

Riding the Saddle: How Cross-Market Communications Can Create a Major Slump in Sales

Using data on a large number of innovative products in the consumer electronics industry, the authors find that between one-third and one-half of the sales cases involved the following pattern: an initial peak, then a trough of sufficient depth and duration to exclude random fluctuations, and eventually sales levels that exceeded the initial peak. This newly identified pattern, which the authors call a "saddle," is explained by the dual-market phenomenon that differentiates between early market adopters and main market adopters as two separate markets. If these two segments—the early market and the main market—adopt at different rates, and if this difference is pronounced, then the overall sales to the two markets will exhibit a temporary decline at the intermediate stage. The authors employ both empirical analysis and *cellular automata*, an individual-level, complex system modeling technique for generating and analyzing data, to investigate the conditions under which a saddle occurs. The model highlights the importance of cross-market communication in determining the existence of a saddle. At low levels of this parameter, more than 50% of the cases of new product growth involved a saddle. This percentage gradually decreased as the parameter increased, and at values close to the within-market parameters, the proportion of saddle occurrences dropped below 5%.

The year 1985 was not a good one for personal computer (PC) manufacturers and vendors. Although the state of the U.S. economy could not be described as recessionary, sales were reported to be "sluggish" and the market was described as "despondent." In December 1985, *BusinessWeek* reported that "Importers of two new Asian imitations of the IBM PC are betting that their low prices will boost a despondent personal computer market" (Lewis 1985a, p. 142D). This slowdown in sales was all the more unexpected because it followed two years of rapid growth that exceeded an average annual growth rate of 50%. In light of the satisfactory health of the U.S. economy, other explanations for the slump were offered, ranging from lack of training to lack of compatibility to industry shakeout (Bonnett 1985; Roman 1985; Steffens 1994). With today's hindsight, it is now known that the market was to lose 30% of the 1984 peak sales, creating a slump that lasted for seven years before sales recovered and returned to their previous high levels.

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This phenomenon, which we term a "saddle" in this article, is not isolated. As an illustration, Figure 1 presents three markets in which a saddle is apparent: PCs, videocassette recorder (VCR) stereo decks, and cordless telephones. A saddle is a pattern in which an initial peak predates a trough of sufficient depth and duration to exclude random fluctuations, which is followed by sales eventually exceeding the initial peak (a detailed definition is given subsequently).

In each case, a local maximum of sales is indicated (occurring in 1984 for PCs, 1987 for VCRs with stereos, and 1984 for cordless telephones) after the initial takeoff. After this local maximum, a considerable drop in sales occurs over a period of a few years (a drop of 30% for PCs over seven years, 30% for VCRs over three years, and 35.5% for cordless telephones over three years).

These cases are not isolated incidents; in fact, we found that the saddle pattern is quite prevalent. The three cases presented in Figure 1 constitute part of a data set compiled by the Consumer Electronics Association of 32 innovations. In approximately one-third of these cases, a saddle is evident. Using a different data set, Golder and Tellis (1998) also report a phenomenon of an early peak and slowdown in sales during the growth stage of the product life cycle.

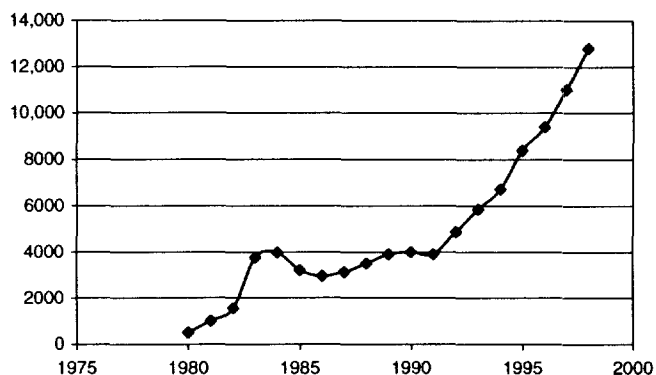
Cases of significant and unexpected decline in sales in the relatively early stages of the product life cycle are critical to marketers, as such a decline inevitably casts doubt on product viability. In the case of the PC market in 1985, the following quotation represents one view of the contemporary market, admittedly reflecting a more pessimistic position: "Stephen Wozniak, founder of Apple Computers and now head of his own California firm, seems to have lost his optimism about the personal computer (PC) industry that he

helped to pioneer. Wozniak feels that there is no market for PCs as an aid to carrying out household chores, and that most small businesses can get along with only a couple of small computers" (Lewis 1985b, p. 32).

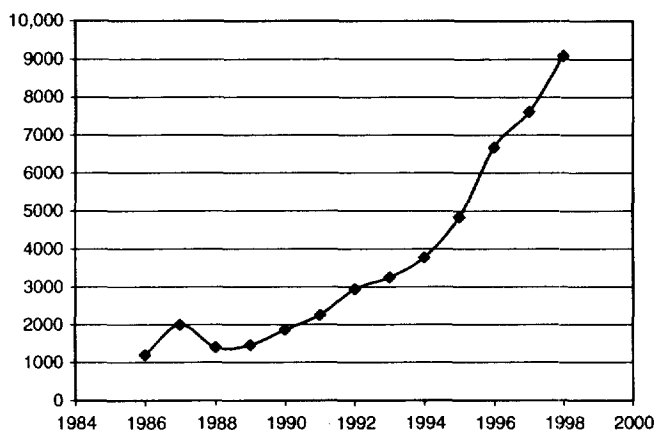
Although reactions to a significant decline in sales may be diverse, ranging from trying to save the product by pour-

FIGURE 1
Prevalence of Saddles

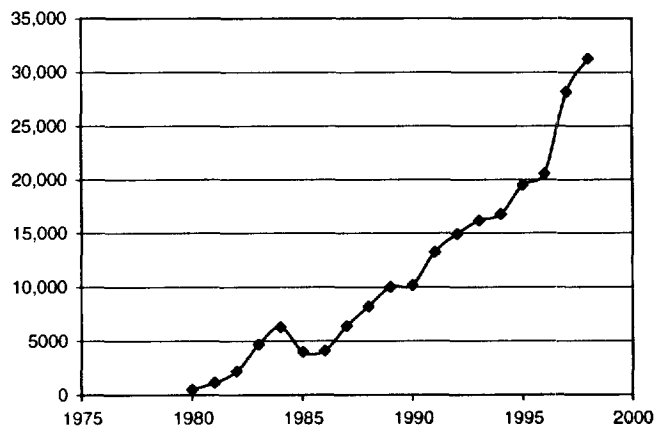
A: Saddle in PCs



B: Saddle in VCR Decks with Stereo



C: Saddle in Cordless Telephones



ing more money into aggressive marketing campaigns to pulling the plug and terminating the product altogether, both types of decisions involve an investment of considerable financial and personal stakes by the firm and its executives. Given both the large percentage of cases in which we found a saddle and the criticality of this phenomenon to marketing decisions, an investigation of the phenomenon, its sources, and its managerial implications is of considerable importance.

The Prevalence of Saddles

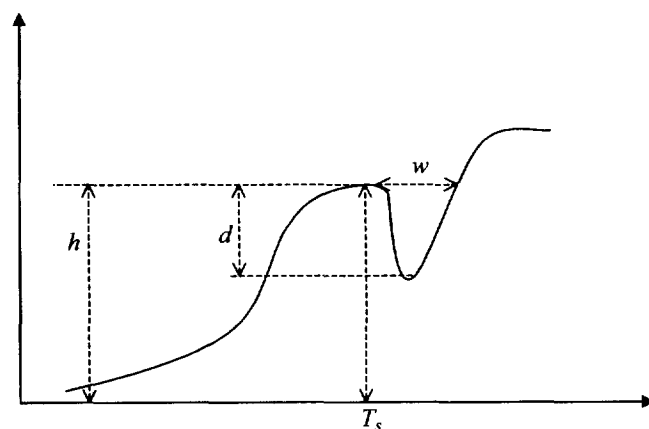
Before we measure the prevalence of saddles, a careful definition of the phenomenon is necessary to exclude both fluctuations in the sales of a new product and noise in measurements. Let d be the depth of the saddle, measured as the sales difference from the initial peak to the minimum of the saddle. Let w be the duration of the saddle, measured as the time elapsing from the time of the initial peak (T_s) to the time at which sales recovered their previous peak levels. To distinguish between a saddle and random perturbations in the market growth pattern, both parameters w and d must be of some minimal size for the pattern to be considered a saddle. Because any specification of these minimal sizes is of an arbitrary nature, we selected the following conservative measures to define a saddle as a trough following an initial peak in sales, reaching a depth of at least 20% of the peak (10% for the relaxed case), lasting at least two years, followed by sales that ultimately exceed the initial peak.

