODEL ESTIMATION

We estimate the brand sales model by iterative nonlinear least squares (INLLS) similar to the method proposed by Hahn and colleagues (1994), because the cumulative trials CT_{it} in Equation 3 are not observable. In this method, we perform the following steps:

(1) Select a value of ρ_i^s and calculate CT_{it} from the equation $CT_{it} = CT_{i(t-1)} + T_{it}$, $t > 0$, where $T_{it} = S_{it} - \rho_i^s CT_{it}$. Note that CT_{it} are the cumulative trials at the end of period t, so that $CT_{i0} = 0$.

(2) Obtain parameter estimates of a_i, b_i, M_i, β_{i0}, and ρ_i through nonlinear least squares (NLLS) using the calculated variable CT_{it}.

(3) If $|\rho_i^s - \rho_i| < \lambda$, where λ is some predetermined small number (e.g., .001), terminate the procedure. Otherwise, start the iteration again by replacing the ρ_i^s in step 1 with the ρ_i obtained in step 2.

To get starting values for the parameters in the nonlinear brand sales model, we first estimated a model of trials without marketing mix effects using NLLS after step 1. We used the parameters from this model as the first set of starting values for the corresponding parameters in the final model. To ensure that global optimum is reached, we used ten different sets of starting values (using a grid search procedure) and checked the resulting parameter values for convergence. We constrained the exponent on marketing mix spending to be less than one to reflect diminishing returns to marketing mix expenditures. We tested for autocorrelation and normality of residuals. The null hypothesis of normal distribution of residuals cannot be rejected in each brand sales model, which suggests that the assumption of normality of errors holds. The first-order autocorrelation of the residuals did not exceed .25 for any of the brands, which suggests that autocorrelation is not a major problem (Srinivasan and Mason 1986).[11]

[9]We asked physicians to rate the innovativeness of each brand as they perceived the brand when it was launched and as they perceived it at present. These two sets of ratings are consistent because the means of the ratings in all the dimensions across the two time frames are not significantly different for the 13 brands in our sample.

[10]Based on t-tests of differences of the overall innovativeness ratings of the brands in each category ($p < .05$).

[11]To ensure that our results are not idiosyncratic to our model specification, we compare our brand sales model with a comparable alternative model. We discuss the alternative model formulation and results in the Appendix.

Table 3
SUMMARY STATISTICS OF MARKET DATA[a]

Brands (Category)	*Average Sample Size (Months)*	*Average Monthly Sales (Prescriptions) (in thousands)*	*Average Sales in Last Month of Data (Prescriptions) (in thousands)*	*Average Monthly Marketing Spending (in thousands of dollars)*
Pioneer (I)	157	1000.7	988.0	1229.6
Innovative Late Mover (I)	86	1071.9	1722.0	2201.5
Noninnovative Late Movers (I)	31	140.4	226.7	1629.7
Pioneer (II)	124	732.9	832.0	1683.2
Innovative Late Mover (II)	87	1040.8	1539.0	1464.3
Noninnovative Late Movers (II)	35	211.3	268.2	1588.3

[a]Used with the expressed written permission of IMS America, Ltd.

RESULTS

Brand Growth

Tables 4 and 5 provide the parameter estimates from the brand-level model for the pioneer and late movers in categories I and II, respectively. The models fit well; the R^2 values lie between .914 and .996. The results show that both the diffusion parameters (a_i and b_i) are significant for the pioneer, the innovative late entrant, and the first noninnovative late entrant in both categories ($p \leq .05$).

H_{1a} predicts that noninnovative late entrants will grow faster than the pioneer, so that $a_N \geq a_P$ and $b_N \geq b_P$, with at least one being a strict inequality. The results show that this holds only for noninnovative late mover 1 in category I, for which $a_{N1} = .0110 > a_P = .0044$ ($p < .01$) and $b_{N1} = 4.9 \times 10^{-6} > b_P = 5.5 \times 10^{-7}$ ($p < .05$), and for noninnovative late mover 1 in category II, for which $a_{N1} = .0194 > a_P = .0021$ ($p < .01$) and $b_{N1} = 1.0 \times 10^{-6} \approx b_P = 1.7 \times 10^{-6}$ ($p > .05$). None of the other seven noninnovative late entrants diffuses faster than the pioneer; the a_N's of these seven noninnovative late entrants are not significantly different from zero, and six of the b_N's, except for that of noninnovative late mover 4 in category II, are not significantly different from zero.

H_{1b} predicts that innovative late entrants grow faster than the pioneer and noninnovative late entrants, so that $a_I \geq a_P$ and $b_I \geq b_P$, with at least one being a strict inequality. The results show that $a_I = .0181 > a_P = .0044$ ($p < .01$) and $b_I = 13.0 \times 10^{-7} > b_P = 5.5 \times 10^{-7}$ ($p < .05$) in category I, and $a_I = .0389 > a_P = .0021$ and $b_I = 5.8 \times 10^{-6} \approx b_P = 1.7 \times 10^{-6}$ in category II ($p < .05$). Thus, the results show that innovative late movers grow faster than the pioneer, which supports H_{1b}.

H_{1c} predicts that innovative late entrants will grow faster than noninnovative late entrants. In category I, the innovative late entrant grows faster than noninnovative late entrants 2 and 3 but not noninnovative late entrant 1, which has a larger word-of-mouth coefficient ($b_{N1} = 4.9 \times 10^{-6} > b_I = 1.3 \times 10^{-6}$, $p \leq .05$). Noninnovative late entrants 2 and 3 have diffusion coefficients that are at least as large as those for the innovative late entrant, but these coefficients are not significantly different from zero. In category II, the innovative late entrant grows faster than all other brands ($p \leq .05$). Only noninnovative late entrant 1's diffusion coefficients are significant, and they are smaller than those of the innovative late entrant.

