Getting a Grip on the Saddle: Chasms or Cycles?

The “saddle” is a sudden, sustained, and deep drop in sales of a new product, after a period of rapid growth following takeoff, followed by a gradual recovery to the former peak. The authors test for the generalizability of the saddle across products and countries and for three rival explanations: chasms in adopter segments, business cycles, and technological cycles. They model both boundary points of the saddle—start of the sales drop and recovery to the initial peak—using split-population models. Empirical analysis of historical sales data from ten products across 19 countries shows that the saddle is fairly pervasive. The onset of the saddle occurs in 148 product-country combinations. On average, the saddle occurs nine years after takeoff, at a mean penetration of 30%, and it lasts for eight years with a 29% drop in sales at its depth. The results support explanations of chasms and technological cycles for information/entertainment products and business cycles and technological cycles for kitchen/laundry products. The authors conclude with a discussion of the findings, contributions, and implications.

Keywords: new product diffusion, international marketing, chasm, business cycles, hazard models

“A saddle” is a phenomenon characterized by a sudden, sustained, and deep drop in sales of a new product, after a period of rapid growth following takeoff, followed by a gradual recovery to the former peak (Figures 1 and 2). Recent studies have empirically documented this phenomenon of a trough in sales. For example, Goldenberg, Libai, and Muller (2002) find a saddle in up to 50% of 32 consumer electronics products in the United States. Golder and Tellis (2004) define a “slowdown” (or start of the saddle) as the end of the growth phase in a product’s life cycle and find that the slowdown occurs in 96% of a sample of 23 products in the United States.

Empirical support for the saddle is based on studies using only U.S. data. Is the phenomenon generalizable across countries? Researchers also propose differing explanations for the saddle. Goldenberg, Libai, and Muller (2002) emphasize the role of chasms in adopter segments; however, although they note that changes in technology or macroeconomic events may lead to the saddle, they do not empirically test these explanations. Golder and Tellis (2004) emphasize the role of negative cascades, which they measure as change in gross national product.

As Hauser, Tellis, and Griffin (2006) note, the limited empirical evidence and differing explanations for the saddle underscore the need to thoroughly document and explain this phenomenon across a wider cross section of countries and products. Because a saddle involves a sudden and sharp decline in sales that were previously increasing rapidly, accurately testing its generalizability and understanding its drivers has far-reaching managerial implications. Such declines may have adverse consequences for managers of new products, who may have overcommitted manufacturing capacity, built large inventories, or expanded their sales staff during the period of growth. Worse still, if they believe that the phenomenon is permanent for their product, they may drastically reduce capacity, inventory, or staff and suffer from missed orders and sales when the growth resumes.

The goal of this study is to develop a better understanding of the phenomenon of the saddle. In particular, we seek answers to three questions:

1. How pervasive is the saddle across countries and categories?
2. What are the characteristics of the saddle in terms of start, depth, and duration of decline?
3. What theories explain the saddle?

4. Can a model predict a saddle?

The next section discusses rival theories of the saddle. The subsequent three sections present the method, results, and discussion.

**Rival Theories of the Saddle**

**Definitions**

A “product” refers to a group of brands that are close substitutes and fulfill a distinct need from the consumer’s viewpoint (Golder and Tellis 2004)—for example, DVD players. We use the term “product–country combination” to refer to a specific product in a specific country. The term “sales” refers to the total of all consumer purchases of all brands of a specific product. “Takeoff” is a dramatic increase in sales that marks the transition from the introduction stage to the growth stage of the product life cycle (Agarwal and Bayus 2002; Golder and Tellis 1997). Linking the phenomenon of the saddle to the concept of takeoff has two advantages. First, we avoid considering products that did not make it to a mass market—that is, those that simply failed. Second, it can help distinguish characteristics of the saddle compared with takeoff. We further define two boundary points of the saddle: start and recovery: The “start of the saddle” is the first year of decreasing product sales, and “recovery” is the first year in which sales cross the prior initial peak.

**Chasms in Adopter Segments**

Previous research has viewed the product life cycle as a social phenomenon, driven primarily by communication processes that transfer new product information between members of a social system (Golder and Tellis 2004). Rogers (1995) classifies product adopters into five distinct groups (innovators, early adopters, early majority, late majority, and laggards) according to the normal penetration curve. The traditional view is that the diffusion process can be fueled by simply targeting the innovators and the early majority, thereby triggering an unbroken word-of-mouth communication process across other adopter segments (Mahajan and Muller 1998; Rogers 1995).

However, some researchers have debated this notion of continuity in the communication process (Goldenberg, Libai, and Muller 2002; Mahajan and Muller 1998; Moore 1991; Van den Bulte and Joshi 2007). Moore (1991) suggests that “cracks in the bell curve” may exist between groups of adopters in the case of high-technology products. According to Moore, the biggest crack, or a “chasm,” separates the early adopters from the early majority (Figure 3). The early adopters and the early majority have different characteristics and needs; thus, the former do not form a good word-of-mouth reference point for the latter. Van den
Bulte and Joshi (2007) point out one implication of this theory: Product offerings appealing to technology enthusiasts need not appeal to the mainstream market; thus, mainstream customers discount adoptions by technology enthusiasts and care only about adoptions by other mainstream customers. Goldenberg, Libai, and Muller (2002) classify adopter segments as early market and main market according to the timing of new product adoption. They argue that weak communication between the early and main markets may lead these segments to adopt products at substantially different rates; in other words, the main market takes off after the early market peaks, thus creating a saddle (Figure 4, adapted from Goldenberg, Libai, and Muller 2002). Following this logic, the literature suggests the following hypothesis:

**Alternative:** $H_{A1}$: A saddle is likely to occur during a discontinuity in the transition between the early and late markets (or a chasm).

We test this hypothesis against the null hypothesis:

**$H_0$:** There is no association between a discontinuity in the transition between the early and late markets (or a chasm) and a saddle.

**Business Cycles**

Prior marketing research has concentrated on the positive impact of income changes on product diffusion (Golder and Tellis 1998; Talukdar, Sudhir, and Ainslie 2002). However, researchers have not studied the differences between the effect of economic contractions on sales of information/entertainment and kitchen/laundry products. Recently, researchers have shown the impact of business cycles on the sales of consumer durables (Deleersnyder et al. 2004), growth of private labels (Lamey et al. 2007), and role of marketing strategy (Srinivasan, Rangaswamy, and Lilien 2005). In the excitement of post-takeoff growth, managers may believe that their new product’s sales will be immune to economic contractions and continue to increase. However, a saddle may begin even in the growth stage as a result of economic contractions. For example, Figure 5 shows the sales of dishwashers (denoted by the dotted line) and economic contractions (denoted by the dark bars) in Germany. Note that sales peak in 1973, and the saddle begins in 1974, coinciding with the economic contraction of 1974.