Denoting h as the initial peak sales level, and d^* as the relative depth, that is, d/h , we then define the following conditions for the occurrence of a saddle (see Figure 2):

$$w \geq 2 \text{ and } d^* = d/h \geq \begin{cases} 20\% & \text{strict definition} \\ 10\% & \text{relaxed definition} \end{cases}$$

Note that the strict definition leads to a conservative estimation of saddle occurrences in any sample. In Figure 1, all three sales patterns satisfy our strict definition. However, in

FIGURE 2
Saddle Parameters



Notes: $d^* = d/h$ = saddle relative depth; w = saddle duration; T_s = time of beginning of saddle.

the full data set, there are saddles that are definitely noticeable yet do not satisfy our conditions, and they are not included in our analyses. We therefore added a more relaxed definition using a relative depth of at least 10%, so as to include cases in which the saddle is less dramatic but still noticeable. A minimum depth is required in any event to exclude random deviations.

We begin with a preliminary inquiry that demonstrates the prevalence of the saddle phenomenon. Our empirical analysis is based on a comprehensive data set of new product sales made available by the Consumer Electronics Association, a major source of data on new product growth. The original data set includes 62 innovations, primarily in the consumer electronics industry. By eliminating all cases that contained less than eight points of data or that did not contain data on unit sales, we remain with a sample of 32 valid cases.

Table 1 lists descriptive data of the sample investigated. Of the 32 cases, 10 are found to have a duration and relative depth that satisfied our strict condition (a relative depth of at least 20% and a minimum duration of two years), and one case satisfies our relaxed condition. Note that the resulting frequency of 31% increases to 50% if the constraints are further relaxed to include saddles of a minimum duration of one year or a minimum relative depth of 10%. We therefore conclude that an occurrence of a saddle in new product growth is indeed common.

The Saddle as a Dual-Market Symptom

In the remainder of this article, we show that a saddle can be the direct consequence of a dual-market phenomenon, and we continue to explore the conditions under which a saddle

TABLE 1
Distribution of Saddles in Sample Data

Product Description	Saddle	Relative Depth (%)	Duration (Years)
PC monitors	Yes	25.8	5
Blank audio cassettes	Yes*	6.6	2
Blank floppy disks			
Video cassettes			
Camcorders	Yes*	5	2
Cellular telephones			
Color television	Yes	35.6	4
Color television with stereo			
Compact audio systems	Yes	53.5	11
Digital corded telephones	Yes	36.7	7
Cordless telephones	Yes	36.5	2
Direct broadcast satellite (DBS)	Yes*	21.4	1
Fax machines			
Home radios	Yes	33.6	6
Laser disk players	Yes*	11.8	1
LCD monochrome television			
LCD color television			
Fax modems			
Monochrome television	Yes	27.8	3
PC printers	Yes	25.8	5
PCs	Yes	25.8	5
Word processors			
Portable compact disk equipment			
Projection television	Yes*	12.3	1
Rack audio systems			
Portable tape and radio			
Answering machines			
Compact disk players			
Television/VCR combination			
VCR decks	Yes*	18.7	5
VCR decks with stereo	Yes	30	3
Videocassette players			
Percent saddle (strict definition)	34.4		
Percent saddle (* definition)	50		
Averages (strict definition)		31.8	5.1
Averages (* definition)		25.4	3.9

Notes: Yes* denotes cases in which a trough exists but its relative depth is less than 20% (but above 10%) or the trough lasts less than two years (this is an even more relaxed condition than that described in the text). For example, the trough in the videocassettes case had a relative depth of 7.4% with only a one-year duration. We therefore did not include it as a saddle. If we include the yes* cases as well, exactly half of the cases would have included a saddle.

is likely to occur. If two segments of the market—an early market and a main market—adopt at different rates and if the difference is pronounced, then overall sales to the two markets will exhibit a temporary decline at the intermediate stage. Note that, other than the existence of a dual market, the only assumption we make regards the relative magnitudes of the communication parameters.

A recent perspective in the marketing literature views the market for many new products as composed of early and main markets, which require differential treatment by marketers (Mahajan and Muller 1998). The basis of this approach is the premise that adopters in the early market are sufficiently and meaningfully different from main market adopters as to call for a significant differentiation in product and/or marketing strategy. This view is supported by the observation of the existence of segments of adopters that differ in their inclination or reluctance to adopt new concepts and innovative products (see, e.g., Rogers 1995; Tanny and Derzko 1988). Another premise is the existence of a discontinuity in the diffusion process or, stated otherwise, deficient communications between early market adopters and main market consumers (Moore 1991).

Although Rogers (1995) uses the term “innovators” to describe the first 2.5% of the population that ultimately adopts a given product, “innovators” has also been used in a more general sense to describe the early market, which consists of the first 16% of adopters, a group that includes Rogers’s innovators and early adopters (Mahajan and Muller 1998; Midgley 1977).

Until recently, it was accepted as fact that these innovators tend to be opinion leaders (Kotler 1997; Perreault and McCarthy 1996). Opinion leaders can be viewed as those who “exert disproportionate influence on others through personal influence” (Summers 1971). Early adopters seek guidance from this group of opinion leaders, whose influence lies in their tendency to spread information by word of mouth (Perreault and McCarthy 1996). This view is supported by Rogers (1995, p. 274), who suggests that early adopters, more than any other group, show a high degree of opinion leadership.

Moore (1991) builds on Rogers’s normal diffusion curve and his division into adopter categories along the curve to explain how new products spread in the market. He identifies a discontinuity in the process after approximately 16% of the population adopts the innovative product. The social process of contagion is broken at this point, because the later adopters (whom Moore labels the main market) refuse to rely on the earlier adopters (the early market) for information.

Main-market adopters are different from early-market adopters. Recent literature suggests that, at least regarding high-tech products, not only are main-market adopters not opinion leaders, but they also have no personal influence over others who have yet to adopt the product (Moore 1991, 1995). In addition, industry studies claim that the early- and main-market consumers adopt an innovative product for different reasons: Whereas main-market consumers are fundamentally utilitarian and are primarily interested in a product’s functionality, early-market adopters are attracted to attributes that are not exclusively functional. In high-tech markets, early-market adopters are characterized as technophiles, fascinated by cutting-edge technology and applications.

A dual-market perspective has also been suggested by academic researchers in various disciplines. In the field of communications, Rogers (1986) suggests that for interactive innovative products—innovative products consumers use for communications—diffusion can be analyzed as a two-phase process, that is, before and after a critical mass of sales is reached. In the organizational science literature, Cool, Dierickx, and Szulanski (1997) expand this critical market mass concept to include diffusion of innovations within organizations. In marketing, Mahajan and Muller (1998) posit that market failures can be avoided by modifying marketing strategy and concentrating efforts on tailoring product attributes to main-market needs or by reallocating the respective resources invested in early versus main markets.

The technology management literature (e.g., Anderson and Tushman 1990; Utterback 1994) has focused on the impact of what is conceptualized as a “dominant design,” or standard, on the evolution of technologies, exploring various penetration processes preceding and following the establishment of a product’s dominant design. In geography, Brown (1981) links the early market to the duration required to set up distribution outlets for a new innovation. Behind these diverse approaches lies the common idea that the initial product offered to consumers is meaningfully different from that offered in the later phase and that the consumers in the two stages of the product life cycle differ in a meaningful way.

From all this literature, we adopt the dual-market concept of an early and a main market, each of which is relatively homogeneous, with a strong word-of-mouth effect within each market and weaker communication ties between markets.

The relationship of the dual market to the saddle phenomenon can be best illustrated by Figure 3. The two markets begin at the same point in time, and though not isolated from each other (more precise parameters of the relationship between the two markets are specified subsequently), each has its own market attributes and potential, which are indicated when the diffusion and growth of the product are plotted and calculated separately for each market.

In the schematic illustration of Figure 3, a saddle phenomenon is observable if the growth of sales in the main market begins late; that is, the main market takes off shortly after sales in the early market reach their peak (see Figure 3, Panel A). If the two markets take off simultaneously or, as is the case in Figure 3, Panel B, the main-market takeoff begins slightly before the early-market sales reach their peak, then a saddle is not observable.

The Dual Market for Citizens Band Radios¹

As an illustration of the dual-market phenomenon, consider the case of the citizens band (CB) radio market, a two-way communications radio that any civilian (as distinguished from police) can use to communicate with any other person who operates a CB radio. The beginning of the CB radio industry is considered 1958, when the Federal Communica-

¹The following section is based on sources including Smith (1977), Bibb (1976), and Perkowski and Stral (1976) and various issues of *CB Yearbook*, *Electronic Market Data Book*, and *FCC Annual Report*.

tions Commission formed the basis for the citizens band, as we know it today. The early diffusion of CB radios peaked around 1963 and afterward generally declined. Growth began again in the early 1970s and increased rapidly in the mid-1970s, creating what was described in the popular press as a “market explosion.” By 1976, the CB radio was considered the “consumer electronics star performance of the year” (*Electronic Market Data Book* 1976), and more than five million CB license applications were submitted in 1977 alone. After 1977, demand decreased but remained considerably higher in the 1980s than in the early years.

