GETTING A GRIP ON THE SADDLE: CHASMS OR CYCLES?

Deepa Chandrasekaran

Gerard J. Tellis

Deepa Chandrasekaran is an Assistant Professor at Lehigh University, 621 Taylor St., Bethlehem, PA (Email : dec207@lehigh.edu, Tel: 610-758-6582) and Gerard J. Tellis is Director of Center for Global Innovation, Neely Chair of American Enterprise, and Professor of Marketing at the Marshall School of Business, University of Southern California, Los Angeles, CA 90089. (Email: tellis@usc.edu; Tel: 213-740-5031).

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Abstract

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. This paper tests for the generalizability of the saddle across products and countries and for three rival explanations: chasms in adopter segments, business cycles, and technological cycles. The authors 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 10 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 9 years post-takeoff, at a mean penetration of 30%, lasting for 8 years with a 29% drop in sales at its depth. Results support explanations of chasms and technological cycles for information/entertainment products and business cycles and technological cycles for kitchen/laundry products. The authors discuss 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 papers empirically document 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 US. 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 within the US.

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; while 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 GNP.

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 over-committed manufacturing capacity, built large inventories, or expanded their sales staff during the period of growth. Worse still, if they believe the phenomenon to be permanent to their product, they may drastically reduce capacity, inventory, or staff, and suffer from missed orders and sales once the growth resumes.

This study aims to develop a better understanding of the phenomenon of the saddle. In particular, it seeks 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

This section first defines the terms in use and then discusses three alternate theories or causes of the saddle that have been proposed in the prior literature: chasms in adopter segments, economic cycles, and technological cycles.

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" refer to the total of all consumer purchases of all brands of a specific product.

"Takeoff" is defined as 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, i.e., that simply failed. Second, it can help distinguish characteristics of the saddle relative to 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

The product life cycle is viewed 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) based on the normal penetration curve. The traditional view has been that the diffusion process can be fuelled 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 debate 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 different 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 possess very different characteristics and needs. Hence 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 that product offerings appealing to technology enthusiasts need not appeal to the mainstream market; hence 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 based on the timing of adoption of a new product. They argue that weak communication between the early market and the main market may lead these segments to adopt products at substantially differing rates, that is, the main market takes off *after* the early market peaks, thus creating a saddle (Figure 4, adapted from Goldenberg, Libai and Muler 2002). Following this logic, the literature suggests the following hypotheses:

> 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 again the null hypothesis:

> Null: H_{01}: 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, prior research has 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 grow. However, a saddle may start even in the growth stage due to economic contractions. For instance, Figure 5 shows the sales of dishwashers (denoted by the dotted line) and economic contractions (denoted by the dark bars) in Germany. Note, sales peak in 1973, and the saddle starts in 1974, coinciding with the economic contraction of 1974.

The saddle may 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 expenditure, 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 may 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).

The above 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; Holak et al 1987; Doyle and Saunders 1985). John, Weiss and Dutta (1999) argue that while significant improvements may prompt purchases once 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). Further, 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. Hence, we may expect a saddle to start during times of multiple important technological advances, due to 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 above argument suggests the following testable hypothesis:

H_3: A saddle is likely to occur during times of important technological advances.

Method

This section describes the model, measures, and data sources.

Model

Since 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 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; Golder and Tellis 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; Allison 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 the start of the saddle). We next describe the events and the split population formulations of the model.

Events. We model two events: 1) the start of saddle given takeoff and 2) the recovery given the start of saddle. The hazard of the start of a saddle is the probability that a product-country combination, i, experiences a start of the saddle in time, t, given 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 to 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 till the series gets censored. For each of these

observations, the dependent variable takes on a value 1 if the event occurs during that time period, otherwise 0. Explanatory variables take on whatever value occurs during that time period. For the proportion of products where we have observed the event, we have duration data that constitute a complete series. However, for the products where 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 or not, where A_i=1 means event occurrence and A_i=0 means 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 where the event is observed during a given time interval, the contribution to the likelihood is (1-c)*(probability of survival to end of previous time interval)*(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. Hence the contribution to the likelihood from a censored survival time is c + (1-c)*(probability of survival to end of the given time interval).

Let d_i be the observable binary censoring indicator indicating whether or not the i^{th} product-country combination experiences the event in (0, t), with d_i =1 if the event occurs and d_i = 0 if right-censored. We can then estimate by maximum likelihood the proportion of product-country combinations which never experience the event, together with the parameters characterizing the hazard rate for the remainder of the population. Hence, the Likelihood contribution for product-country combination i with survival time *t* is

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

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

(2) $$S_{it} = \prod_{j=1}^{t} (1 - h_{ij})$$

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

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 later 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 next sub-section.