The saddle can occur during periods of economic contractions for four reasons: First, an economic contraction shrinks income and depresses buying power. As a result, consumers are likely to cut back on discretionary expenditures, such as purchases of consumer durables. Second, consumers may lose trust during a contraction more quickly than they gain confidence during the ensuing expansion, leading to cyclical asymmetries in the purchase of durables (Deleersnyder et al. 2004; Lamey et al. 2007). Third, firms engage in cyclical marketing strategies, such as cutting advertising expenditures (Deleersnyder et al. 2004; Lamey et al. 2007) or investments (Mascarenhas and Aaker 1989) during contractions. These actions can further aggravate the decline in sales during a contraction. Fourth, the onset of a recession may trigger a negative cascade in new product sales. If a positive cascade first triggers a run-up in sales, when faced with a recession, some consumers may decide to wait before purchasing the new product. When other consumers become aware of these decisions, a negative cascade may begin, triggering a sharp drop in sales at the onset of maturity (Golder and Tellis 2004). These reasons point to a strong but previously ignored driver of the saddle in new product sales: economic contractions. This reasoning suggests the following testable hypothesis:

**$H_2$:** A saddle is likely to occur during periods of economic contractions.

**Technological Cycles**

Consumers’ beliefs about the significance or size of anticipated improvements in technology may influence new product sales (Balcer and Lippman 1984; Doyle and Saunders 1985; Holak, Lehmann, and Sultan 1987). John, Weiss, and Dutta (1999) argue that whereas significant improvements may prompt purchases when they arrive, they may have a chilling effect when they are expected imminently. Consumers may be uncertain about the nature and extent of the technological change and decide to wait and watch (John, Weiss, and Dutta 1999) or may leapfrog a product generation in expectation of product improvements or price declines (Goldenberg, Libai, and Muller 2002; Weiss 1994). Furthermore, Van den Bulte and Stremersch (2004) propose...
that when faced with multiple competing standards, even innovative consumers may postpone adoption until the uncertainty about what standard will dominate has been resolved. Doyle and Saunders (1985) say that such anticipatory effects may cause even retailers to hold off their purchases in anticipation of changes. Thus, a saddle can be expected to begin during times of multiple important technological advances as a result of uncertainty in the minds of consumers and retailers. This theory points to a strong but empirically untested driver of the saddle in new product sales: technological advances. The preceding argument suggests the following testable hypothesis:

H3: A saddle is likely to occur during times of important technological advances.

Method

Model

Because the occurrence of the saddle is a time-dependent event with two boundary points, start of the saddle and recovery to initial peak, we model it using two separate split-population hazard models. Each hazard model captures one of the two boundary events. The standard hazard model explains the conditional probability that an individual i will experience an event in a time period t given that it has not already occurred, as a function of a baseline hazard plus some explanatory variables (Singer and Willett 2003). In new product research, the hazard function has been used to analyze diffusion (Bass 1969) and hazard models have been used to predict takeoff (Agarwal and Bayus 2002; Chandrasekaran and Tellis 2008; Golder and Tellis 1997, 2004; Tellis, Stremersch, and Yin 2003).

The standard hazard model assumes that every case eventually experiences the event (Prins and Verhoef 2007). However, a proportion of the cases may never actually observe the occurrence of the event. A split population hazard model allows for some cases never to experience the event (Schmidt and Witte 1989). For example, split population models have been used in the marketing literature to study the diffusion of automated teller machines (Sinha and Chandrashekaran 1992), the emergence of dominant designs (Srinivasan, Lilien, and Rangaswamy 2005), and the adoption timing of a new e-service (Prins and Verhoef 2007).

The discrete-time specification of the hazard model allows for great flexibility in specifying the time function and for incorporating time-varying explanatory variables (Allison 1982, 1995; Singer and Willett 1993). Jenkins (2001) outlines a procedure for a discrete-time split population survival model, which enables us to incorporate time-varying covariates in a discrete time hazard framework while taking into account the possibility that a proportion of the products may never experience the event (either the start of the saddle or the recovery following it). Next, we describe the events and the split population formulations of the model.

Events. We model two events: (1) the start of the saddle given takeoff and (2) the recovery given the start of the saddle. The hazard of the start of a saddle is the probability that

![FIGURE 5](image-url)
a product–country combination, i, experiences a start of the saddle in time \( t \), given that it has not done so yet but takeoff has occurred. The hazard of recovery is the probability that a product–country combination experiences a recovery past the initial peak, given it has not done so yet but the saddle has started.

Each product’s history is broken into a set of distinct observations, one for each year, up to and including the year of the event or until the series is censored. For each observation, the dependent variable takes on a value of 1 if the event occurs during that period and 0 if otherwise. Explanatory variables take on whatever value occurs during that period. For the proportion of products for which we observed the event, we have duration data that constitute a complete series. However, for the products for which the event is not observed, the observations are interpreted as incomplete series and are censored.

**Split population formulation.** Split population models assume that a proportion, \( c \), never experience the event and estimate this unobserved proportion. Let \( A_i \) be an indicator of whether a product–country combination i eventually experiences the event, where \( A_i = 1 \) indicates event occurrence and \( A_i = 0 \) indicates that the event never occurs. Let the probability of \( (A_i = 1) = 1 - c \) and the probability of \( (A_i = 0) = c \).

For those product–country combinations in which the event is observed during a given time interval, the contribution to the likelihood is \((1 – c) \times (\text{probability of survival to end of previous time interval}) \times (\text{probability of the event in the given interval})\). Censored observations consist of those that never observe the event plus those not yet observed to fail. Thus, the contribution to the likelihood from a censored survival time is \( c + (1 – c) \times (\text{probability of survival to end of the given time interval})\).