According to industry literature, there was a noticeable difference between the average CB user in the 1960s and the user in the 1970s. The former were considered more serious users who needed CB radios for work (such as farmers or boat owners who wanted to have a connection with shore) and deeply involved hobbyists interested in radio transmission. In the 1970s, CB radio became a mainstream market composed of many consumers with no record of or high need for radio communication. The product became a widespread hobby available through mainstream consumer out-

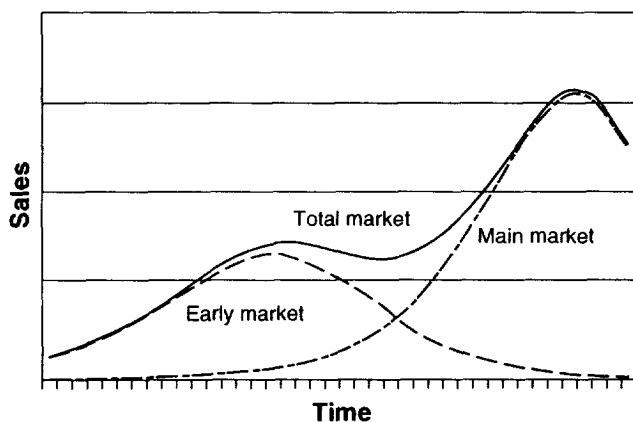
lets. By the end of the 1970s, many CB enthusiasts had left the market, turning to new hobbies.

Because of the different scales involved in the early and late CB unit sales growth, we present the penetration of CBs as occurring in two stages. The early penetration of CBs to the U.S. market, based on Federal Communications Commission records, is presented in Figure 4, Panel A, and the later years in Figure 4, Panel B.

The increase in demand for CB radios in the early 1970s after the decrease of the late 1960s is intriguing, because no major change in the product itself or its price can account for it. The Electronics Industry Association, the main industry data source that followed the growth of CB radio, attributed the change to communication factors, suggesting that it was an “increased awareness of the availability and utility of citizens radio,” which happened around 1972, that brought about the change (*Electronic Market Data Book* 1976, p. 60). It does not report which was more influential on this awareness among mainstream market adopters: the word-of-mouth communication of the early market of the 1960s or the advertising and mass media; but what is clear is that a

FIGURE 3
The Dual-Market Case

A: The Saddle Case



B: The Nonsaddle Case

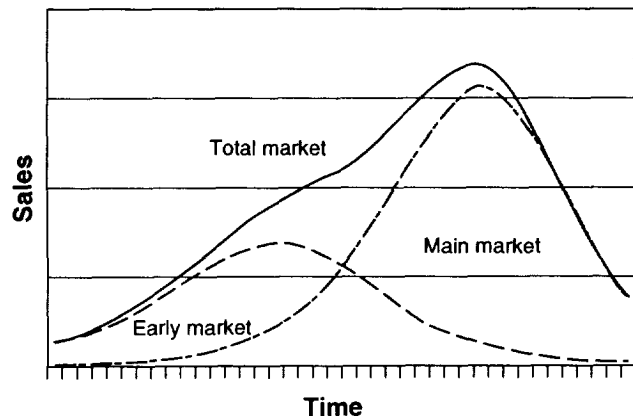
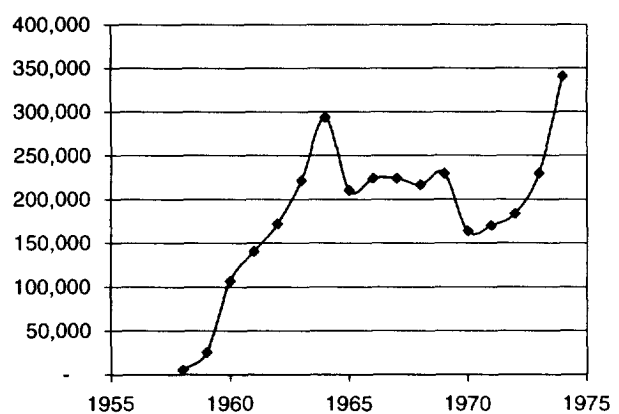
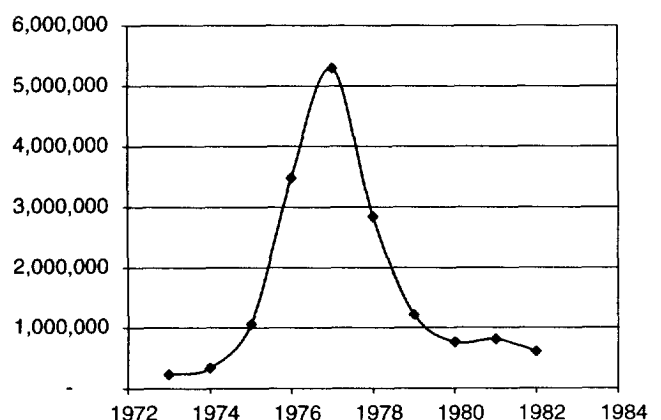


FIGURE 4
Penetration of CB Radios

A: 1958–75



B: 1973–82



large mainstream market emerged in the early 1970s, which created a clear and strong saddle effect.

In the next section, we move beyond the specific examples given in Figures 3 and 4 to a more general analysis and understanding of the driving forces behind saddles in the dual-market case. To do that, we employ an important simulation tool called *cellular automata*.

The Cellular Automata Model

Social interactions among consumers in distinct segments and the aggregation of these interactions can be considered a *complex system* problem. The social sciences have recently exhibited an increasing interest in complex systems (Anderson 1999), which are systems consisting of a large number of members who maintain linear interactions with one another to form nonlinear macrobehavior (Casti 1996). A well-established technique, which is both appropriate and convenient to model such complex systems, is cellular automata (Casti 1996; Rosser 1999; Wolfram 1984).

Cellular automata models are simulations of aggregate consequences that are based on local interactions among members of a population. The models track members' changing states and parameters over time (for detailed descriptions of this technique, see Adami 1998; Goldenberg, Libai, and Muller 2001; Toffoli and Margolus 1987).²

Applying this approach to our context here, consider a cellular automata model in which an environment is characterized as an array of cells. Each cell, representing a potential consumer, can accept one of two states: 0, representing a potential consumer who did not adopt the innovative product, and 1, representing a consumer who has adopted the new product. In addition, irreversibility of transition is assumed, so that consumers cannot "un-adopt" after adoption.

The rules that define transitions of potential adopters from State 0 to State 1 can be classified into two types:

1. *External factors*: Some probability p exists, such that in a certain time period, a consumer will be influenced by external influence mechanisms, such as advertising or mass media, to adopt the innovative product.³
2. *Internal factors*: Some probability q exists, such that during a single time period, a consumer will be affected by an interaction with a single other person who has already adopted the product.

For illustration purposes, consider a simple homogeneous case in which p and q are constant for all potential adopters.

²Cellular automata stochastic dynamics have been analyzed using specific methods to discover their statistical properties (e.g., partition function, cross entropy, renormalization groups). For a review of these methods and the unique statistical properties, see Parisi's (1998) book. The fundamental idea of the analysis of cellular automata is presented by Von-Neuman (1966). Technical aspects of the analysis on a practical level are presented by Burks (1970) and Toffoli and Margolus (1987).

³Although it is customary in the diffusion literature to think of the external parameter as representing marketing variables, in reality they can represent any influence other than interaction with other market participants.

In such a case, a time-dependent individual probability of adoption, $PA(t)$, given that the consumer has not yet adopted, is based on the following binomial formula:

$$(1) \quad PA(t) = 1 - (1 - p)(1 - q)^{k(t)},$$

where $k(t)$ is the number of previous adopters with whom the consumer maintains interactions.

We solve this general cellular automata model computationally by running a stochastic process in which, at each period, each individual probability of adoption is given by Equation 1. The results for a particular realization of the stochastic process are depicted in Figure 5.