Hence, the hazard function consists of time-varying covariates, time-invariant covariates, as well as 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

This section describes the measures to assess takeoff, the boundary points of saddle, chasms in adopter segments, economic cycles, technological cycles, and the control variables.

Year of takeoff. We measure takeoff using the rule proposed by Tellis, Stremersch and Yin (2003), who define takeoff 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 which is 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, where 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 instance, 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 mentioned in the theory section, prior research has classified adopter categories based on the penetration curve (.e.g., Mahajan, Muller and Srivastava 1990; Mahajan and Muller 1998; 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., see Chandrasekaran and Tellis 2007; Muller and Yogev 2006).

So, a *mean penetration level*, for each product, that reflects adoption by the early market and non-adoption by the late market, 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 to be located. To resolve this problem, we can take advantage of the fact that we have data across countries for each product. Based on the literature cited above we make the reasonable assumption that adopter segments are likely to be common across countries but unique for each product.

So, we first 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:

$$Dispersion_{it} = Abs(Penetration_{it-1} - Meanpen) \quad (4)$$

Note that we use penetration in the year before, and drop the focal country from the calculation of meanpen, to allay concerns that the measure is tautological. Hypothesis testing (e.g. Sawyer & Peter, 1983), tests 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, then the hazard of a saddle should not increase as distance from meanpen decreases. On the other hand, if the testing of this hypothesis results in a negative coefficient in the hazard model, that would lead us to reject the null and conclude in favor of the chasms theory captured by hypothesis H_{A1}.

Business cycles. We construct a measure to capture economic contractions and expansions based on recent marketing literature (Deleersnyder et al. 2009; Deleersnyder et al. 2004; Lamey et al. 2007). These studies estimate business cycles by extracting the cyclical component from the 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). The HP filter first 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, based on the HP filter.

We next 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. We set this indicator variable to 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. Patents have been used in prior research as an important indicator of technological activities and innovation in an industry (e.g., Ahuja and Katila 2001; Tellis, Prabhu and Chandy 2009). The US patent collection contains the list of all patents issued by the US Patent and Trademark Office (USPTO) since 1974. We consider US patents that have been granted to be a valid indicator of technological activity for the product across countries because most important innovations either originated in the US or the firms involved have filed US patents to protect this large market (Tellis, Prabhu and Chandy 2009). For each product, we extract all US patents from Delphion's patent database, sort the patents based on the Inventive IPC 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 was cited by other patents. Trajtenberg (1990) finds a close association between citation-based patent indices and the social value of innovations from an empirical analysis of a particular innovation (Computed Tomography scanners). Further, 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. Hence, 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.

$$WPC_t = \sum_{j=1}^{n_t} (1 + C_j) \quad (5)$$

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 allows us to take into account both the number of citations and the count of 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 just communication behaviors among consumers and environment factors within a country but also by 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; Everdingen, Stremersch and Fok 2009). We control for cross-country learning effects, using "prior saddles", which is the number of saddles that occur in the *previous* year in other countries for each product.

Prior research suggests that greater inter-connectivity, 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 in which an innovation was commercialized across all countries in the sample. Finally, we control for within-innovation duration dependence, by considering "product age", operationalized as the time elapsed since the product was commercialized in each country. Following Agarwal and Bayus (2002) and Chandrasekaran and Tellis (2008), we use the word "commercialization" to reflect the fact that databases seem to include a product only when it has become available to the mass market or achieved some minimal level of sales or penetration. We look for the earliest year of commercialization for each country from the sales and penetration data for each product in each country. We further validate each of these dates by checking that penetration in the year of commercialization has not exceeded 0.25%, which is a stricter rule than the 0.5% rule recommended by Tellis, Stremersch and Yin (2003).

Data and Sources

We assemble a database on historical sales and market penetration of both kitchen/laundry products and information/entertainment products. We obtain data on 6 kitchen/laundry products (dishwashers, dryers, freezers, microwave ovens, refrigerators and washing machines) and 4 information/entertainment products (DVD players, PCs, VCRs, and video cameras). We track these products across 16 European countries (Austria, Belgium,

Denmark, Finland, France, Germany, Greece, Italy, Ireland, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and U.K.), Japan, Canada and the US, from 1950 through 2008, for a total of over 1300 observations. For the U.S., in some cases, we had data extending before 1950. We put together this detailed time-series data, 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 US, Consumer Europe, European Marketing Data and Statistics), and proprietary industry data.