Let \( d_i \) be the observable binary censoring indicator signifying whether the ith product–country combination experiences the event in \((0, t)\), with \( d_i = 1 \) if the event occurs and \( d_i = 0 \) if right-censored. Then we can estimate by maximum likelihood the proportion of product–country combinations that never experience the event, together with the parameters characterizing the hazard rate for the remainder of the population. Thus, the likelihood contribution for product–country combination i with survival time \( t \) is

\[
(1) \quad \ln L_i = d_i \ln[(1 – c)(h_{it})(S_{it-1})] + (1 – d_i) \ln[c + (1 – c)(S_{it})],
\]

where \( S_{it} \) is the discrete-time survivor function and \( h_{it} \) is the (complementary log-log) discrete-time hazard rate, expressed as

\[
(2) \quad S_{it} = \prod_{j=1}^{t} (1 – h_{ij})
\]

\[
(3) \quad h_{it} = 1 – \exp[-\exp(D(t) + bX_{it})],
\]

where \( D(t) \) summarizes the duration dependence in the hazard model common to each i. We specify a flexible functional form of \( D(t) = t + t^2 + \log(t) \) and subsequently test the robustness of the analysis to the linear specification \( D(t) = t \). \( X_{it} \) consists of the independent variables and control variables, described in the “Measures” subsection.

Thus, the hazard function consists of time-varying covariates, time-invariant covariates, and the effect of time. If \( c = 0 \), a testable hypothesis, the split population survival model reduces to the standard discrete-time proportional hazards model (or complementary log-log model). We use the STATA procedure `SPSURV` (Jenkins 2001) to estimate the model. The estimation procedure uses the maximum-likelihood complementary log-log model to derive starting values. The complementary log-log model is particularly useful when data from discrete time intervals are used to capture a continuous underlying process (Allison 1995; Prins and Verhoef 2007).

**Measures**

**Year of takeoff.** We measure takeoff using the rule Tel- lis, Stremersch, and Yin (2003) propose. They define “take-off” as the first year in which a product’s growth rate relative to its previous year’s unit sales is higher than the threshold for takeoff based on market penetration.

**Boundary points of the saddle.** We operationalize the two boundary points of the saddle. The start of the saddle is the first year of a trough in sales following takeoff, in which sales drop for at least two consecutive years to a depth of at least 10% from an initial peak. This rule ensures that we avoid modeling transient sales drops spuriously as a saddle. It also ensures consistency across products and countries. Our measure is similar to others proposed in the literature. For example, Goldenberg, Libai, and Muller (2002) operationalize the saddle as a trough following an initial peak in sales, reaching a depth of at least 20% of the peak (strict definition) or 10% of the peak (relaxed case), lasting at least two years, followed by sales that exceed the initial peak. Golder and Tellis (2004) measure slowdown (or start of the saddle) as the first year of two consecutive years, after takeoff, in which sales are lower than the peak of previous sales. The end of the saddle, the recovery, is the first year following the start of a saddle in which the sales surpasses the previous peak.

**Chasm in adopter segments.** As we mentioned in the section “Rival Theories of the Saddle,” prior research has classified adopter categories according to the penetration curve (e.g., Mahajan and Muller 1998; Mahajan, Muller, and Srivastava 1990; Moore 1991; Muller and Yogev 2006; Rogers 1995). Muller and Yogev (2006) determine that in a dual-market setting, the main market outnumbers the early market at a penetration level that varies between 3% and 33%, depending on the product. Because of this high variation, the point of chasm would vary by product category, though it is likely to be the same across countries. Indeed, prior research has shown that diffusion parameters are unique to particular products (e.g., Chandrasekaran and Tellis 2007; Muller and Yogev 2006).

Therefore, for each product, a mean penetration level that reflects early market adoption and late market non-adoption can serve as a proxy for the location of the chasm. However, theory is silent about the exact penetration percentage at which the chasm is likely located. To resolve this
problem, we use the data across countries for each product. On the basis of the literature cited previously, we make the reasonable assumption that adopter segments are likely to be common across countries but unique for each product.

Thus, first, we calculate from the data the mean penetration in the year of the saddle across all countries, except the focal country, for each product ("meanpen"). Here, we use the information only from product–country combinations that experience the event. Next, we define a variable “dispersion” to capture the distance of the actual penetration in the year before for the target product–country combination from the mean penetration calculated in the previous step, as follows:

\[\text{Dispersion}_t = |\text{Penetration}_{t-1} - \text{Meanpen}|.\]

Note that we use penetration in the previous year and drop the focal country from the calculation of meanpen to allay concerns that the measure is tautological. Hypothesis testing (e.g., Sawyer and Peter 1983) examines the probability of the data if the null hypothesis is true. Now, given that adopter categories are likely to persist across countries for a product, if the null were true, the hazard of a saddle should not increase as distance from meanpen decreases. In contrast, if testing this hypothesis results in a negative coefficient in the hazard model, we would reject the null and conclude in favor of the chasms theory captured by \(H_{A1}\).

Business cycles. We construct a measure to capture economic contractions and expansions using recent marketing literature (Deleersnyder et al. 2009; Deleersnyder et al. 2004; Lamé et al. 2007). These studies estimate business cycles by extracting the cyclical component from the gross domestic product (GDP) series using the Hodrick and Prescott (1997) filter. The Hodrick and Prescott (HP) filter decomposes a time \(y_t\) series into a trend component \(l_t\), which varies smoothly over time and a cyclical component \(c_t\), by fitting a smooth curve through a set of points defined by the log-transformed GDP series (Stock and Watson 1999). First, the HP filter obtains the long-term trend and then obtains the cyclical component, which fluctuates around that trend, by subtracting the long-term trend from the original time series (Lamey et al. 2007). We use the software program EViews to estimate the cyclical component of the GDP series for each of the 19 countries, using the HP filter.

Next, we create an indicator variable termed “economic contraction” for the state of the economy. We set this indicator variable to 1 for decreases in the cyclical component of GDP corresponding to contractions and 0 for increases in the cyclical component of GDP corresponding to expansions. A positive coefficient for the measure of economic contraction in the hazard model would imply that a saddle is more likely during an economic contraction than during an economic expansion.

Technological cycles. We measure technological cycles using patenting activity. Prior research has used patents as an important indicator of technological activities and innovation in an industry (e.g., Ahuja and Katila 2001; Tellis, Prabhu, and Chandy 2009). The U.S. patent collection contains the list of all patents issued by the U.S. Patent and Trademark Office since 1974. We consider U.S. patents that have been granted a valid indicator of technological activity for the product across countries because most important innovations either originated in the United States or the firms involved have filed U.S. patents to protect this large market (Tellis, Prabhu, and Chandy 2009). For each product, we extract all U.S. patents from Delphion’s patent database, sort the patents according to the Inventive International Patent Classification code, and retain patents that are most directly associated with the focal product.