Unlike the simple case described previously, the dual-market perspective assumes that adopters are more often affected by information flows within their own proximal group than by communications disseminated throughout the entire population. We consider, therefore, a market that is divided into two main groups: (1) the early market (indexed by i) and (2) the main market (indexed by m), for which we define the following parameters:

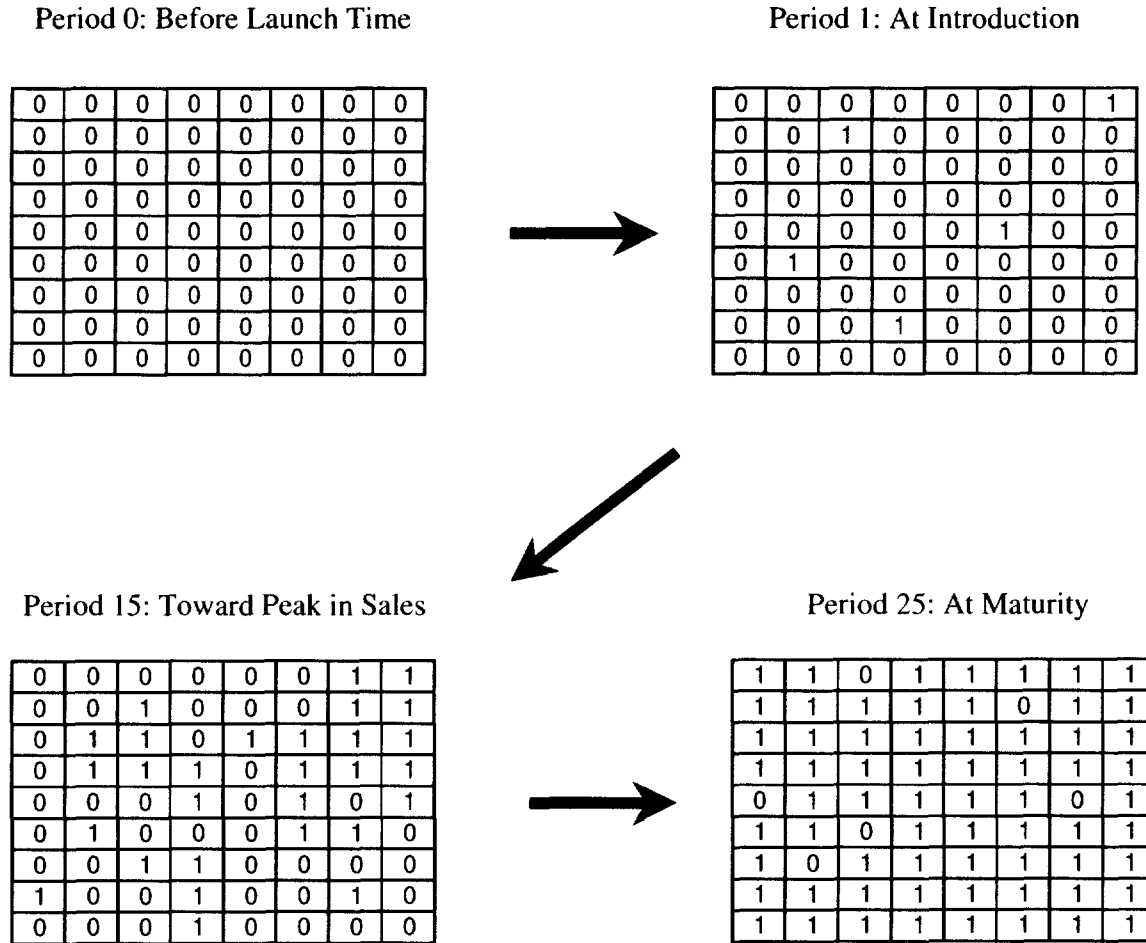
- p_i = the probability that an early-market consumer will adopt the innovative product as a result of external forces such as marketing efforts,
- p_m = the probability that a main-market consumer will adopt the innovative product as a result of external forces such as marketing efforts,
- q_{ii} = the probability that an early-market consumer will adopt an innovative product because of an interaction with another consumer from the same group (within-early-market communication parameter),
- q_{mm} = the probability that a main-market consumer will adopt an innovative product because of an interaction with another consumer from the same group (within-main-market communication parameter), and
- q_{im} = the probability that a main-market consumer will adopt an innovative product because of an interaction with a consumer from the early market (cross-market communication parameter).

Whereas q_{ii} and q_{mm} represent within-market communications, associated with strong ties within each community of adopters, q_{im} represents cross-market communications between the early market and the main market, whose ties are typically weaker.

Models of this type are frequently solved computationally (Casti 1989). The following step-by-step outline describes the cellular automata algorithm for a dual-market case:

- Period 0*: This is the initial condition, in which none of the consumers has yet adopted the product (receiving the value of 0).
- Period 1*: The probabilities for each consumer $p(t)$ are realized. Only advertising is at work during this period, because word of mouth requires consumers who have already adopted the product to start the process. A random number U is drawn from a uniform distri-

FIGURE 5
Illustration of the Cellular Automata Process



Notes: A value of 0 represents a potential consumer who has not adopted the product and a value of 1 represents a consumer who has adopted the product.

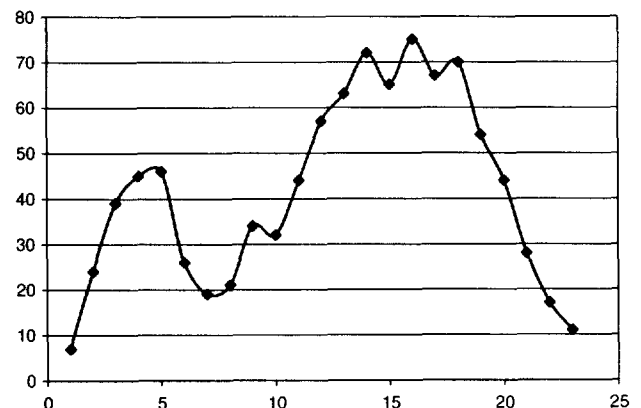
bution in the range $[0,1]$. If $U < p(t)$, then the consumer moves from nonadopter to adopter (receiving the value of 1). Otherwise, the consumer remains a nonadopter.

Period 2: The consumers who have adopted the product begin the word-of-mouth process by deploying communications within their own market (early or main) and cross-market communications from the early to the main market. Probabilities are realized as in Period 1, and the random number is drawn so that when $U < p(t)$, the consumer moves from nonadopter to adopter.

Period n : This process is repeated until 95% of the total market (e.g., 1000 consumers) has adopted the product.

To illustrate the outcomes of a computational solution, consider a hypothetical case of $p_i = .01$, $p_m = .0005$, $q_{ii} = .005$, $q_{mm} = .0005$, and $q_{im} = 5 \times 10^{-7}$. The results of this case are presented in Figure 6. In this case, a saddle with a relative depth of 59% and duration of seven periods is indicated.

FIGURE 6
A Saddle Formation in Cellular Automata Data



The cellular automata solution approach consists of running the program for a range of parameters, allowing sensitivity analysis to identify the crucial factors that govern the phenomenon. To generate realistic data sets, it is essential to define a proper range of parameters. In the area of new product growth, the Bass model is one for which a large body of empirical data exists. It is therefore reasonable to use the parameter range of this body of knowledge to calibrate our cellular automata parameter range. We followed previous research on the values of the Bass model parameters (Parker 1994; Sultan, Farley, and Lehmann 1990) and assumed that the individual-level parameters relate to the aggregate-level ones in the following manner:

- The relationships between cellular automata probabilities (lowercase letters) and the aggregated Bass parameters (uppercase letters) are fairly simple: P (Bass) and p (cellular automata probability) are of the same order of magnitude, because they both represent probabilities of adoption as influenced by external sources of information.
- The case of the communications parameters is more complicated: Q , the aggregate-level internal effect parameter, refers to the overall internal effect on an individual potential adopter. However, q_{ii} , q_{mm} , and q_{im} , our cellular automata individual-level parameters, are the probabilities that a given potential adopter will be affected by a single previous adopter. To the extent that many potential adopters exist, these parameters are smaller than Q , by a magnitude equal to the potential market population size (in our case, $M + I = 1000$). For example, where $q_{ii} = .0005$, the probability that one potential early adopter will be affected by his or her interaction with all the other previous adopters, given as 500, will be $1 - (1 - .0005^{500}) = .22$.
- Following the dual-market view, we set the range of p_i to be of an order of magnitude larger than the range of p_m . Note that this does not exclude cases in which marketing effects have an equal impact on the early and main markets, because the entire range of parameters is scanned.
- The same rationale leads us to set the range of q_{ii} (normalized by the size of the group) higher by an order of magnitude than the normalized range of q_{mm} .
- Consistent with the assumption that low levels of communications are maintained between adopters across the two markets, we set q_{im} to be smaller than q_{mm} .