Combined, the results from testing H_{1a}, H_{1b}, and H_{1c} show that most noninnovative late entrants tend to diffuse more slowly than the pioneer. Innovative late entrants, conversely, diffuse faster than the pioneer in both markets and faster than most noninnovative late entrants. These results differ from previous findings. Kalyanaram and Urban (1992) show that later entrants diffuse faster than early entrants, which suggests that the pioneer diffuses slowest. Our results show that pioneers do not diffuse more slowly than seven late entrants but diffuse more slowly than two innovative late entrants, which suggests an important role for innovation in the rate of diffusion.

Competitor Diffusion

H_{2a} predicts that greater diffusion of innovative late movers slows the pioneer's diffusion; that is, $c_{PI} < 0$. Our results show that in category I, $c_{PI} = -1.6 \times 10^{-5}$ ($p < .05$), and in category II, $c_{PI} = -2.6 \times 10^{-7}$ ($p < .01$). Therefore, in both categories, greater diffusion of the innovative later entrant slows the pioneer's growth significantly, which supports H_{2a}.

H_{2b} predicts that greater diffusion of noninnovative late movers will not affect the pioneer negatively; that is, $c_{PN} \geq 0$. Our results show that in category I, $c_{PN} = -4.6 \times 10^{-5}$ (t = −.72), and in category II, $c_{PN} = -4 \times 10^{-7}$ (t = −1.11). Therefore, in both categories, the coefficient is not significant. These results indicate that greater diffusion of noninnovative late movers has no significant effect on the pioneer's growth.

These findings suggest an important impact of innovative late entrants. Previous analyses implicitly assume that the diffusion of other brands leaves the brand diffusion process unaffected (e.g., Kalyanaram and Urban 1992; Urban et al. 1986). Our results suggest that such an assumption is reasonable in markets in which a pioneer is followed only by noninnovative late entrants. In cases in which the pioneer is followed by an innovative late entrant, however, the impact of that innovative late entrant on the diffusion of other brands can be significant.

Market Potential

H_{3a} predicts that an innovative late entrant will enjoy a market potential at least as high as the pioneer's. The estimates of market potential M_i are significant for all 13 brands ($p < .001$). The market potential of the innovative late mover (M_I = 24,777) is statistically at least as high as the pioneer (M_P = 22,253) in category I ($p < .01$), whereas it is significantly higher in category II (M_I = 22,759 > M_P = 14,777, $p < .01$). Therefore, both innovative late entrants have market potentials at least as high as the pioneers, which supports H_{3a}.

H_{3b} predicts that the pioneer's market potential will exceed that of each noninnovative late entrant. The results support H_{3b} in each category ($p < .01$). These two findings indicate that innovative late movers evidently create a larger pool of potential adopters that appears difficult for noninnovative late movers to duplicate.

Marketing Expenditures Effectiveness

The marketing mix coefficients for pioneers and innovative late entrants are significant in both categories. H_4 predicts that noninnovative late entrants will have less effective marketing spending than either pioneers (H_{4a}) or innovative late entrants (H_{4b}).

We have $\beta_{P0} = .110$ in category I and $\beta_{P0} = .099$ in category II. In four cases, namely, noninnovative late entrants 2 and 3 in category I and 2 and 4 in category II, we have negative and insignificant marketing spending effects. Of the remaining entrants, noninnovative late entrant 1 in category I has a positive but insignificant marketing spending effect, and noninnovative late entrants 1, 3, and 6 in category II have positive but insignificant marketing spending effects. Because these are insignificant, whether positive or negative, we conclude the corresponding pioneer's marketing spending effect is larger. Only one noninnovative late mover, namely, entrant 5 in category II, has a significant marketing spending parameter with $\beta_{N0} = .252$, which is significantly higher than the corresponding β_{P0} of .099 ($p \leq .05$). Thus, the results are generally consistent with H_{4a}.

We have $\beta_{I0} = .078$ in category I and $\beta_{I0} = .118$ in category II. Applying the same testing procedure as in H_{4a}, we con-