We exclude product-country combinations for which we have less than 10 years of data. We also exclude product-country combinations for which the sales data in the first year exceeds 100 (in '000s of units) or the penetration in the first year exceeds 0.5%. For the US, we drop washing machines, where we do not have early enough data to estimate takeoff. As can be seen from Web Appendix W1, 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 paper 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 W1).

For calculating the time of economic contractions across countries, we use a measure for Real GDP from the Groningen Growth and Development Centre and the Conference Board, Total Economy Database, (http://www.ggdc.netis). We use Total GDP, in millions of 1990 US$ (converted at Geary Khamis PPPs). We determine GDP for the pre 1950 years from

Statistics on World Population, GDP and per-capita GDP, 1-2006 AD (www.ggdc.net/maddison).We obtain patent data from the Delphion database. The Delphion database (www.delphion.com) is a subscription-based database that contains detailed historical records on patents granted and applied for both in the US and other countries, and has been used in prior studies (e.g., Tellis, Prabhu and Chandy 2009).

Results

This section presents descriptive statistics, results of the estimation of the hazard models for start and recovery of saddle, and tests of robustness.

Descriptive Statistics

This section describes characteristics of the saddle and its convergence over time.

Characteristics of the saddle. Out of the 156 product-country combinations where 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% reported in Golder and Tellis (2004), and similar to the 86% reported by Goldenberg et al (2006). Out of the 148 product-country combinations that see the start of the saddle, 120 cases (81%), experience a recovery to the previous peak. Both the start and a recovery are observed in 86% of kitchen/laundry products and 61% of information/entertainment products (Table 1). The numbers observed for the latter are somewhat higher than the 33-50% reported in Goldenberg, Libai and Muller (2002). However, our sample is the most global of such studies.

46% of the 156 products experience an average depth of 20% during the saddle, as well as 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 (2002).

We see censoring in some categories such as DVD players. In the censored cases, either the saddle may start at a later point in time or the saddle may never occur. The split hazard model can distinguish between these two possibilities.

Table 2 gives a description of the key statistics of timing, duration, and depth of the saddle. For the 148 products 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% seen in Golder and Tellis (2004). 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 to 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 grow 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 reported in Goldenberg, Libai and Muller (2002), while the relative depth estimates are comparable to the 32% reported in Goldenberg, Libai and Muller (2002). The average penetration at recovery is 41% with a standard deviation of 27.

Convergence over time. Prior research has indicated a growing convergence in the year of takeoff over time (Chandrasekaran and Tellis 2008), which may be due to 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 see 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 a growing 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 too find substantial differences in the descriptive statistics and occurrence of saddles across product class. Hence, we examine the results of the split population hazard model separately by product class. Subsequently, we discuss the model's performance. The correlation matrices are in Web Appendix W2. 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. While the correlations are high, they are not close to 1, indicating some independence across the categories.

Information/entertainment products. Table 3 gives 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 implemented as a boundary-value test (Jenkins, 2001). The results of the chi bar-squared test statistic from the likelihood ratio test of H0: c = 0 versus H1: c > 0 finds that the Prob >= chibar2 =.06. We find that the split population model has a lower log-likelihood (-128.5), and a lower AIC statistic (275.91) than the log-likelihood (-129.57) and AIC (277.13) reported from a standard discrete time proportional hazards model estimated on the same data. These results justify the appropriateness of the use of the split-population hazard model instead of the standard hazard model.

The results from Model 1 indicate that the coefficients 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 and conclude 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). Hence, 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 find support for 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. The results for estimating the hazard of the start of the saddle for kitchen/laundry products are in Model 2 of Table 3. 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. Further, 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. Hence, 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. Hence, 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. The likelihood ratio tests and consistency of the model with the hypotheses provide support for the validity of the model. In addition, we present the results of out-of-sample predictive validity.

Out–of–sample prediction. We use a jackknife approach (similar to Golder and Tellis 1997) to ascertain the out-of-sample predictive validity of the hazard model, in the following way. We re-estimate Equation 1 with the variables showing significant effects, n times, for each of the n products that see a saddle, 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 1 year is $(1\text{-}hi_1)$, after 2 years is $(1\text{-}hi_1).(1\text{-}hi_2)$ 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 $c + (1\text{-}c)*S_{it}$, 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 based on 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 4 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. Once 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", as opposed to "economic contraction") for ease of exposition.