In the next section, we first use cellular automata to conduct two studies. Study 1 explores the effect of communications across the early and main markets (q_{im}) on saddle occurrence. Study 2 explores the effect of all available parameters on the depth of a saddle and its duration. Following the cellular automata studies, Study 3 empirically tests the model to replicate the occurrence of saddles.

Study 1: Cross-Market Communications and the Occurrence of Saddles

We begin our analysis by closely examining the effect of q_{im} —or the parameter of communications across the early and main markets—on saddle prevalence. We emphasize this particular parameter for two reasons: First, the main contention of this article is that saddles are driven by the two-market phenomenon. What makes two markets differ-

ent is that the communications between them are different from those within each one. Thus, the level of communications across markets is central to their definition as a dual market. Indeed, dual-market proponents such as Moore (1991) claim that lack of communications between the two markets is the main reason for a “chasm” in new product growth. As we presently show, our results support the relationship between low-level cross-market communications and the existence of saddles. However, a complete break in communications between the early and main markets is not a necessary condition for the creation of a saddle.

A second reason for a specific interest in the cross-market communications effect is the lack of empirical knowledge on its range of values. The new product diffusion literature provides a wealth of information on what may constitute reasonable levels of communications within a group. However, there is almost no indication regarding the value of q_{im} , especially given that much of the material on the dual-market phenomenon is qualitative in nature.

Method

The purpose of this study is to demonstrate the importance of the cross-market communications parameter (q_{im}) on the prevalence of the saddle. Unlike the next study, in which we change all parameter values, here we keep the following parameters fixed at these values (for parameter range justification, see the previous section): $p_i = .01$, $p_m = .001$, and the ratio between the sizes of the early market and the main market is fixed at 1:9. We focus on the internal communications parameters and therefore change them as follows: q_{ii} from .001 to .04, q_{mm} from .0001 to .0009, and q_{im} from .00006 to .0006. Manipulating three parameters so as to receive nine different values each, we obtain 729 different adoption processes generated by cellular automata. For each process, we identify the existence of a saddle using a SAS application. The results are reported for the more relaxed saddle definition of 10%; however, nearly identical results appear for the 20% case as well.

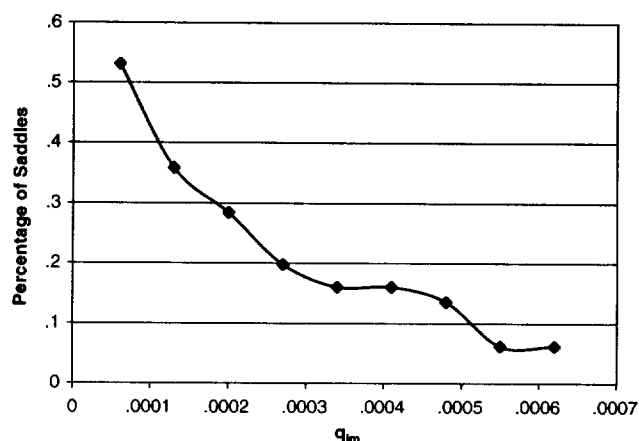
Results

To show the centrality of the cross-market communications parameter in the existence of saddles, we computed the percentage of times a saddle appeared for each value of q_{im} . For example, for a value of .0005, there were 81 different adoption processes, corresponding to nine different values each for the other communications parameters (q_{mm} and q_{ii}). Of these 81 cases, 11 cases (i.e., 13.6%) showed a saddle. These results are summarized in Figure 7.

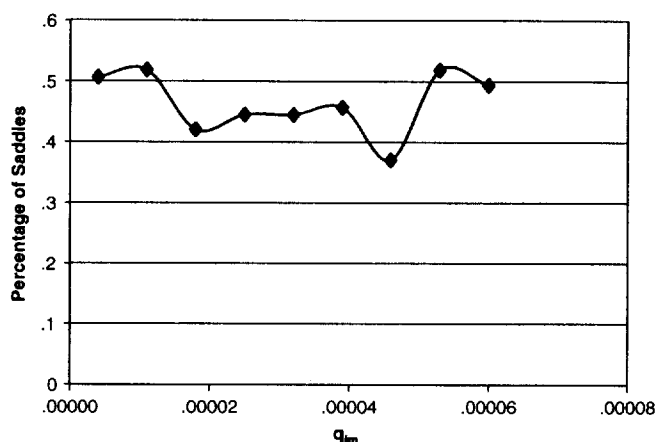
The striking feature of Figure 7, Panel A, is that in the dual-market model, for a wide range of relatively large values of the cross-market communications parameter, this parameter has a considerable influence in determining the existence of a saddle. Thus, for a q_{im} of .00006, more than 50% of the cases involved a saddle. This percentage gradually decreases as this parameter increases, until at values that are close to the within-market parameters (q_{ii} and q_{mm}), the percentage of saddles drops to below 5%. In a narrower

FIGURE 7
Prevalence of Saddles as a Function of
Communications Between Markets (q_{im})

A: The Upper Range ($.00006 < q_{im} < .0006$)



B: The Lower Range ($.00004 < q_{im} < .0006$)



Notes: The scales are different in the two figures. Whereas the upper range covers a wide interval of values of q_{im} , the lower range covers a much more limited interval.

range of relatively low values of the cross-market communications parameter, there is no clear-cut relationship between the values of this parameter and the existence of saddles, as shown in Figure 7, Panel B.

No consistent relationship was found between the within-market communications parameters (q_{ij} and q_{mm}) and the prevalence of a saddle. Moreover, a logistic regression on the existence of a saddle indicates that the (standardized) coefficient of the cross-market parameter is by far the largest of the three.

Thus, our contention that the dual market drives the saddle phenomenon receives strong support from Study 1. As the difference between the two markets is reduced (when we allow the cross-market communications parameter to come closer to the within-market parameters), the occurrence of a saddle becomes more rare.

Study 2: Determinants of Saddles' Depth and Duration

Although the previous study clearly indicates that the dual market drives the saddle prevalence for a wide range of the cross-market communications parameter values, this does not hold in its smaller values. Some other factors are at work, determining the fate of saddles in this smaller range. Therefore, we conduct another study that explores the effect of all available parameters when the cross-market communications parameter is relatively small.

Method

The purpose of this study is to explore the effect of all available parameters on the depth of a saddle, its slope, and its duration when the cross-market communications levels are relatively low.

The cellular automata model is set to represent a social system of 1000 potential adopters, varying p_i from .01 to .09, p_m from .001 to .009, q_{ij} from .01 to .09, q_{mm} from .0001 to .0009, q_{im} from 10^{-7} to 25×10^{-7} , and the ratio between the sizes of the early market and the main market from .11 to .20 (relative market size is reflected by changing I , while M is kept constant at 900).

To cover all the various values in the defined ranges (six parameters receiving five different values each), we generated 15,625 different adoption processes by cellular automata modeling. For each process, we automatically identified and analyzed a saddle using a SAS application. For each identified saddle, we calculated the starting time, depth, duration, and slope parameters according to the definitions specified previously (see Figure 2). We assigned a dummy variable to reflect the existence versus nonexistence of a saddle in the process.

We calculated initial descriptive statistics with the aim of isolating the parameter ranges implicated in saddle formation, allowing further exploration of the general structure of saddles. We performed regressions between the model parameters and the saddles' parameters to analyze and uncover saddle formation mechanisms and prediction probabilities of occurrence. We report the results for the more relaxed saddle definition of 10%; however, nearly identical results appear for the 20% case as well. In addition, we performed discriminant analysis (for two groups, with and without saddle) to provide support for our ability to predict the formation of a saddle.

Results

The results indicate that when we compare the relative depths of the saddles in our sample data and the cellular automata data, the relative depths of the saddles in the real-life cases are smaller than those in the cellular automata results (32% compared with 58%). However, we suggest that this difference is due to a selection bias in our sample. For example, some cellular automata saddles reflect a relative depth of 70%. In real life, firms experiencing such a severe drop in sales may either consider the product a failure or encounter consequent financial problems. In both cases, the cessation of marketing efforts and the termination

of the product are realistic options. Consequently, we filtered data reflecting the more pronounced end-of-saddle parameters from our sample. Our results indicate that at least some of these products might ultimately have become successful if the decline after the initial peak had not been interpreted as the end of the product's life cycle. Table 2 presents the results of a regression analysis performed for the saddle cases identified by cellular automata; each column represents a different dependent variable.

The effect of early market size. Given the existence of a saddle, the larger the early market, *ceteris paribus*, the larger are the relative depth and duration of a saddle. When the main market is slow enough to adopt so as to create a saddle, an increase in the initial peak leads to a corresponding increase in saddle parameters. The main effect is indicated in the saddle's depth rather than in its duration.