We have data on both the number of patents and the forward citations received by the patents for each product at each time period. Forward citations refer to the number of times the focal patent is cited by other patents. Trajtenberg (1990) finds a close association between citation-based patent indexes and the social value of innovations from an empirical analysis of a particular innovation (computed tomography scanners). Furthermore, Chandy et al. (2006) argue that patent citations are a valid measure to capture important ideas because they are objective, readily available, and unlikely to be either inflated or understated. Thus, we use the patent citations as an index of the importance or value of the patents. We weight patent counts by this measure, as in Trajtenberg (1990), to create a measure “weighted patent counts” as follows:

\[\text{WPC}_t = \prod_{j=1}^{n_t} (1 + C_j),\]

where \(n_t\) is the number of patents issued during the year \(t\) and \(C_j\) is the number of forward citations received by a patent \(j\) for the product. This linear weighting scheme enables us to take into account the number of both citations and patents. A positive coefficient for this measure in the hazard model would indicate that an increase in technological activity is driving the start of the saddle.

Control variables. In a globalized world, consumers’ adoption of new products may be influenced by not only communication behaviors among consumers and environment factors within a country but also cross-national learning flows from lead markets (Ganesh and Kumar 1996; Putsis et al. 1997; Takada and Jain 1991). Prior research has pointed out the presence of cross-country learning effects influencing the takeoff of new products (Chandrasekaran and Tellis 2008; Tellis, Stremersch, and Yin 2003; Van Everdingen, Stremersch, and Fok 2009). We control for cross-country learning effects using “prior saddles,” or number of saddles that occurred in the previous year in other countries for each product.

Prior research has suggested that greater interconnectivity, media penetration, demographic changes, and technology improvements encourage availability, awareness, and appeal of new products (Chandrasekaran and Tellis 2008; Van den Bulte 2000) and may lead to faster diffusion or takeoff of new products. On the one hand, this may create a cascade in sales for newly commercialized products, leading to an earlier or steeper saddle in sales. On the other hand, newly commercialized products may enjoy a sustained sales momentum, reducing or delaying the possibility of a saddle in sales. We operationalize “product vintage” as the first year
We have fewer than ten years of data. We also excluded proprietary industry data.

Data and Sources

We assembled a database on historical sales and market penetration of both kitchen/laundry and information/entertainment products. We obtained data on six kitchen/laundry products (dishwashers, dryers, freezers, microwave ovens, refrigerators, and washing machines) and four information/entertainment products (DVD players, personal computers, VCRs, and video cameras). We tracked these products across 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK), Japan, Canada, and the United States, from 1950 through 2008, for a total of more than 1300 observations. For the United States, in some cases, we had data extending before 1950. We assembled these detailed time-series data, which are based on several hundred research hours, from a variety of sources: subscription-based sources (Euromonitor Global Marketing Information Database, World Development Indicators Online, Fast Facts Database from the Consumer Electronics Association), archival search of several secondary sources (Historical Statistics of Japan, Electrical Merchandising, Merchandising, Merchandising Week, and Dealerscope journals for the United States, Consumer Europe, European Marketing Data and Statistics), and proprietary industry data.

We excluded product–country combinations for which we have fewer than ten years of data. We also excluded product–country combinations for which the sales data in the first year exceed 100 (in thousands of units) or the penetration in the first year exceeds .5%. For the United States, we dropped washing machines because we do not have early enough data to estimate takeoff. As Web Appendix A (http://www.marketingpower.com/jmjuly11) indicates, the scope of our study is larger than the majority of the prior studies on diffusion of new products, which have typically included either very few products or very few countries, or very few combinations of both. The additional challenge in this study was to obtain sales and penetration data. As such, this is the one of the largest studies that uses both sales and penetration data (see Web Appendix A).

For calculating the time of economic contractions across countries, we used a measure for real GDP from the Groningen Growth and Development Centre and the Conference Board, Total Economy Database (http://www.ggdc.net). We used total GDP, in millions of 1990 U.S. dollars (converted at Geary Khamis PPPs). We determined GDP for the pre-1950 years from Statistics on World Population, GDP, and per capita GDP, 1–2006 AD (www.ggdc.net/maddison). We obtained patent data from the Delphion database (www.delphion.com), a subscription-based database that contains detailed historical records on patents granted and applied for both in the United States and other countries, and has been used in prior studies (e.g., Tellis, Prabhu, and Chandy 2009).

Results

Descriptive Statistics

Characteristics of the saddle. Of the 156 product–country combinations for which takeoff has occurred, we observe the start of the saddle in 148 cases (99% of the kitchen/laundry products and 88% of the information/entertainment products). These numbers are slightly lower than the 96% Golder and Tellis (2004) report and similar to the 86% Goldenberg et al. (2006) report. Of the 148 product–country combinations in which the start of the saddle occurs, 120 cases (81%) experience a recovery to the previous peak. We observe both the start and recovery in 86% of kitchen/laundry products and 61% of information/entertainment products (Table 1). The numbers observed for the latter are somewhat

<table>
<thead>
<tr>
<th>Products</th>
<th>Applicable Cases</th>
<th>Start</th>
<th>Recovery</th>
<th>Mean Year of Saddle</th>
<th>Range Year of Saddle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dishwashers</td>
<td>16</td>
<td>16</td>
<td>15</td>
<td>1980</td>
<td>26</td>
</tr>
<tr>
<td>Dryers</td>
<td>18</td>
<td>17</td>
<td>14</td>
<td>1983</td>
<td>45</td>
</tr>
<tr>
<td>Freezers</td>
<td>15</td>
<td>15</td>
<td>13</td>
<td>1975</td>
<td>39</td>
</tr>
<tr>
<td>Refrigerators</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>1966</td>
<td>42</td>
</tr>
<tr>
<td>Microwave ovens</td>
<td>18</td>
<td>18</td>
<td>12</td>
<td>1993</td>
<td>19</td>
</tr>
<tr>
<td>Washing machines</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>1975</td>
<td>19</td>
</tr>
<tr>
<td>Personal computers</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>1989</td>
<td>8</td>
</tr>
<tr>
<td>VCRs</td>
<td>15</td>
<td>15</td>
<td>11</td>
<td>1988</td>
<td>14</td>
</tr>
<tr>
<td>Video cameras</td>
<td>15</td>
<td>12</td>
<td>9</td>
<td>1993</td>
<td>5</td>
</tr>
<tr>
<td>DVD players</td>
<td>14</td>
<td>10</td>
<td>1</td>
<td>2005</td>
<td>4</td>
</tr>
<tr>
<td>Total</td>
<td>156</td>
<td>148</td>
<td>120</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Higher than the 33%–50% Goldenberg, Libai, and Muller (2002) report. However, our sample is the most global of such studies. Of the 156 product-country combinations, 46% experience an average depth of 20% during the saddle and see a recovery to the original peak. These include 45% of kitchen/laundry products and 47% of information/entertainment products. These numbers correspond to the strict definition of the saddle used in Goldenberg, Libai, and Muller. We see censoring in some categories such as DVD players. In the censored cases, the saddle either begins at a later point or may never occur. The split hazard model can distinguish between these two possibilities.