Table 4
SUMMARY OF BRAND-LEVEL SALES MODEL RESULTS—CATEGORY I

Parameter/Relevant Hypothesis	*Pioneer (P) Value (SE)*	*Innovative (I) Late Mover Value (SE)*	*Noninnovative (N) Late Mover 1 Value (SE)*	*Noninnovative (N) Late Mover 2 Value (SE)*	*Noninnovative (N) Late Mover 3 Value (SE)*
Coefficient of external influence (a_i)/H_1	.0044**	.0181*	.0110***	.0282	.0243
	(.0017)	(.0041)	(.0032)	(.0202)	(.0223)
Coefficient of word of mouth (b_i)/H_1	5.5×10^{-7}**	1.3×10^{-6}***	4.9×10^{-6}**	1.1×10^{-6}	1.2×10^{-6}
	(2.1×10^{-7})	(2.2×10^{-7})	(1.9×10^{-6})	(3.2×10^{-5})	(3.7×10^{-5})
Diffusion coefficient of innovative competitors (c_{iI})/H_2	-1.6×10^{-5}*	—	-1.1×10^{-6}*	-2.3×10^{-7}	-3.3×10^{-7}
	(7.0×10^{-6})		(4.5×10^{-7})	(4.5×10^{-7})	(3.9×10^{-6})
Diffusion coefficient of noninnovative competitors (c_{iN})/H_2	-4.6×10^{-5}	-1.8×10^{-7}	1.3×10^{-5}	-3.0×10^{-7}	-1.3×10^{-7}
	(6.4×10^{-5})	(3.1×10^{-7})	(5.5×10^{-5})	(7.5×10^{-6})	(4.0×10^{-7})
Market potential (M_i)[a]/H_3	22253***	24777***	7442***	2917***	1850***
	(1701)	(1998)	(539)	(245)	(223)
Marketing mix parameter (β_{i0})/H_4	.1099**	.0783*	.3955	−.2312	−.0821
	(.0385)	(.0331)	(1.0837)	(.2316)	(.1463)
Marketing mix coefficient of innovative competitors (β_{iI})/H_5	-1.2×10^{-6}*	—	1.3×10^{-5}	-2.2×10^{-7}	-1.0×10^{-6}
	(5.2×10^{-7})		(7.4×10^{-6})	(8.0×10^{-6})	(3.3×10^{-6})
Marketing mix coefficient of noninnovative competitors (β_{iN})/H_5	-1.2×10^{-6}	8.9×10^{-7}	-1.0×10^{-5}	-1.4×10^{-7}	-2.3×10^{-7}
	(1.6×10^{-6})	(2.8×10^{-6})	(8.7×10^{-6})	(5.4×10^{-6})	(9.0×10^{-7})
Repeat purchase rate (ρ_i)/H_6	.0660***	.0880***	.0530**	.0569**	.0411*
	(.0009)	(.0076)	(.0131)	(.0168)	(.0205)
Sample size (n)	157	86	46	30	19
R^2	.970	.945	.990	.982	.914

*Significant at the .05 level.
**Significant at the .01 level.
***Significant at the .001 level.
[a]The market potential value is in thousands.
— not applicable.

Table 5
SUMMARY OF BRAND LEVEL SALES MODEL RESULTS—CATEGORY II

Parameter/ Relevant Hypothesis	*Pioneer (P) Value (SE)*	*Innovative (I) Late Mover Value (SE)*	*Noninnovative (N) Late Mover 1 Value (SE)*	*Noninnovative (N) Late Mover 2 Value (SE)*	*Noninnovative (N) Late Mover 3 Value (SE)*	*Noninnovative (N) Late Mover 4 Value (SE)*	*Noninnovative (N) Late Mover 5 Value (SE)*	*Noninnovative (N) Late Mover 6 Value (SE)*
External influence (a_i)/H_1	.0021* (.0009)	.0389* (.0014)	.0194** (.0016)	.0753 (.0473)	.0066 (.0047)	.0073 (.0281)	.0014 (.0009)	.0012 (.0108)
Word of mouth (b_i)/H_1	1.7×10^{-6}*** (4.2×10^{-7})	5.8×10^{-6}* (2.7×10^{-6})	1.0×10^{-6}*** (1.5×10^{-7})	5.1×10^{-5} (5.5×10^{-5})	2.1×10^{-6} (1.6×10^{-5})	1.0×10^{-6}** (4.0×10^{-7})	3.4×10^{-6} (9.1×10^{-6})	2.6×10^{-5} (6.3×10^{-5})
Diffusion coefficient of innovative competitors (c_{iI})/H_2	-2.6×10^{-7}* (1.3×10^{-7})	—	8.9×10^{-6}* (4.0×10^{-6})	2.5×10^{-5} (2.5×10^{-5})	-2.6×10^{-6} (2.3×10^{-6})	-1.2×10^{-4}** (2.3×10^{-5})	-1.7×10^{-6} (2.3×10^{-6})	-1.0×10^{-5}* (4.2×10^{-6})
Diffusion coefficient of noninnovative competitors (c_{iN})/H_2	-4.0×10^{-7} (3.6×10^{-7})	3.4×10^{-6} (4.6×10^{-6})	-3.9×10^{-6} (6.9×10^{-6})	-1.2×10^{-5} (2.0×10^{-5})	-4.1×10^{-6} (5.3×10^{-6})	1.0×10^{-4}** (1.8×10^{-5})	-1.6×10^{-6} (2.3×10^{-5})	-7.3×10^{-6} (4.3×10^{-5})
Market potential (M_i)[a]/H_3	14777*** (1319)	22759*** (1440)	8490*** (738)	13543*** (1110)	1844*** (260)	2525*** (371)	2105*** (294)	2216*** (426)
Marketing mix (β_{i0})/H_4	.0986* (.0458)	.1184*** (.0497)	.5838 (.5926)	−.0529 (.1702)	.1010 (.0634)	−.0411 (.1057)	.2515* (.1238)	.0112 (.1262)
Marketing coefficient of innovative competitors (β_{iI})/H_5	-6.2×10^{-7}** (2.0×10^{-7})	—	4.6×10^{-5} (3.6×10^{-5})	1.9×10^{-5} (3.7×10^{-5})	-1.6×10^{-5} (2.8×10^{-5})	8.3×10^{-5} (8.8×10^{-5})	-2.8×10^{-5} (4.7×10^{-4})	-1.9×10^{-5} (8.8×10^{-5})
Marketing coefficient of noninnovative competitors (β_{iN})/H_5	3.1×10^{-6} (3.3×10^{-6})	-7.4×10^{-6} (6.5×10^{-6})	-3.9×10^{-5} (3.3×10^{-5})	1.4×10^{-5} (3.6×10^{-5})	-3.3×10^{-5} (2.1×10^{-5})	-5.2×10^{-5} (2.9×10^{-5})	-3.0×10^{-5} (4.3×10^{-4})	-3.6×10^{-5} (3.2×10^{-4})
Repeat purchase (ρ_i)/H_6	.0721*** (.0058)	.0962*** (.0010)	.0475*** (.0068)	.0350*** (.0018)	.0210* (.0099)	.0390* (.0187)	.0214* (.0089)	.0191* (.0086)
Sample size (n)	124	87	64	64	23	22	22	17
R^2	.986	.989	.994	.994	.996	.989	.989	.993