The main market effect. Both the marketing efforts parameter p_m and the within-market communications parameter q_{mm} have a strong, negative impact on the relative depth and duration of the saddle. The rationale for this indication is that, to the extent that p_m and q_{mm} increase, main-market adopters become a more powerful factor in the total market at an earlier stage in the process. Accelerated main-market growth decreases saddle parameters in terms of both relative depth and duration.

The effect of the cross-market communications parameter. Recall that the Study 1 finding that cross-market communication drives saddle prevalence for a wide range of the q_{im} parameter values did not hold for smaller values. Because Study 2 involves these smaller values of q_{im} , it is not surprising that q_{im} has a very small (and insignificant) main effect on saddle parameters at these levels. In contrast to Study 1, in this study, within-market communication parameters (q_{mm} and q_{ii}) have a significant impact on saddle formation.

The effect of within-early-market communications on saddle depth. Of all the parameters, early-market word of mouth (q_{ii}) has the largest effect on relative saddle depth. This result is consistent with our observation that word-of-

mouth effects are stronger than marketing effects (represented here by p_i).

The effect of within-early-market communications on saddle duration. Counterintuitively, high values of q_{ii} significantly reduce saddle duration. When q_{ii} is large, we expect the early market to adopt at a faster rate, creating a larger window for the more reluctant main-market consumers to adopt. Accordingly, saddle duration would be expected to increase when within-early-market communications accelerate early-market growth (especially in the case of a reluctant main market). However, our findings indicate that in such a situation, saddle duration decreases.

To explore this seemingly counterintuitive finding further, we added a nonlinear term (q_{ii}^2) and an interaction term ($q_{ii}q_{im}$). Indeed, the resulting sign of the nonlinear parameter is negative, indicating that saddle duration increases, but only for larger values of q_{ii} . What is the reason for this nonlinearity in effect? Recall that with small values of q_{ii} , saddle formation is possible only with small values of q_{mm} and p_m . In this subrange of parameters, a small increase in q_{ii} increases the pool of early-market buyers, allowing cross-market communications (q_{im}) to activate the main market earlier. This indirect effect induces a reduction in w (but only for small values of q_{ii}). Supporting this explanation is the finding that the interaction term of q_{im} with q_{ii} is significant, even though the main effect of q_{im} is not significant.

The effect of early-market marketing efforts. Another seemingly counterintuitive result is the negative impact of marketing efforts directed at the early market (p_i) on the relative depth and duration of the saddle. To understand this result, note that all of these correlations are contingent on a saddle existing. Thus, given the existence of a saddle, for small values of p_i , q_{ii} must be large. However, this also implies that early market growth is steep (Mahajan, Muller, and Srivastava 1990; Rogers 1995), leading, in turn, to a high initial peak. As p_i increases, the range of q_{ii} expands to include increasingly lower values, which results in a slower rise to a somewhat lower initial peak and a shallower relative saddle depth. Such a formation will not occur when p_i is large to begin with, as is evidenced by the positive effect of

TABLE 2
Summary of Regressions Results

		d* Relative Depth (Standardized)	d* Relative Depth (Nonstandardized)	w Saddle's Duration (Standardized)	w Saddle's Duration (Nonstandardized)
1	I Size of group I	.20	.001	.04	.007
2	p_m Marketing to majority	-.57	-50	.33	-499
3	q_{mm} Within-majority-market communications	-.35	-433	-.59	-12,609
4	q_{im} Cross-market communications	-.01	-3499	-.02	-83,171
5	q_{ii} Within-early-market communications	.59	6	-.55	-101
6	p_i Marketing to early market	-.39	-3	-.52	-74
7	$q_{ii}q_{im}$	-.01	-111,745	-.001	-106,844
8	q_{ii}^2	-.52	-62	.34	696
9	p_i^2	.31	27	.34	499
10	Adjusted R ²	.36	.36	.41	.41

Notes: All variables are significant at the $p < .01$ level except for Rows 4 and 7 (q_{im} and $q_{ii}q_{im}$).

p_i^2 (ninth row of Table 2). This also explains the effect on saddle duration: To the extent that the initial peak is higher, a longer duration is required to regain the initial peak level of sales.

The interplay between early-market size and the delay in adoption of the main market. Note that of all the main and significant effects, early-market size (I) has the least impact on saddle duration (column w of Table 2). The reason for this is that, *ceteris paribus*, large values of I delay the initial peak, requiring more time for most early-market members to become buyers. This delay enables the main market to enter the process at a stage preceding the completion of the early-market adoption process. Therefore, an increase in I , in its lower range of values, will induce higher values of w , and an increase in early-market size at the higher range of values decreases the saddle's duration.

If we are correct in our hypothesis that the saddle phenomenon is governed, *inter alia*, by an intrinsic dynamic mechanism, predicting its appearance is an imperative. We performed discriminant analysis using the identified parameters. Table 3 presents the confusion table of the discriminant analysis. The model correctly predicts 77% of the saddles and 79% of the nonsaddle cases. These results strongly imply that the selected parameters govern a noticeable portion of the saddle formation dynamics.

Study 3: Empirical Estimations of Saddles

Studies 1 and 2 demonstrate the frequency and influencing factors of the saddle phenomenon in simulated markets. However, the question remains whether we can tie our dual-market model to the saddle phenomena identified in real markets, as presented in Table 1. In this study, we use the data in Table 1 to examine the extent to which a dual-market model using the mean of the stochastic cellular automata framework can help us understand the aggregate-level saddle phenomenon.

Method

To examine the dual-market model with the aggregate-level product growth data in Table 1, we constructed a dual-market aggregate model that is based on the individual-level model presented in the cellular automata Studies 1 and 2. The model we employed uses the mean of the stochastic cellular automata model presented previously to describe the growth of a market in a dual-market case. Basically, such a model should have seven parameters: two external marketing variables (one for each market), p_i and p_m ; two internal

word-of-mouth parameters (one for each market), q_{ii} and q_{mm} ; one cross-market communication parameter, q_{im} ; and two market potentials, N_i and N_m . Calculating the mean probabilities of adoption given these parameter values, we can estimate at each period the expected number of adopters (from both early and main markets), compare the number of adopters with the actual data that contain saddles, and investigate (1) whether the model fits the data using classical fit measures such as R-square and (2) specifically, whether it can capture the saddle phenomenon identified in the data.

However, shifting to an aggregate level of analysis raises problems similar to those of classic aggregate-level modeling, namely, the need to examine complex multiparameter models with few data points. In our case, of the ten cases with saddles in our sample data, seven cases had 19 data points or fewer. Because fitting fewer than 19 points of data with seven parameters is highly unstable, we made the following changes in the model to reduce the number of parameters.

First, as noted previously, we can focus on the ratio between the market potentials of the early and mainstream markets rather than on the potentials themselves. Therefore, we fixed the size of the main market and estimated the size of the early market N_i . Second, we set the main-market external marketing coefficient (p_m) to zero. Thus, the early-market word of mouth is left as the only external influence working on the mainstream market.⁴ We therefore run a standard nonlinear search procedure on a five-parameter model instead of seven, acknowledging that even in this case our ability to generalize from the results is limited.

Results

Figure 8 presents the estimation results for the PC case we highlighted in this article. The saddle is well captured by our estimated saddle, beginning in 1984 and lasting for five years, just like the real one.

Capturing the saddle phenomenon. In general, we find that of the ten cases with saddles (see Table 1), the estimated growth pattern produces a saddle in eight cases. Of these eight cases, six are saddles according to our strict definition. These are PC monitors, compact audio systems, digital corded telephones, cordless telephones, personal computers, and VCRs with stereo. Two more cases involve a saddle in the predicted growth pattern that does not meet the strict criteria: The growth pattern of PC printers has a saddle of a 7.7% relative depth, and in the growth pattern of monochrome television, the model captures the saddle but not the peak, such that the estimated peak is lower than the estimated saddle. Still, even in the last two cases, the real saddle is explained by the early and late markets. Only two of the eight did not produce a saddle: color television and home radios. Of these two, although in color television

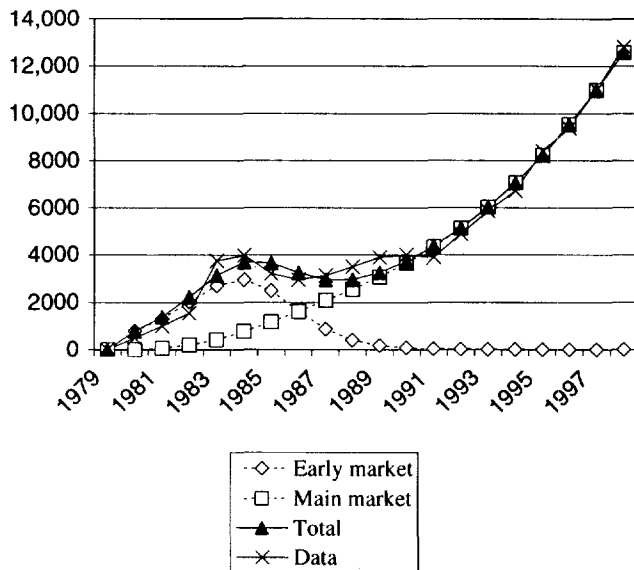
TABLE 3
Discriminant Analysis Confusion Table

	Observed Saddle (%)	Observed Nonsaddle (%)
Predicted saddle	77.2	22.8
Predicted nonsaddle	21	79

Notes: The average correct prediction is 78.1%.