Table 2 presents a description of the key statistics of timing, duration, and depth of the saddle. For the 148 product-country combinations that experience the start of the saddle, the average time from takeoff to the start of the saddle is roughly 9 years. The average penetration at the start of the saddle is 31%, which is similar to the 34% Golder and Tellis (2004) observe. The average time from takeoff to the start of the saddle is 6.7 years for information/entertainment products and 10.3 years for kitchen/laundry products. The average penetration at the start of the saddle is 26% for the information/entertainment products and 33% for kitchen/laundry products. The average decline in the first year of the saddle for information/entertainment products is 17%, compared with 10% for kitchen/laundry products.

The duration of the saddle is the time from the start of the saddle to the recovery, when the sales increase past the initial peak. We can trace such a recovery for 120 cases. For these 120 cases, the average duration is 8 years (6.6 years for the 36 information/entertainment products and 8.5 years for the 84 kitchen/laundry products that experience a recovery in sales). The relative depth of the saddle is 29%. The duration estimates are higher than the average duration of 5 years Goldenberg, Libai, and Muller (2002) report, while the relative depth estimates are comparable to the 32% Goldenberg, Libai and Muller report. The average penetration at recovery is 41%, with a standard deviation of 27.

Convergence over time. Prior research has indicated an increasing convergence in the year of takeoff over time (Chandrasekaran and Tellis 2008), which may be a result of the convergence in the year of commercialization or the underlying drivers over time. We find a similar “convergence,” or a decrease in the standard deviation of both the year of the saddle and the time from takeoff to saddle over time, for the countries that have experienced the saddle. Figure 6 plots the standard deviation in the year of the start of the saddle across product vintage (the year of first commercialization of each product category), as well as the standard deviation in the time from takeoff to saddle in years across product vintage. We observe a downward trend and a dramatic drop in the standard deviation of year of saddle over time. This drop indicates that various countries increasingly experience the start of the saddle at the same time. We see a downward but more gradual trend in the standard deviation in time to saddle. This drop indicates an increasing similarity across countries in the time span between takeoff and saddle. To understand the reasons behind the start of the saddle and the subsequent recovery, we next examine the estimates of the split population hazard model, separately for the start and end of saddle.

### Hazard of Start of Saddle

Prior literature has highlighted distinct differences across product classes in terms of their diffusion patterns (Chandrasekaran and Tellis 2008; Tellis, Stremersch, and Yin 2003). In our sample, we also find substantial differences in the descriptive statistics and occurrence of saddles across product class. Therefore, we examine the results of the split population hazard model separately by product class. Subsequently, we discuss the model’s performance. Web Appendix B (http://www.marketingpower.com/jmjuly11) presents the correlation matrixes. To examine a potential concern about the independence of product categories across countries, we also examine the correlations for the year of saddle, and time to takeoff, across countries. Although the correlations are high, they are not close to 1, indicating some independence across the categories.

### Information/entertainment products

Table 3 presents the results of estimating the hazard model for the start of saddle. Model 1 is the split-population model for information/entertainment products. The estimated probability of never seeing a saddle is 2% for information/entertainment products. The likelihood ratios test of whether c = 0 is imple-

---

**TABLE 2**

<table>
<thead>
<tr>
<th>Descriptive Statistics</th>
<th>Takeoff to Saddle (Years)</th>
<th>% Sales Decline at Saddle</th>
<th>Penetration at Saddle</th>
<th>Relative Depth (%)</th>
<th>Time to Recovery (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Information/Entertainment Products</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>6.76</td>
<td>-16.75</td>
<td>25.81</td>
<td>32</td>
<td>6.55</td>
</tr>
<tr>
<td>SD</td>
<td>2.50</td>
<td>17.05</td>
<td>21.98</td>
<td>13</td>
<td>3.45</td>
</tr>
<tr>
<td>Count</td>
<td>52</td>
<td>52</td>
<td>52</td>
<td>36</td>
<td>36</td>
</tr>
<tr>
<td><strong>Kitchen/Laundry Products</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>10.35</td>
<td>-9.88</td>
<td>32.90</td>
<td>28</td>
<td>8.43</td>
</tr>
<tr>
<td>SD</td>
<td>5.51</td>
<td>9.60</td>
<td>25.13</td>
<td>8</td>
<td>6.19</td>
</tr>
<tr>
<td>Count</td>
<td>96</td>
<td>96</td>
<td>96</td>
<td>84</td>
<td>83</td>
</tr>
<tr>
<td><strong>Overall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>9.09</td>
<td>-12.29</td>
<td>30.40</td>
<td>29</td>
<td>7.86</td>
</tr>
<tr>
<td>SD</td>
<td>4.97</td>
<td>13.08</td>
<td>24.36</td>
<td>10</td>
<td>5.56</td>
</tr>
<tr>
<td>Count</td>
<td>148</td>
<td>148</td>
<td>148</td>
<td>120</td>
<td>120</td>
</tr>
</tbody>
</table>
TABLE 3