*Significant at the .05 level.
**Significant at the .01 level.
***Significant at the .001 level.
[a]The market potential value is in thousands.
— not applicable.

clude that the innovative late entrant in each of the two categories has more effective marketing than the noninnovative late entrants in the corresponding category with the exception of noninnovative late mover 5 in category II, which has a significant marketing spending parameter with $\beta_{N0} = .252$. This is significantly higher than the corresponding β_{I0} of .118 ($p \leq .05$). These results are generally consistent with H_{4b}.

These results draw an important contrast with previous findings based on models assuming symmetric effects of marketing mix efforts (e.g., Kalyanaram and Urban 1992; Urban et al. 1986). These previous models assume that all entrants have equally effective marketing mixes. Our results show that marketing spending of noninnovative late entrants is significantly less effective than those of pioneers and innovative late movers. Comparing the marketing effectiveness of innovative late movers with pioneers, we find that they are equally effective in both categories.

Competitor Impact on Marketing Expenditures Effectiveness

Our results also show that the pioneer's marketing spending effectiveness is affected significantly by the innovative late mover's diffusion but not by the noninnovative late movers' diffusion.

H_{5a} states that the diffusion of innovative late entrants will reduce the pioneer's marketing spending effectiveness. Our results show that $\beta_{PI} = -1.2 \times 10^{-6}$ ($p < .05$) in category I and $\beta_{PI} = -6.2 \times 10^{-7}$ ($p < .01$) in category II, which supports H_{5a}.

H_{5b} states that the diffusion of noninnovative late movers will not reduce the pioneer's marketing spending effectiveness. Our results show that β_{PN} is not significantly different from zero in either category.

These results reveal an asymmetry in competition associated with innovative late entry. As the innovative late mover's sales grow, the pioneer's marketing spending effectiveness falls. In contrast, the pioneer's marketing spending is not affected by sales growth of noninnovative late movers. This asymmetry could be an important source of late mover advantage.

Repeat Purchase Rate

Finally, the results for repeat purchase rate ρ_i show that the repeat purchase parameters are significant for all the brands ($p \leq .05$).

H_{6a} predicts that each noninnovative late entrant has a repeat purchase parameter significantly less than the pioneer's. The results in categories I and II confirm this expectation. $\rho_P = .066$ in category I is greater than that of the three noninnovative late movers ($p < .05$), and $\rho_P = .072$ in category II is greater than that of the six noninnovative late movers ($p < .05$).

H_{6b} predicts a higher repeat purchase parameter for the innovative late entrant compared with all other brands. The repeat rates of the innovative late movers in categories I and II ($\rho_I = .088$ and .096, respectively) are higher than those of other brands in these categories, which supports H_{6b} ($p \leq .05$).

Although the results for pioneers versus noninnovative late entrants are consistent with Kalyanaram and Urban's (1992) finding on repeat rates, the results on innovative late movers suggest a source of advantage for innovative late movers relative to other brands. Thus, noninnovative late movers are disadvantaged with respect to pioneers, but innovative late entrants are advantaged relative to pioneers in repeat purchases. With higher repeat rates, more trials of the innovative late movers are converted to repeat purchases, which means the cost of building sales is significantly lower for an innovative late entrant than for the other brands.

Summary

The results of the brand-level sales model show that innovative late movers grow faster than the pioneer, slow its diffusion, and reduce its marketing mix effectiveness, which is consistent with our hypotheses. The market potentials of innovative late movers are higher than those of noninnovative late entrants and equal to or greater than that of the pioneer. Innovative late movers also enjoy higher repeat rates than either the pioneer or noninnovative late movers. These benefits can create a late mover advantage, enabling an innovative late entrant to outsell a pioneer.

ENTRY TIMING AND INNOVATIVENESS

Our results show an advantage associated with innovative late entry in two categories. In both cases, however, the innovative late entrants entered considerably before the noninnovative late entrants (month 72 versus months 112, 127, and 139 in category I, and month 38 versus months 61, 102, 103, and 108 in category II), which suggests that timing of entry might be another possible explanation for our results. To explore the relative contribution of innovativeness and entry timing to the pattern of parameters observed, we construct the following regression model that links each key estimated parameter to innovativeness and entry timing:

$$Z_{ki} = \alpha_k + \gamma_k \, INN_i + \delta_k \, TIM_i + u_{ki}, \tag{4}$$

where Z_{ki} is the estimate of parameter k of brand i from the brand sales model, $k \in \{a, b, M, \beta_0, \rho\}$, INN_i is a measure of innovativeness of brand i, TIM_i is the timing of its entry, α_k, γ_k, and δ_k are regression coefficients associated with parameter k, and u_{ki} is an error term. We allow this error term to be heteroscedastic, because the estimated parameters from different brand level models have different standard errors. We point out that this regression analysis is limited by the number of brands available, which in this instance is 13.