⁴It should be noted that by deleting the main-market marketing parameter from the empirical analysis, we do not suggest that it is insignificant in real life but rather that, for the data set we have, it is the one parameter that has the least effect. Indeed, when we checked the inclusion of the parameter on the three products in our sample data that have more than 40 data points, the difference in the results was minimal.

FIGURE 8
Growth of PC: A Dual-Market Empirical Model



there is a breakdown between early and late markets, the estimated break between the two is enough to cause a delay but not a saddle. Only in home radios do we find that the model does not work; apparently, the saddle should be explained by factors other than the existence of early and late markets.

Considering, for example, the case of the PC presented in Figure 8, 1987 can be viewed as a milestone in the development of this market. In this year, which is right in the midst of the saddle, the number of mainstream new adopters equaled that of the early market. Examining industry publications from that time, we indeed find that increasing attention began to be drawn to the mainstream market that was expected to fuel the expected growth (e.g., Murphy 1987).

Model fit. Considering the model estimation, the model shows good fit to the data. The adjusted R-square varies from 79% to 99.1%, with an average of 92.9%.

Note, however, that we do not consider the relative success of Study 3 to be demonstrated merely with high measures of fit. High R-squares indicate that the model fits the data, but that itself is insufficient, because a standard aggregate-level Bass equation also yields reasonably high measures of fit. What the Bass model cannot capture, however, is a saddle, because the Bass model necessarily has a single maximum. In contrast, as presented previously, the dual-market model we examine captures the saddle in most cases and can give us an impression of the dynamics between early and main markets in these cases.

Cross-market communication. On the basis of the dual-market theory and the cellular automata results, we expect that the cross-market communication level (q_{im} parameter) should be (1) lower than the early and main within-market communication levels (q_{ii} and q_{mm}) and (2) smaller for cases of larger saddles.

The empirical results of Study 3 support both these points. First, on average, we find that the value of the cross-market parameter is lower than the within-market parameters (one-half and one-tenth of q_{ii} and q_{mm} , respectively; we do not report statistical differences because of the low number of cases).

To examine the second point, we also estimate the model for the six smaller saddles of the relaxed definition of the saddle (see Table 1 and our definition in the second section of the article) and compare it with the strict definition analyzed previously. We expect that the cross-market communication parameter for the larger saddles of the strict definition would be considerably lower than that of the smaller saddles of the relaxed definition. Indeed, we find that, on average, q_{im} in the strict case is much lower: 9.4% of the value of q_{im} in the relaxed case.

In a concluding remark to this study, the aggregate-level results seem to give empirical support to the dual-market theory of the saddle presented previously. However, although they support our theory, they also highlight the advantage of the cellular automata approach. As an example, consider Figure 7, which depicts a monotonic decline in the number of saddles as the value of the cross-market communication parameter increases. It is difficult to envision the extensive set of empirical data needed to replicate this result. For example, for a specific value of q_{im} , we would need a few different adoption processes, corresponding to different values each, for the other communications parameters (q_{mm} and q_{ii}). The cellular automata gave us the possibility of generating 81 such simulated markets with pure individual-level assumptions.

Discussion

In this article, we demonstrate that the saddle is a relatively common phenomenon. Using a data bank of a large number of innovative products in the consumer electronics industry, we found that a saddle pattern was evident in one-third to one-half of the cases investigated. From a managerial point of view, this pattern warrants attention, because a significant and unexpected decline in sales in the relatively early stages of a product's life cycle may erroneously cast doubt on the product's viability. This is especially true for high-tech and innovative products that are in the vulnerable point after introduction to the market, when firms typically engage in further research and development (R&D) and product improvements. The occurrence of a saddle may lead to a sudden, unexpected drop in cash flow just as the firm is in the highly precarious situation of simultaneously launching and improving the product.

We offer an explanation of the saddle phenomenon based on the dual-market approach. If two segments of the market—an early market and a main market—adopt at different rates and if the difference is pronounced, then overall sales to the two markets will exhibit a temporary decline at the intermediate stage. Other explanations for the saddle phenomenon exist. The temporary decrease in sales may be attributed to stockpiling, changes in technology, industry performance, or macroeconomic events. As we explain next, although these idiosyncratic explanations are certainly valid

in many cases, we do not believe that any of them can give a comprehensive explanation for the saddle.

- *Stockpiling*: The data we report are based on shipments rather than sales, and these data do not always track sales. Therefore, it is possible that if resellers overforecast sales, they accumulate excess inventory and reduce orders accordingly, thus creating an artificial peak.
- *Changes in technology*: Rapid changes in technology might induce a period in which consumers are reluctant to adopt a new product, causing them to skip one generation and leapfrog directly to the next one. This postponement in adoption might create a temporary dip in sales.
- *Industry performance*: Poor industry performance phenomena such as slow emergence of dominant design or a perceived low quality/price ratio might induce a decline in sales when consumers become fully aware of these shortcomings.
- *Macroeconomic events*: Macroeconomic conditions such as a recession will have a dampening effect on sales, thus creating a saddle.
- *Other product-specific variables*: Golder and Tellis (1998) suggest that the phenomenon of an early peak and slowdown could be explained on the basis of product-specific variables such as market penetration, price, and year of takeoff.

It is not clear, however, to what degree these variables yield a comprehensive and unified explanation of the saddle phenomenon. For example, in Table 1 we report a duration of 5.1 years for the average saddle. This duration is incompatible with the stockpiling explanation. In the same fashion, we found no correlation between recessionary periods and saddles.

Our model highlights the importance of cross-market communications in determining the existence of a saddle. For low levels of this parameter, more than 50% of the cases in the cellular automata data involve a saddle. This percentage gradually decreases as the cross-market communications parameter increases, until at values that are close to the within-market parameters, the percentage of saddles drops to below 5%. The parameters governing the depth and duration of a saddle are the intensity of the various channels of communications within and across the two consumer groups (early market and main market), as well as the relative sizes of these markets.

It should be noted that though we find that cross-market communications are an important factor driving a saddle, our results do not necessarily support Moore's (1991) view that there is no communication between the early and the main markets. We suggest that a lower level of cross-market communication is correlated with saddles, but not necessarily that cross-market communication is completely absent. Furthermore, the fact that in most cases of the data we present (both sample data and data generated by cellular automata), a saddle does not appear suggests that often this cross-market communications level is high enough, even among product categories close to the ones that Moore himself describes.

What options are open to firms that wish to reduce the parameters of a saddle, after it is predicted? The parameters under the direct control of the firm are the marketing effort parameters, p_i and p_m . Assuming a fixed budget, increasing p_m at the expense of p_i will reduce the delay in the adoption pattern of the main market, thus diminishing the size of the saddle.

Such action will be effective if firms are aware of the differences between the two types of market groups and are able to address them separately. In contrast, firms can have only limited control over word-of-mouth parameters. Examples of such indirect influence are programs in which the firm rewards customers who enlist friends and acquaintances as further customers.

Intuitively, to reduce the size of a saddle, firms need to increase both the within-main-market communications parameter and the cross-market communications parameter. However, our findings indicate that low levels of the latter parameter have no significant effect on the saddle, implying that firms can more efficiently achieve reduction of saddle size by stimulating main-market word of mouth.

We also find that the within-early-market communications parameter (q_{ii}) has the strongest effect on relative saddle depth. However, a high value of q_{ii} , though necessary for a rapid takeoff and penetration process, simultaneously precipitates increased relative depth and duration of the saddle. The sharp decrease in sales may be erroneously interpreted as a signal of the rejection of the product by the market, rather than a consequence of intensive word-of-mouth communications in the early market.

Assuming that firms have some degree of control over saddle size, it is questionable whether firms would prefer to eliminate the saddle entirely, for example, by reducing p_i to zero. In such a case, no saddle would form, and a consequent later takeoff should be expected. However, minimizing the adverse effects of a saddle by eliminating the early market is only one—and the least desirable—of several possible strategies.