Results of Split Population Model for Start of Saddle

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>(1) Information/Entertainment Products</th>
<th>(2) Kitchen/ Laundry Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product vintage</td>
<td>.038* (1.86)</td>
<td>.003 (–.50)</td>
</tr>
<tr>
<td>Product age</td>
<td>1.904*** (3.46)</td>
<td>.044 (.16)</td>
</tr>
<tr>
<td>Age square</td>
<td>–.049*** (–3.10)</td>
<td>–.001 (–.27)</td>
</tr>
<tr>
<td>Log(Product age)</td>
<td>–6.133*** (–3.00)</td>
<td>.881 (.33)</td>
</tr>
<tr>
<td>Economic contraction</td>
<td>.144 (.49)</td>
<td>.820*** (3.61)</td>
</tr>
<tr>
<td>Dispersion</td>
<td>–.033** (–1.97)</td>
<td>–.017 (–1.38)</td>
</tr>
<tr>
<td>Weighted patent counts</td>
<td>.0004** (2.24)</td>
<td>.001** (2.25)</td>
</tr>
<tr>
<td>Prior saddles</td>
<td>.082 (.70)</td>
<td>.220** (2.56)</td>
</tr>
<tr>
<td>Constant</td>
<td>–76.044* (–1.91)</td>
<td>–.869 (–.08)</td>
</tr>
<tr>
<td>Observations</td>
<td>400</td>
<td>727</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>–128.5</td>
<td>–236.1</td>
</tr>
</tbody>
</table>

*p < .1.
**p < .05.
***p < .01.

Notes: z–statistics are in parentheses.

FIGURE 6

Standard Deviation of Year of Saddle and Time from Takeoff to Saddle by Vintage

The results of the chi-bar-squared test statistic from the likelihood ratio test of $H_0$: $c = 0$ versus $H_1$: $c > 0$ finds that the Prob $\geq$ chi-bar2 = .06. We find that the split population model has a lower log-likelihood (–128.5), and a lower Akaike information criterion (AIC) statistic (275.91) than the log-likelihood

The results from Model 1 indicate that the coefficient of product age is positive and significantly different from zero, while age square and log age have negative and significant coefficients. The coefficient of prior saddles is not significantly different from zero. The effect of dispersion from the mean penetration at saddle is negative and significantly different from zero. This result leads us to reject the null hypothesis in favor of the alternative hypothesis $H_{A1}$ (a saddle is likely to occur during a discontinuity in the transition between the early and late markets). Therefore, chasms are likely to lead to the start of a saddle for information/entertainment products. The effect of economic contraction is not significantly different from zero. This result does not support $H_2$ (a saddle is likely to occur during periods of economic contractions). The coefficient of weighted patent counts is positive and significantly different from zero, supporting $H_3$ (a saddle is likely to occur during times of important technological advances). In summary, for information/entertainment products, we find support for two explanations leading to the saddle: chasms in adopter segments and technological cycles.

Kitchen/laundry products. Model 2 in Table 3 presents the results for estimating the hazard of the start of the sad-
dle for kitchen/laundry products. The estimated probability of never seeing a saddle is so small that the split population hazard model reduces to a standard proportional hazard model, which assumes $c = 0$. This result implies that all kitchen/laundry products are at risk for experiencing a saddle. Furthermore, this result has face validity in that a saddle occurs in 98% of the kitchen/laundry products.

In Model 2 for kitchen/laundry products, we do not find a significant effect for product vintage or the specifications for product age. We find a positive and significant effect for prior saddles, indicating that the hazard of a saddle increases significantly with the number of prior saddles in other countries. We do not find a significant effect for dispersion from mean penetration; thus, we do not find support for $H_{A1}$. The positive and significant coefficient for economic contraction indicates that the hazard of the saddle is significantly higher during periods of economic contractions, consistent with $H_2$. The coefficient of weighted patent counts is positive and significantly different from zero. Therefore, the hazard of a saddle increases significantly during times of important technological advances, consistent with $H_3$. In summary, for kitchen/laundry products, we find empirical support for two explanations, controlling for duration dependency and cross-country learning effects.

**Model performance and out-of-sample prediction.** The likelihood ratio tests and consistency of the model with the hypotheses provide support for the validity of the model. To ascertain the out-of-sample predictive validity of the hazard model, we use a jackknife approach (similar to Golder and Tellis 1997) in the following way. We reestimate Equation 1 with the variables showing significant effects, $n$ times, for each of the $n$ products for which a saddle occurs, each time excluding one product. Then, we use the estimated parameters of the model to predict the hazard of the start of the saddle for the excluded product. The linear prediction is based on the value of the independent variables of the excluded product for that year and country. We determine the estimated year of the start of the saddle to be when the probability of no saddle (the survival probability) falls below 60%. The estimate for survival probability $S_{it}$ after one year is $(1 - h_{i1})$, after two years is $(1 - h_{i1})(1 - h_{i2})$, and so on (Golder and Tellis 1997). Recall that we use a split population hazard model. For this model, we account for the split population probability by refining the survival probability as $c + (1 - c) \times S_{it}$, where $c$ is computed from each iteration of the estimation.

Using this approach, we make a prediction for the start of the saddle, for each product-country combination. We compute the mean absolute deviation (MAD) in start of the saddle according to the differences between the predicted year and actual year of the start of the saddle across these product–country combinations. We carry out this analysis for four recent products in 19 countries, which actually experience a saddle. The mean absolute deviation in predicted start of the saddle is 2.4 years. This error is comparable to similar out-of-sample predictions hazard models, such as 2 years in Golder and Tellis (1997) and 2.5 years in Srinivasan, Lilien, and Rangaswamy (2005).

### Hazard of Recovery

The analysis of the hazard of recovery uses the 148 product–country combinations that experience the start of the saddle. We observe a recovery in 120 product–country combinations. Again, we run the split population hazard model separately by product class. We control for the effects of time using three variables: “time since the start of the saddle” to account for duration dependence, the “year of commercialization” of a product in a country, and the “time from commercialization to saddle” to account for any dependence of duration with the prior event. We control for cross-country learning effects by including a variable “prior recoveries,” which is the number of recoveries that occur in the previous year in other countries for each product. We examine the impact of business cycles and technological cycles using the measures described previously. For business cycles, we use the variable “economic expansion,” rather than “economic contraction” for ease of exposition.