We expect innovativeness to have a positive effect and timing of entry to have a negative effect on each parameter. Thus, we expect the coefficient of innovativeness γ_k to be positive and that of timing of entry δ_k to be negative in each model. We estimate five cross-sectional models, one for each parameter k. Although the parameters from the brand sales model, a, b, β_0, and ρ, are comparable across the two categories, the market potential parameter M is not. Therefore, we use a relative market potential measure (RM_i) as the dependent variable, where RM_i is the ratio of brand i's market potential to that of the pioneer. For a standardized measure of entry timing that is comparable across categories, we use the ratio of the month of a brand's entry to the month of transition from the early growth to the late growth stages in its category.[12]

[12]To determine the period of transition between the early and late growth stages in the life cycle, we model each category's sales as an S-shaped curve and find the inflection point on this curve. Among the three possible S-shaped functional forms we tried for modeling category sales, namely, logistic, log-reciprocal, and advertising budget (ADBUDG) forms, the logistic model provided the best fit of category sales for both categories. The inflection points of the logistic category sales model in categories I and II occur in months 66 and 68, respectively.

Results

Table 6 summarizes the results of the regression model. It shows that both innovativeness and timing of entry significantly influence the relative market potential of a brand in the expected direction (coefficients of 3.849 and –.412, respectively, $p < .01$) and the correlation of predicted and actual values of the dependent variable is high (.923).[13] The results indicate that innovativeness increases a brand's relative market potential, whereas late entry decreases a brand's potential. The relationship of repeat purchase rate with innovativeness and timing of entry is also strong (correlation of .889). More innovative brands have higher repeat purchase rates (coefficient of .724). The coefficient of timing of entry, however, is not significant, which means that timing of entry cannot explain differences in repeat purchase rates. This suggests that the low repeat purchase rates of noninnovative late movers relative to pioneers that we found in our analysis of brand sales models is due to the lower innovativeness of the noninnovative late mover brands and not to late entry. This result differs from that of Kalyanaram and Urban (1992), who report that repeat purchases declined with order of entry, which suggests a penalty in repeat rates for delayed entry. Our results do not indicate any penalty in repeat rates associated with later entry but suggest that a perception of inferiority with respect to the pioneer in innovativeness hurts late entrants. Therefore, brands with greater innovativeness enjoy both higher market potential and greater repeat rates than other brands, whereas earlier entrants benefit only from a higher market potential than later entrants.

The coefficient of external influence increases with innovativeness ($p < .01$), which is consistent with our expectation. But the coefficient of external influence also increases with entry timing ($p < .05$), which is contrary to our expectation. The overall fit of this regression model, however, is poor as indicated by the correlation between predicted and actual values of the dependent variable (.274). Innovativeness and timing of entry do not have significant influences on the word-of-mouth effect and the marketing mix parameter ($p < .05$). Thus, our prediction is not supported for these two parameters. The fits of these two regression models are also poor as can be seen by the correlation coefficients.

A possible explanation as to why the results are consistent with our prediction for market potential and repeat purchase rate is that these parameter estimates are significant for all 13 brands and therefore have less unreliability. This is not the case for the coefficient of external influence or the word-of-mouth or the marketing mix parameters, in which several estimates are insignificant.

The regression model results suggest a trade-off between innovation and entry timing. An analysis of optimal entry timing for an innovative late mover is outside the scope of this work and is discussed in the Further Research section. However, we can illustrate some of the implications of this trade-off for market potential, an important factor in the entry timing decision (Kalish and Lilien 1986a, b).[14] Table 7

[13]The correlation between actual and predicted values of the dependent variable is reported because the R^2 of GLS (weighted least squares) regression is not interpretable in terms of proportion of explained variance (Judge et al. 1985). Because we cannot ascertain the variance of relative market potential estimate (it is the ratio of two estimated parameters), we use OLS (ordinary least squares) estimation for the regression of relative market potential with innovativeness and entry timing. However, we estimated a model of absolute market potential with innovativeness and entry timing using GLS regression and found the results to be consistent with those of OLS regression.

[14]We considered the possibility of the sales of the innovative late movers in both categories arising primarily from switching by users of the pioneering brand, which might reflect a pure substitution phenomenon. However, we concluded that this was not the predominant case in these two categories because physicians seldom switched prescriptions for patients using one brand to a new brand, both to ensure continuity of the treatment program and to avoid the possibility of adverse medical reaction in patients that could arise from changing brands. Thus, because first purchases dominate brand choice and switching is not common, market potential is a key determinant of competitive advantage for brands in these categories.

Table 6
REGRESSION ANALYSIS OF BRAND SALES MODEL PARAMETERS

Parameter	*Intercept (SE)*	*Innovativeness[a] (SE)*	*Timing[b] (SE)*	*Correlation of Predicted and Actual Values of the Dependent Variable*
Coefficient of external influence (a_i)	–.303** (.088)	.309** (.087)	.013* (.006)	.274
Coefficient of word of mouth (b_i)	-6.5×10^{-7} (2.0×10^{-6})	1.4×10^{-6} (2.0×10^{-6})	3.1×10^{-7} (2.4×10^{-7})	.213
Relative market potential (RM_i)	–2.689* (1.091)	3.849** (1.060)	–.412*** (.100)	.923
Marketing mix parameter (β_{i0})	–.150 (.413)	.262 (.401)	–.058 (.146)	.287
Repeat purchase rate (ρ_i)	–.657*** (.094)	.724*** (.093)	–.002 (.007)	.889

*Significant at the .05 level.
**Significant at the .01 level.
***Significant at the .001 level.
[a]Innovativeness is measured as a ratio of the brand's perceived innovativeness over the pioneer's.
[b]Timing of entry is measured as a ratio of the time of entry to the time taken for the category sales to slow down.