First, ascribing the responsibility for product adoption and takeoff to the main market is an expensive decision. Manipulating the reluctant main-market adopters may be far more costly than investing in the early market. Second, by reducing or eliminating the early market, firms lose a critical source of information. By "listening to their voices," firms leverage feedback from the early market as important input in further R&D and product improvements. The costs of longer and more isolated R&D, as well as marketing to a slow response group, may be too high for the launching of brand new products.

This argument implies that a saddle might be a necessary stage for the successful introduction of an innovative product, enabling simultaneous introduction and improvement. In this case, firms may prefer to optimize the saddle size and timing by allocating their resources and deciding on appropriate marketing strategies based on the saddle's predicted appearance.

One question is whether it is possible to know a priori which real-life cases are more prone to saddle occurrences. Our results suggest that a principal communication channel that governs the saddle appearance is the cross-market communications between the early and the main markets. The smaller the cross-market communications, the more likely a saddle is to appear. We therefore expect that certain variables that influence this value would be dominant in a priori evaluations of the likelihood of a saddle appearance.

As an example of a product-based variable, consider the issue of dominant design (Utterback 1994). If the new product versions are not compatible with one another or with previous products, communications between the main market and the early market are less likely to occur. The main

market might view the early market as much too tolerant for the personal discomfiture caused by incompatibility of designs. The early market's level of risk taking, as manifested by its immediate approval and adoption of a new, incompatible technology, is also suspect by the main market. In addition, the existence of many incompatible products and technologies is likely to inhibit effective personal communications, because communications are likely to be more effective among users of the same technology. Thus, the larger the role of a dominant design in the evolution of a market and the larger the difference between predominant design and the standard platforms, the larger is the expected place of a saddle in the new product growth. Similarly, an increased novelty level of a new product is expected to reduce cross-market communications as well as lack user friendliness and the frequency of product attribute changes.

Limitations

Our study has several limitations. The data presented are limited to electronics-based durable goods. Although this factor is in line with much of the anecdotal evidence related to the kinds of products that drive a dual-market phenomenon, further research is needed to examine the saddle on a broader product base. From a modeling point of view, we present a simple dual-market model, making only a few assumptions. In a total modeling of real life, the communications pattern should be more complex and involve a large number of parameters.

One of the advantages of the use of cellular automata is the knowledge that a complication of the model is feasible and there is no uncertainty regarding an analytical solution. However, in our view, that our simple dual-market assumptions modeling approach drives a clear saddle phenomenon gives stronger support to the relationship between the two than more complicated models would.

In this study, we investigate the determinants of the occurrence of a saddle and its attributes in terms of depth and duration. We have not discussed the important issue of the timing of a saddle, which would require a comprehensive study that dealt with both the empirical issues and the theoretical underpinning of the timing of a saddle.

In addition, we rely on prior theory to support the dual-market phenomenon that drives the result of this study. In some cases, however, more than two segments of various sizes could be present. The results could change according to whether this segmentation is significantly different from the dual segmentation used in this article.

One question associated with the robustness of our cellular automata results involves their sensitivity to the definition of a saddle. We checked in both studies whether the saddle definitions conform to either the strict or the relaxed definitions. The differences in the results are minimal. The main reason is that the requirement of a two-year duration is the one that distinguishes between a saddle and a random perturbation. When we impose the two-year duration condition, the difference between 10% or 20% depth is not critical. For example, in the first study, if we relax the condition of the two-year duration, the number of saddles increases by

70%, but if we relax the depth requirement from 20% to 10%, total saddle occurrence increase is less than 10%.

In addition, the difference in the results in terms of both the graphs and the regressions is minimal in the case of the depth conditions. However, we believe that the two-year requirement is important, because idiosyncratic forces such as the ones discussed in the previous section could be powerful explanatory variables in the case of a one-year perturbation.

Another approach would specify the depth criterion as a function of the standard error of the time series. This type of volatility measure is common in other fields, such as finance. When no pattern of growth is evident, the standard error itself is used; that is, the errors are measured from the mean of the series. However, if consistent growth is noticeable, the errors are measured from a regression line; that is, a model is used to predict the growth curve, and the errors are measured from the line. For a growth curve to emerge that will serve as a basis for comparison, we develop a two-stage aggregate-level diffusion model in the spirit of Mahajan and Muller's (1998) model.

We checked the deviations of the time series from the model's prediction for three products: cellular telephones, camcorders, and telephone answering devices. We chose these products because none of them has a saddle and they belong to relatively noncorrelated industries. We computed the standard deviation from the real data in each case as a percentage of the average sales level to be the following: 6.4%, 7.7%, and 7.4%, respectively. The average of the three is 7.2%. Thus, the 20% rule that is approximately three times the average error seems a conservative measure, so we used 10% as an alternative. As we mentioned, we found few differences in the analyses of these two cases.

In a more general sense, the two-stage aggregate diffusion model could be viewed as a substitute for the cellular automata model. The performances of this approach in predicting a saddle are limited by the stochastic nature of the market. For example, a specific innovator may appear to be the last one to adopt, and a laggard can be among the first adopters because of pressure. An aggregate model cannot capture this aspect and therefore can be used only for sensitivity analysis.

In contrast, cellular automata models take into account the stochastic aspect (indeed a cell, or consumer, can adopt with a certain probability at a time other than expected). By running the cellular automata repeatedly on the same values, we can evaluate the odds that a saddle will appear, as well as the range of its timing, depth, and duration. Thus, the final result of our modeling is a curve with stochastic disturbances, as we would expect in reality. Distinguishing a saddle in such an environment is more of a challenge and is closer to reality than if we were to take the aggregate approach, which results in smooth curves.

Conclusions

Returning to our PC market example, we are left to verify that the dual-market concept can explain the saddle that occurred during 1984–91 (the PC industry recovered its lost

ground and exited the saddle in 1991, as shown in Figure 1). If our proposed explication of the saddle is tenable, we should be able to find evidence that implicates the main market in the industry's steep (second) takeoff. In 1994, in his *Fortune* magazine column, Kirkpatrick (1994a) attributed the rapidly growing home segment in the PC market to the following five factors: More consumers were working from home, prices were falling, PCs were becoming easier to set up, shopping for PCs was becoming more convenient, and customers were attracted by exciting new software.

In our view, these are signals that the dominant player had become the main market, with its orientation to product functionality, rather than the early-market technophiles. Note that the Internet was not even mentioned as a contributing factor; the real explosion in PC sales was yet to come. Seven months after his report, Kirkpatrick (1994b, p. 110, emphasis added) cited major industry sources that identified the main market as the source of the growth: "With less than four months to go, this is already shaping up as the landmark year for that rapidly evolving electronic marvel, the personal computer.... Consumers will pay \$8 billion to buy 6.6 million PCs..., add in the \$3.4 billion that *ordinary Joes and Janes* will shell out for PC software, and the total is more than Americans will spend on televisions [this year]."

Appendix

Practical Aspects in Cellular Automata Modeling

In this Appendix, we detail our experience in applying the cellular automata model to new product growth. Although the market for new products is indeed a complex system on the aggregate level, often the behavior on the individual level can be broken into relatively simple and known relationships among individuals. When this is the case, the cellular automata approach is capable of untying the complexity of the phenomenon so as to better understand the underlying governing mechanisms. This approach, however, requires careful attention to some aspects.

Cellular automata modeling requires a reliable micro representation of the relations among the individuals. Therefore, this modeling technique needs a strong individual-level theoretical background.

Although cellular automata models are not limited by the number of variables, it is recommended to develop a parsimonious model to reduce the level of the statistical analysis in the second stage and to increase the understanding of the underlying mechanisms.

We should note that the individual-level probabilities are different in both their values and their interpretation when compared with the aggregate-level parameters that are often reported in the marketing literature (e.g., Q from the Bass model differs from q_i or q_m).

Assigning ranges of small values to q (low level of interactions among individuals) leads to regimes with excessive levels of volatility. This regime is not likely to represent real-life situations and therefore can be used as an indicator to the lower bound of values.

When a phenomenon is monotonic or linear in most of its duration, aggregate-level modeling (e.g., simple diffusion models) may be more convenient to employ, and the results are plausible. In contrast, when the phenomenon becomes complex, with nonlinear or nonmonotonic regimes with a noticeable duration, it is much more expedient and accurate to employ cellular automata modeling.

When extreme levels of values are used, cellular automata can uncover hidden regimes that compose the boundaries of the phenomenon under discussion. Cellular automata is more representative at its boundaries.

Our analysis in this article is based on a C program written specifically for this study. Although the advantages of a computer language-based program are clear, including the ability to conduct complex experiments, we found that a simple cellular automata can be built using an Excel spreadsheet. Although limited in its size and manipulation ability, the spreadsheet can promote intuition and a first impression of whether the model itself has the potential to capture the observed phenomenon.

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