Table 4 shows the estimates of the model for recovery for information/entertainment and kitchen/laundry products. For information/entertainment products (Model 3), all three time indicators are significantly different from zero. Time since the start of saddle has a positive and significant coefficient. This result indicates that as the time since the start of the saddle increases, the product is more likely to see a recovery. The coefficient of year of commercialization is negative and significantly different from zero. This result indicates that a recovery is less likely in the observation period for those products that were commercialized later. Both these results are validated by the high censoring in recovery for newly introduced information/entertainment products. For example, in the case of the DVD player, we observe a recovery in just one of ten countries in which the saddle begins. The coefficient of time from commercialization to saddle is negative and significant, indicating that as the time to saddle decreases, the hazard of recovery increases. The estimate for prior recoveries is positive and significant, indicating that a prior recovery in another coun-

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>(3) Information/Entertainment Products</th>
<th>(4) Kitchen/Laundry Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year of commercialization</td>
<td>$-0.220^{* * *}$ (−2.73)</td>
<td>$-0.022$ (−1.27)</td>
</tr>
<tr>
<td>Time since start of saddle</td>
<td>$0.222^{* *}$ (3.73)</td>
<td>$0.009$ (0.51)</td>
</tr>
<tr>
<td>Economic expansion</td>
<td>$0.253$ (0.73)</td>
<td>$0.440^{*}$ (1.82)</td>
</tr>
<tr>
<td>Weighted patent counts</td>
<td>$0.002^{* *}$ (2.54)</td>
<td>$0.00$ (0.04)</td>
</tr>
<tr>
<td>Time from commercialization to saddle</td>
<td>$-0.165^{* *}$ (−2.05)</td>
<td>$-0.017$ (−0.85)</td>
</tr>
<tr>
<td>Prior recoveries</td>
<td>$0.270^{* *}$ (2.44)</td>
<td>$-0.341^{*}$ (−1.87)</td>
</tr>
<tr>
<td>Constant</td>
<td>$433.038^{* * *}$ (2.72)</td>
<td>$4.794$ (1.19)</td>
</tr>
<tr>
<td>Observations</td>
<td>362</td>
<td>837</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>$-104.3$</td>
<td>$-242.0$</td>
</tr>
</tbody>
</table>

Notes: $z$–statistics are in parentheses.
try may trigger a recovery in the focal country. The coefficient of economic expansion is not significantly different from zero. The coefficient for weighted patent counts is significant and positive, indicating that significant technological advances that occur during the saddle triggers recovery. However note that this variable has a positive sign for both the start of the saddle and the recovery, contrary to what may be expected. We discuss this result in a subsequent section.

Furthermore, the estimate of $c$ is .11, indicating that 11% of the product–country combinations may never experience a recovery in sales. The results of the chi-bar test statistic from the likelihood ratio test of $H_0: c = 0$ versus $H_1: c > 0$ finds that the Prob $\geq$ chibar2 = .03. For example, VCRs in Portugal and Spain experienced some growth after the start of the saddle but never recovered their initial peaks. Both products experience a decline in product sales by the end of the observation period.

In contrast, for kitchen/laundry products (Model 4), we find we only gain some insight on what may drive their recovery with the variable economic expansion ($\rho < .10$). To provide further support for this result, 60% of the products in this category see a recovery during times of economic expansion. The estimate of $c$ is close to 0. This result implies that all kitchen/laundry products eventually experience recovery.

**Test of Robustness**

**Alternative measure of saddle.** We first test the robustness of our results to an alternate measure of the start of the saddle proposed by Golder and Tellis (2004) and Stremerch and Tellis (2004), which they term as slowdown. These authors operationalize start of the saddle as the first year of two consecutive years, after takeoff, in which sales are level with, or lower than the highest previous sales. We find 159 occurrences of the event using this rule, and in 25 cases (16%), we identify an earlier year of the start of the saddle with this new measure. We rerun the regressions using this new rule for the start of the saddle. For both product classes, the split population model does not converge, and we use the standard discrete-time proportional hazards model. For information/entertainment products, the results (Model 1 in Web Appendix C at http://www.marketingpower.com/jmjuly11) show support for the chasms theory but not the theories of economic or technological cycles. For kitchen/laundry products (Model 2 in Web Appendix C), the results show support for all three theories. However, the measure for the start of the saddle does not require a fixed percentage drop for the saddle to occur and thus is a weaker measure. Moreover, the model based on this measure is unable to detect a significant proportion where the event never occurs. Thus, our original measures provide a better test of the three theories.

**Alternative measure of economic cycles.** We test the robustness of the analysis to an alternate measure capturing economic cycles, using economic growth rather than economic contraction, which is based on the Hodrick and Prescott (1997) filter. We use the percent growth rate in GDP to capture economic cycles, similar to Golder and Tellis (2004). Next, we create an indicator variable termed “economic growth contraction” for the state of the economy. We set this indicator variable to 1 for decreases in the growth rate of GDP corresponding to contractions and 0 otherwise. A positive coefficient for this measure in the hazard model would imply that the likelihood of a saddle increases during periods of lower economic growth. The results for information/entertainment products indicate support for the explanations of chasms and technological cycles, similar to Table 3, as well as economic cycles (Model 3 in Web Appendix C at http://www.marketingpower.com/jmjuly11). For kitchen/laundry products (Model 4 in Web Appendix C), using the discrete-time proportional hazard model, we find support for the theories of economic and technological cycles only, consistent with the prior results.

**Alternative hazard model specification.** We examine the robustness of the analysis of the start of the saddle to the presence of unobserved heterogeneity. Using the same data set, we estimate by maximum likelihood two discrete time proportional hazards regression models, one for kitchen/laundry products, one for information/entertainment products, incorporating a gamma mixture distribution to summarize unobserved individual heterogeneity.

Specifically, the discrete time hazard rates for product–country combination $i$ in each duration interval $t = 1, ..., t_i$ are as follows:

$$h_{it} = 1 - \exp\{-\exp[D(t) + bX_{it} + \log(e_i)]\},$$

where $X_{it}$ is a vector of covariates, $b$ is a vector of parameters to be estimated, $D(t)$ is a function describing duration dependence in the hazard common to each $i$, and $e_i$ is a Gamma distributed random variable with unit mean and variance $\nu = \sigma^2$. We specify a flexible functional form of the duration dependence as $D(t) = t + t^2 + \log(t)$, consistent with Table 3. We use the PGMHAZ procedure developed by Jenkins (1997) in STATA to estimate the models.

The results are in Models 5 and 6 in Web Appendix C. The size of the variance of the gamma mixture distribution relative to its standard error suggests that unobserved heterogeneity is not significant in this data set. The split population models in Table 3 have lower log-likelihoods and AIC scores, in addition to being able to detect the proportion of products that never experience the saddle.