Table 7
IMPLICATIONS FOR MARKET POTENTIAL OF ENTRY TIMING AND INNOVATION

Scenario (% Incremental Innovativeness)	*Available Waiting Time (Months)*
1 (2%)	38.1
2 (5%)	56.6
3 (10%)	87.5
4 (15%)	118.3

shows that, for example, a late mover that is perceived to be 2% more innovative than the pioneer can wait only 38 months after the pioneer's entry if it wants to achieve the same market potential as the pioneer, whereas a late mover that is considered 15% more innovative can take as long as 118 months to enter.

DISCUSSION

Late Mover Advantage

Our analysis of 13 brands across two ethical drug categories characterized by innovative late entries replicates previous findings on the advantages of pioneering (e.g., Bowman and Gatignon 1996; Kalyanaram and Urban 1992). We show that, compared with noninnovative late entrants, pioneers have higher rates of repeat purchase and more effective marketing spending. In addition, however, we identify three new ways by which pioneers outsell noninnovative late entrants compared with prior research. Pioneers have higher potential markets than noninnovative late movers, tend to diffuse faster than many noninnovative late movers, and are not affected in diffusion and marketing mix effectiveness by noninnovative late entrants. Previous studies show that later entrants grow more quickly than early entrants, which suggests that pioneers will grow more slowly than noninnovative late movers (e.g., Kalyanaram and Urban 1992). Instead, we find that pioneers grow faster than many noninnovative late entrants. Combined with our findings that replicate previous studies, this suggests that noninnovative late movers face even higher hurdles in some cases than previously was recognized.[15]

Our analysis, however, shows that innovative late entry can produce an advantage relative to pioneering. Innovative late movers grow faster than pioneers, have higher market potentials, and have higher repeat rates. In addition, innovative late entry can have a more fundamental impact on a pioneer. It can slow the pioneer's growth and reduce its marketing spending effectiveness. Thus, innovative late entrants are advantaged compared with pioneers. It is important to note that these advantages are asymmetric with respect to other brands. Diffusion of other brands does not have any significant impact on the diffusion and marketing spending effectiveness of innovative late entrants in the two categories analyzed. From Tables 4 and 5, the diffusion and marketing spending coefficients of noninnovative competitors on the innovative late mover (c_{IN} and β_{IN}, respectively) are insignificant in both categories. These results reveal an interesting pattern of competition. The pioneer is advantaged asymmetrically relative to noninnovative late entrants but disadvantaged asymmetrically relative to innovative late movers.

Implications

These findings suggest new strategies for late entry. Assuming that late entrants cannot affect a pioneer's diffusion or marketing effectiveness and that late entrants have lower repeat rates and less effective marketing outlays, few options are available to a late mover. It must identify a superior position, and/or undercut on prices, and/or spend more on its marketing mix to overcome the disadvantages imposed by late entry and beat the pioneer at its own game. In doing so, late entrants face a disadvantage. Although they might gain additional information about the market as they wait to enter, waiting also means that the cost of gaining trial and sustaining repeat purchases will be higher compared with earlier entrants. Even if a late mover achieves the same level of sales as the pioneer, the late mover's cumulative profits might be smaller without the benefit of the monopoly period enjoyed by the pioneer. Despite these obstacles, some late movers have been successful at beating the pioneer at its own game.

Our analysis, however, shows other ways a late mover advantage can be created using a fundamentally different strategy. Rather than spending resources on marketing activities to beat the pioneer at its own game, a late entrant can devote its efforts to redefining the game in such a way that benefits the late mover and disadvantages the pioneer. This strategy is consistent with the preference formation explanation of pioneering advantage (Carpenter and Nakamoto 1989), in which the pioneer gains a competitive advantage by shifting preferences toward itself and becoming associated strongly with the category. If a late entrant can "restart" the learning process, it can redefine the market, become associated strongly with the reshaped category, and thus gain an advantage over the pioneer (Carpenter and Nakamoto 1994). Innovation can help reshape a category. In the process, the advantages of the pioneer become its disadvantages compared with the innovative late mover—it is now associated with an "old" form of the category and suffers as a result.

Further Research

Our findings suggest interesting directions for further research. First, it would be useful to generalize our results to other categories in other industries. It is encouraging that our findings in two product categories provide evidence for the existence of mechanisms of advantage for innovative late movers. The generalizability of our results, however, is limited by the fact that both categories are in the same industry. Replicating our analysis in other categories from other industries would be a useful avenue for further research. Doing so, however, requires data on the sales and marketing efforts of each brand from the start of the category over some sufficient time span for the pioneer and the innovative and noninnovative late entrants. The absence of historical data limits the number of industries that can be examined. Even so, a replication would be useful.

Second, our brand sales model could be expanded. Our research extends repeat purchase diffusion models with

[15]It should be noted that Kalyanaram and Urban (1992) study taste-related products bought in supermarkets where switching and variety seeking are more prevalent than for ethical drugs. Therefore, first purchases and market potential are more important for ethical drugs than for consumer packaged goods. We thank an anonymous reviewer for pointing this out.

marketing mix effects by explicitly including differential competitor influences on a brand's diffusion and marketing mix effects. Two directions for future extensions are to include nonconstant market potential and repeat purchase rates. In some markets, market potential and repeat purchase might vary with the brand's own and competitors' marketing expenditures or prices. Expanding the sales model to capture these effects would be helpful methodologically.

Third, our analysis could be used as a basis for optimal entry timing analysis. As noted previously, our analysis suggests a trade-off between innovativeness and entry timing. Exploring the optimal implications of our response model requires constructing a differential game between entrants in which timing and entry strategy are decision variables (for related work, see Cohen, Eliashberg, and Ho 1996). To do so, we would need information on product development costs and the cost structure associated with the entry strategy. With this additional information, the optimal solution can be determined, most likely through numerical analysis.