Table 4 gives 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 a recovery is less likely within 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 instance, in the case of the DVD player, we observe a recovery in just one out of ten countries in which the saddle starts. 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 country 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. Note however 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.

Further, the estimate of c is 0.11, indicating that 11% of the product-country combinations may never experience a recovery in sales. The results of the chi bar-squared test statistic from the likelihood ratio test of H0: c = 0 versus H1: c > 0 finds that the Prob >= chibar2 = 0.03. For example, VCRs in Portugal and Spain experience some growth after the start of the saddle, but never recover 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 ($p<.10$). 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

This section tests the robustness of the results to an alternate measure of the saddle, an alternate measure of economic contraction, an alternate hazard model specification incorporating unobserved heterogeneity, the inclusion of dummy variables and a different specification of time.

Alternate 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 Stremersch 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 W3) show support for the chasms theory, but not the theories of economic or technological cycles. For kitchen/laundry products (Model 2 in Web Appendix W3), 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 hence is a weaker measure. Further, the model based on this measure is unable to detect a significant proportion where the event never occurs. Hence, our original measures provide a better test of the three theories.

Alternate measure of economic cycles. We test the robustness of the analysis to an alternate measure capturing economic cycles, based on economic growth, instead of economic contraction which was 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). We next 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 W3). For kitchen/laundry products (Model 4 in Web Appendix W3), 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:

$$h_{it} = 1 - \exp(-\exp(D(t) + bX_{it} + \log(e_i))) \quad (6)$$

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 $v = \sigma^2$. 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 W3. 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, as well as 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 W4). 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 where the saddle does not occur.

Similarly, we include region specific dummies and the results remain consistent (models 9 and 10 in Web Appendix W4). 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 where 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 specification of time (D(t)=t) in the hazard model (models 11 and 12 in Web Appendix W4). The results for information/entertainment products remain consistent with prior results. We determine a c of 6% with a Prob>=Chibar2=.00. The results for kitchen/laundry products are substantially similar. The coefficient of dispersion is now negative and significantly different from zero, indicating support for all three theories for kitchen/laundry products.

Discussion

This section discusses the key findings and lists the contributions, implications, and the limitations of this paper.

Key Findings

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. We model both turning points of the saddle. We explore the generalizability

of the saddle across an extensive data set of 156 product-country combinations (from 10 categories across 19 countries) over several decades. This presents as yet the most comprehensive study of this phenomenon. Our key empirical findings are as follows.

1. The saddle is quite pervasive across countries. The onset of the saddle occurs in 148 of 156 product-country combinations.
2. The average time from takeoff to start of the saddle is 9 years, and average depth of the saddle is 29%. The average penetration at saddle is 26% for the 52 information/entertainment products that experience a saddle, and 33% for the 96 kitchen/laundry products that experience a saddle.
3. The duration of the saddle is 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.
4. There is a growing convergence in the year of the saddle and the time from takeoff to saddle over time and across countries.
5. For the start of the saddle, results support the explanations of chasms and technological cycles for information/entertainment products and the explanations of business cycles and technological cycles for kitchen/laundry products.
6. Recovery to the initial peak occurs in 120 of the 148 product-country combinations that experience a saddle, with the others being censored.
7. The results indicate that a recovery for information/entertainment products is influenced by the year of commercialization, time from the start of the saddle, time from commercialization to the start of the saddle, and technological cycles, but not economic expansions; while a recovery for kitchen/laundry products may be influenced by economic expansions.

Contributions

Why does the saddle occur? Based on a review of the literature, we identify three key 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, kitchen/laundry products are generally higher-priced than information/entertainment products and so more susceptible to economic contractions. Second, information/entertainment products are more visible and socially significant and so less susceptible to economic contractions. We further 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. Deleersnyder et al 2004). However, our contribution is the finding of an *asymmetric* impact of economic cycles on the two classes of products. Moreover, compared to the typical length of economic contractions lasting anywhere between 6 and 16 months, reported by the NBER, 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 rather than 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 hence 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 or not 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 US, a lead market, our data indicates 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.

Further, 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 study to use the split population model to examine these turning points in the product life cycle.

Implications

The above findings 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 the 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. While 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 earlier 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 as well synchronization of launch strategies across countries. While 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 as well as 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 Yogev). 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, as this data is 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 future research.