**Inclusion of product-specific and regional dummies.** We include product specific dummies to capture the effects of any product-specific variable not accounted for in our data (Models 7 and 8 in Web Appendix D at http://www.marketingpower.com/jmjuly11). The results for both information/entertainment and kitchen/laundry products remain consistent with prior results. The split population hazard model for information/entertainment products do not detect a significant proportion of cases in which the saddle does not occur. Similarly, we include region-specific dummies and the results remain consistent (Models 9 and 10 in Web Appendix D). The results remain substantially similar to prior results. The split population hazard model for information/entertainment products do not detect any significant proportion of cases in which the saddle do not occur.

**Inclusion of a different specification of time.** We test the robustness of the analysis to the inclusion of a linear
Why does the saddle occur? Our review of the literature identifies three explanations for the saddle: chasms in adopter segments, business cycles, and technological cycles. For kitchen/laundry products, we find support for two explanations: business cycles and technological cycles. For information/entertainment products, we find support for two explanations: chasms in adopter segments and technological cycles.

We make an important theoretical contribution by building a common bridge across the differing explanations for the saddle. Prior research has posited conflicting explanations for the saddle. Golder and Tellis (2004) find that GDP growth, which they use to measure information cascades, has an important impact on the saddle, while Goldenberg, Libai and Muller (2002) support the chasms explanation. The latter authors also mention that technological factors may drive the saddle but do not test this explanation. By analyzing product classes separately, we find that economic cycles, technological cycles, and chasms in adopter segments are all valid explanations but that they have a differential impact across product classes.

The impact of business cycles on the occurrence of the saddle is significant for kitchen/laundry products but not significant for information/entertainment products. There are two probable reasons for these findings. First, in general, kitchen/laundry products are higher-priced than information/entertainment products and thus are more susceptible to economic contractions. Second, information/entertainment products are more visible and socially significant and thus less susceptible to economic contractions. Moreover, we find that for information/entertainment products, recovery is not related to periods of economic expansion. However, for kitchen/laundry products, recovery is more likely to occur during periods of economic expansion. This finding supports prior studies that have established a close relationship between sales and economic growth (e.g., Deeleersnyder et al. 2004). However, our contribution is that we found an asymmetric impact of economic cycles on the two classes of products. Moreover, compared with the typical length of economic contractions lasting anywhere between 6 and 16 months (reported by the National Bureau of Economic Research) the duration of the saddle is substantially longer lasting—on average, 6.5 years for information/entertainment products and 8.5 years for kitchen/laundry products.

The impact of dispersion, capturing the communication chasm between adopter segments, seems to matter for information/entertainment products but not kitchen/laundry products. A probable reason is that the differences in the innovativeness and characteristics across consumer adopter segments may be stronger for information/entertainment products, which tend to be high technology products. For kitchen/laundry products, which are less visible, word-of-mouth communication may be stronger and sustained and thus less discontinuous.

We make an important contribution by modeling the second boundary point of the saddle: recovery. For the categories that do experience the start of a saddle, we examine whether recovery occurs and the factors driving such a recovery, using a second split population discrete time hazard model. The split population hazard model indicates that a full recovery may not always occur for information/entertainment products. Thus, what may appear to be a temporary saddle may in certain conditions lead to a permanent decline in the product category. We observe this phenomenon in some instances for the VCR product category and conjecture that the likely recovery was thwarted by the takeoff of sales of the DVD player. Similarly, our operationalization of both boundary points allows us to account for potential saddles in recent products, such as the DVD player. In the United States, a lead market, our data indicate that DVD players have seen both the slump and the recovery. Such a recovery is widely expected in other countries, from our reading of
individual countries’ product reports. Furthermore, from a modeling perspective, our analysis indicates that it is important to account for the notion that certain products may never experience the start of a saddle, or if they do, may never experience a recovery to the former peak. Our study is the first to use the split population model to examine these turning points in the product life cycle.

**Implications**

The findings of our study may provide managers with a better understanding on the processes that underlie diffusion in the early stages of the product life cycle. There are four main implications of these findings. First, our study indicates that the saddle is a fairly pervasive phenomenon that affects most new products. Thus, growth is not perennial. At the same time, recovery is also very likely. We provide a model to determine the hazard of these two events and a set of explanatory variables that determine what drives these events. Using the values of the independent variables for a new product and estimates of the parameters of the significant coefficients of the hazard model published here, managers can use the model to predict the hazard of the start or end of the saddle for their own new product. In addition, this study provides statistics that indicate the occurrence, depth, and duration of the saddle. Managers can use such predictions and statistics to better plan manufacturing, inventory, and marketing for recovery from the phenomenon or to sustain continuity of new product growth.

Second, managers should be cognizant of the systematic differences between kitchen/laundry products (and perhaps other similar utilitarian products) and information/entertainment products. Although product managers may worry that an economic recession may lead to a reversal in growth of a new product category, our analysis suggests that producers of information/entertainment products may need to worry less about the specific impact of recessions, compared to producers of kitchen/laundry appliances. However, they may need to devote more attention to generating a sustained word-of-mouth momentum. Producers and marketers of kitchen/laundry products may need to pay greater attention to the impact of economic cycles.

Third, our findings point out a dramatic convergence in some aspects of the saddle across countries. These findings, coupled with previous findings on convergence of takeoff of new products, suggest increasing synchronization of new product growth across countries. We suspect that this phenomenon could result from greater globalization in addition to synchronization of launch strategies across countries. Although global companies can hope to balance slowing sales in one country with growth in another country, simultaneous or near saddles may pose a grave challenge to new product managers, especially of kitchen/laundry products. Global marketing managers should be cognizant of saddles and recoveries in all countries. Fourth, our analysis suggests that technological innovations are an important driver of the recovery from a saddle. Thus, managers should consider the importance of innovation for recovery, in addition to the traditional marketing mix variables of pricing and advertising.

**Limitations**

This study has some limitations. First, our dispersion measure is a heuristic that does not directly capture the discontinuities in word-of-mouth communication across adopter segments. Instead, it is a proxy that captures the location of the chasm. However, our results map on to some of the key findings from multi-segment sales diffusion models from earlier studies (e.g., Goldenberg, Libai, and Muller 2002; Muller and Yoge 2006). There is a need for in-depth surveys to trace and analyze such points of transitions and contribute to our understanding of chasms. Second, our data do not enable us to control for several marketing variables such as price, advertising, and distribution. Third, we do not analyze the impact of entry and exit of firms during takeoff and growth, because these data are not available across countries for this extended time period. Fourth, we could not measure information cascades directly as an explanation of the saddle. All these remain useful areas for further research.

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