CONCLUSION

Although late movers outsell pioneers in some markets, the mechanisms through which they do so has received little attention. Our analysis of 13 brands in two ethical drug markets show that innovative late movers outsell pioneers not by "beating them at their own game" but by affecting the diffusion and marketing spending effectiveness of pioneers. In our sample, innovative late movers grew faster than pioneers, slowed the growth pioneers, and reduced the effectiveness of pioneers' marketing efforts. These advantages asymmetrically favor innovative late movers. Their diffusion reduces the sales of other brands, but their sales are not hurt by the corresponding diffusion of other brands. These findings, combined with our results showing that innovative late movers enjoy larger market potentials and higher repeat rates than either the pioneer or other late entrants, suggest significant new mechanisms for outselling pioneers.

APPENDIX: ALTERNATIVE MODEL

Model Formulation

To ensure that our results are not idiosyncratic to our model specification, we compare our brand sales model results with those from an alternative model. Although the models in the literature listed in Table 1 are related models, their structures are subsets of our model structure. A modified version of Lilien, Rao, and Kalish's (1981) sales model that incorporates differential competitive influence on diffusion and market effects, however, has a different structure and can serve as an appropriate alternative model for comparison. This model is

$$\text{(A1)}\quad \begin{aligned} S_{i(t+1)} - S_{it} = {} & (a_{i1}\,TM_{it} + a_{i2}\,TM_{it}^2)(N_i - S_{it}) \\ & + a_{i3}\,TM_{iIt}\,S_{it} \\ & + a_{i4}\left[S_{it} - S_{i(t-1)}\right](N_i - S_{it}) \\ & + a_{i5}\,TM_{iNt}\,S_{it} \\ & + a_{i6}\left[S_{iIt} - S_{iI(t-1)}\right](N_i - S_{it}) \\ & + a_{i7}\left[S_{iNt} - S_{iN(t-1)}\right](N_i - S_{it}), \end{aligned}$$

where

TM_{iIt} = the total marketing spending of innovative competitors of brand i at time t,

TM_{iNt} = the total marketing spending of noninnovative competitors of brand i at time t,

S_{iIt} = the sales of innovative competitors of brand i at time t,

S_{iNt} = the sales of noninnovative competitors of brand i at time t,

N_i = the total number of available adopters during each period of brand i,

a_{i1} through a_{i7} are model parameters, and the other terms are as defined previously.

Because Lilien, Rao, and Kalish's (1981) model considers only detailing spending and does not include the differential impact of competitors, we modify their model to include total marketing spending and separate terms for the effects of innovative and noninnovative competitors to enable comparison with our model.

In this model, we expect the own-marketing mix coefficients a_{i1}, $a_{i2} \geq 0$ and the diffusion coefficient $a_{i4} \geq 0$, as per their original model. In addition, we expect that the competitive coefficients for the pioneer a_{P3}, $a_{P6} \leq 0$ and a_{P5}, $a_{P7} \geq 0$, which is consistent with our predictions on the impact of innovative versus noninnovative brands, respectively. We estimated the alternative model by NLLS.[16]

Results

In Tables A1 and A2, we present the alternate model results for categories I and II, respectively. The models seem to fit well overall, but the fit varies from a low R^2 of .26 for the pioneer in category 1 to a high R^2 of .80 for noninnovative late mover 3 in category 1. Except in four cases, all the parameters, when significant, are in the expected direction. In particular, the impact of the innovative late mover on the pioneer can be seen from a_{P3}, which is negative and significant in category I, and from a_{P6}, which is negative and significant in both categories.

We compare our model with the alternate model on three criteria: degree of fit, proportion of estimates with signs that differ from what industry experts expect, and percentage of significant estimates, as suggested by Hahn and colleagues (1994). Whereas the first criterion is critical from a statistical viewpoint, the last two criteria are important from a managerial decision-making standpoint. Although the R^2 values in our model exceed the corresponding R^2 values of the alternative model, it is not an appropriate criterion because the dependent variables are different in the two models. The alternative model provided only four significant parameter estimates with unexpected signs out of a total of 100 estimates (4%), whereas our model had no significant estimates with unexpected signs. Finally, whereas 21% of the parameters produced by the alternative model are significant and are of the expected sign, 45% of the estimates of our model are significant with expected signs.

[16]We did not consider an alternative two-stage estimation procedure suggested by Lilien, Rao, and Kalish (1981), because this procedure assumes own- and competitive-marketing mix effectiveness to be approximately equal, whereas our purpose is to investigate asymmetry in competitive effects.