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TABLE 1
Saddle Occurrences across Products

Products	Applicable Cases	Start	Recovery	Mean Year Of Saddle	Range-Year Of Saddle
Dishwashers	16	16	15	1980	26
Dryers	18	17	14	1983	45
Freezers	15	15	13	1975	39
Fridges	14	14	14	1966	42
Microwave ovens	18	18	12	1993	19
Washing Machines	16	16	16	1975	19
PCs	15	15	15	1989	8
VCRs	15	15	11	1988	14
Video cameras	15	12	9	1993	5
DVD players	14	10	1	2005	4
Total	156	148	120		

TABLE 2
Descriptive Statistics

		Takeoff To Saddle (Years)	% Sales Decline At Saddle	Penetration At Saddle	Relative Depth (%)	Time To Recovery (Years)
Information/ entertainment products	Mean	6.76	-16.75	25.81	32	6.55
	SD	2.50	17.05	21.98	13	3.45
	Count	52	52	52	36	36
Kitchen/ laundry products	Mean	10.35	-9.88	32.90	28	8.43
	SD	5.51	9.60	25.13	8	6.19
	Count	96	96	96	84	83
Overall	Mean	9.09	-12.29	30.40	29	7.86
	SD	4.97	13.08	24.36	10	5.56
	Count	148	148	148	120	120

TABLE 3
Results of Split Population Model for Start of Saddle

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

Notes:
z-statistics in parentheses
*** p<.01, ** p<.05, * p<.1

TABLE 4
Results of Split Population Hazard Model for Recovery

Explanatory Variables	(3) Information/ Entertainment Products		(4) Kitchen/Laundry Products	
Year of commercialization	-.220***	(-2.73)	-.022	(-1.27)
Time since start of saddle	.222***	(3.73)	.009	(.51)
Economic expansion	.253	(.73)	.440*	(1.82)
Weighted patent counts	.0002**	(2.54)	.000	(.04)
Time from commercialization to saddle	-.165**	(-2.05)	-.017	(-.85)
Prior recoveries	.270**	(2.44)	-.341*	(-1.87)
Constant	433.038***	(2.72)	4.794	(1.19)
Observations	362		837	
Log likelihood	-104.3		-242.0	