Table A1
SUMMARY OF ALTERNATIVE MODEL RESULTS—CATEGORY I

Parameter	*Pioneer (P) Value (SE)*	*Innovative (I) Late Mover Value (SE)*	*Noninnovative (N) Late Mover 1 Value (SE)*	*Noninnovative (N) Late Mover 2 Value (SE)*	*Noninnovative (N) Late Mover 3 Value (SE)*
a_{i1}	4.4×10^{-5}*	3.3×10^{-5}	3.9×10^{-5}	4.0×10^{-6}	.0002
	(2.1×10^{-5})	(5.2×10^{-5})	(8.2×10^{-5})	(2.6×10^{-5})	(.0002)
a_{i2}	-7.7×10^{-9}	8.2×10^{-9}	-1.1×10^{-8}	-8.7×10^{-10}	-4.2×10^{-8}
	(5.4×10^{-9})	(1.7×10^{-8})	(3.5×10^{-8})	(5.6×10^{-9})	(4.4×10^{-8})
a_{i3}	-2.1×10^{-5}***	—	2.0×10^{-5}	-2.0×10^{-5}*	-2.0×10^{-5}
	(4.9×10^{-6})		(1.4×10^{-5})	(9.2×10^{-6})	(4.0×10^{-5})
a_{i4}	–.0003	–.0011***	.0046*	–.0001	.0287
	(.0002)	(.0002)	(.0020)	(.0007)	(.0176)
a_{i5}	7.7×10^{-6}	1.0×10^{-5}*	-2.2×10^{-6}	1.9×10^{-7}	2.0×10^{-5}
	(5.0×10^{-6})	(4.3×10^{-6})	(7.7×10^{-6})	(3.1×10^{-6})	(2.1×10^{-5})
a_{i6}	6.0×10^{-5}*	—	3.9×10^{-5}	-1.7×10^{-7}	–.0059
	(2.9×10^{-5})		(5.8×10^{-5})	(1.1×10^{-6})	(.0038)
a_{i7}	-9.7×10^{-5}	.0011**	–.0002	-2.9×10^{-7}	.0041
	(.0004)	(.0003)	(.0003)	(1.9×10^{-6})	(.0033)
N_i[a]	2620***	933***	187***	407	78***
	(703)	(92)	(51)	(264)	(9)
Sample size (n)	156	85	45	29	18
R^2	.259	.435	.274	.689	.793

*Significant at the .05 level.
**Significant at the .01 level.
***Significant at the .001 level.
[a]in thousands.
— not applicable.

Table A2
SUMMARY OF ALTERNATIVE MODEL RESULTS—CATEGORY II

Parameter	*Pioneer (P)* *Value (SE)*	*Innovative (I)* *Late Mover* *Value (SE)*	*Noninnovative (N)* *Late Mover 1* *Value (SE)*	*Noninnovative (N)* *Late Mover 2* *Value (SE)*	*Noninnovative (N)* *Late Mover 3* *Value (SE)*	*Noninnovative (N)* *Late Mover 4* *Value (SE)*	*Noninnovative (N)* *Late Mover 5* *Value (SE)*	*Noninnovative (N)* *Late Mover 6* *Value (SE)*
a_{i1}	1.0×10^{-5} (2.2×10^{-5})	1.4×10^{-6} (1.6×10^{-5})	5.3×10^{-5} (8.3×10^{-5})	-5.9×10^{-7} (1.4×10^{-5})	-2.3×10^{-5}* (1.2×10^{-5})	5.6×10^{-5} (6.2×10^{-5})	2.5×10^{-4} (4.4×10^{-4})	1.8×10^{-5} (7.8×10^{-5})
a_{i2}	-2.1×10^{-9} (4.2×10^{-9})	4.1×10^{-10} (4.5×10^{-9})	5.2×10^{-9} (3.8×10^{-8})	9.2×10^{-11} (2.1×10^{-9})	3.6×10^{-9} (2.0×10^{-8})	-1.1×10^{-8} (1.4×10^{-8})	-6.8×10^{-8} (1.2×10^{-7})	-2.3×10^{-9} (1.0×10^{-8})
a_{i3}	-1.2×10^{-5} (1.0×10^{-5})	—	4.0×10^{-5}* (1.9×10^{-5})	1.7×10^{-5} (1.6×10^{-5})	2.1×10^{-5} (4.8×10^{-5})	6.7×10^{-5}* (3.1×10^{-5})	4.2×10^{-5} (4.1×10^{-5})	6.4×10^{-5} (5.6×10^{-5})
a_{i4}	−.0002 (.0005)	1.2×10^{-5} (.0001)	.0014 (.0022)	4.1×10^{-5} (.0009)	.0027 (.0098)	−.0018 (.0038)	−.0165 (.0455)	−.0004 (.0032)
a_{i5}	2.0×10^{-6} (1.3×10^{-6})	7.9×10^{-7} (9.8×10^{-7})	-1.0×10^{-6} (1.9×10^{-6})	-2.5×10^{-6} (1.8×10^{-6})	-1.0×10^{-6} (1.6×10^{-5})	-5.8×10^{-6} (5.8×10^{-6})	-6.7×10^{-6} (6.2×10^{-6})	-6.9×10^{-6} (1.2×10^{-5})
a_{i6}	7.4×10^{-5}*** (1.5×10^{-5})	—	-9.5×10^{-4} (8.7×10^{-4})	-1.5×10^{-7} (.0003)	.0003 (.0023)	.0014 (.0022)	.0013 (.0029)	-2.4×10^{-5} (9.0×10^{-4})
a_{i7}	-9.1×10^{-5} (.0002)	-2.3×10^{-5} (.0003)	.0012* (.0006)	1.2×10^{-5} (.0003)	−.0002 (.0017)	−.0011 (.0018)	-7.3×10^{-5} (.0021)	-3.8×10^{-5} (.0007)
N_i[a]	3388*** (703)	4893* (2292)	83* (32)	203* (72)	154* (68)	233* (110)	156* (62)	411* (146)
Sample size (n)	123	86	63	63	22	21	21	16
R^2	.320	.358	.343	.337	.365	.419	.564	.435

*Significant at the .05 level.
***Significant at the .001 level.
[a]in thousands.
—not applicable.

Although the alternative model provided results in the right direction, we select our model over the alternative model from the standpoint of testing our hypotheses because (1) our model formulation decomposes sales into first and repeat purchases, which enables us to compute the repeat purchase rate, (2) it readily provides estimates of parameters determining competitive advantage, such as market potential and repeat rate, and (3) the estimates are consistent with the expectation of industry experts.

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