Notes:
z-statistics in parentheses
*** p<.01, ** p<.05, * p<.1

FIGURE 1
Saddle in New Product Sales

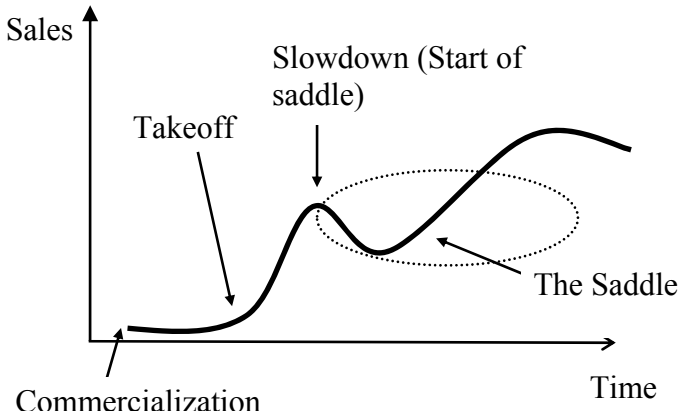


FIGURE 2
Saddles Observed in Sales of PCs and Microwave Ovens

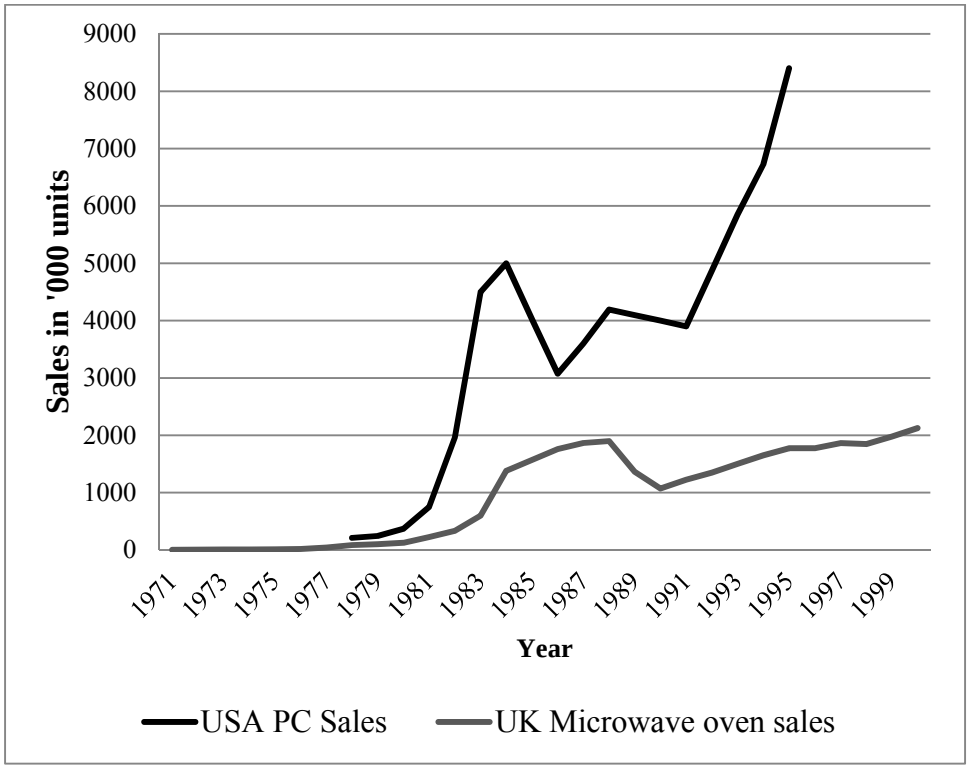


FIGURE 3
Chasms in Adopter Segments

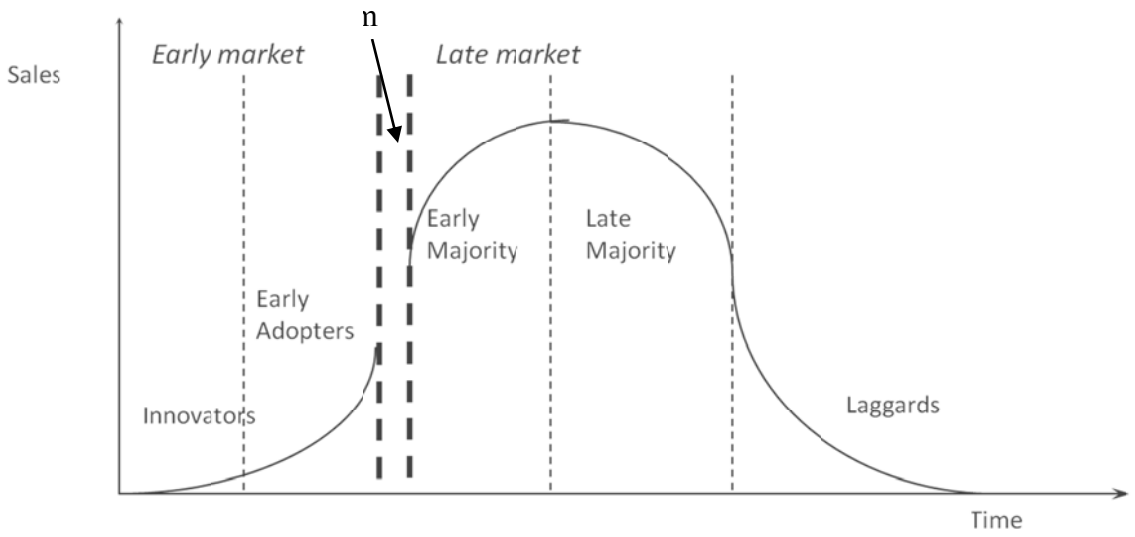


FIGURE 4
Saddle Due to a Chasm

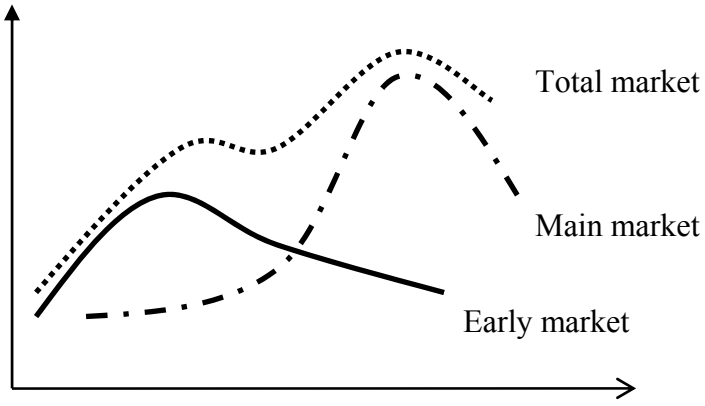


FIGURE 5
Saddle and Economic Contractions

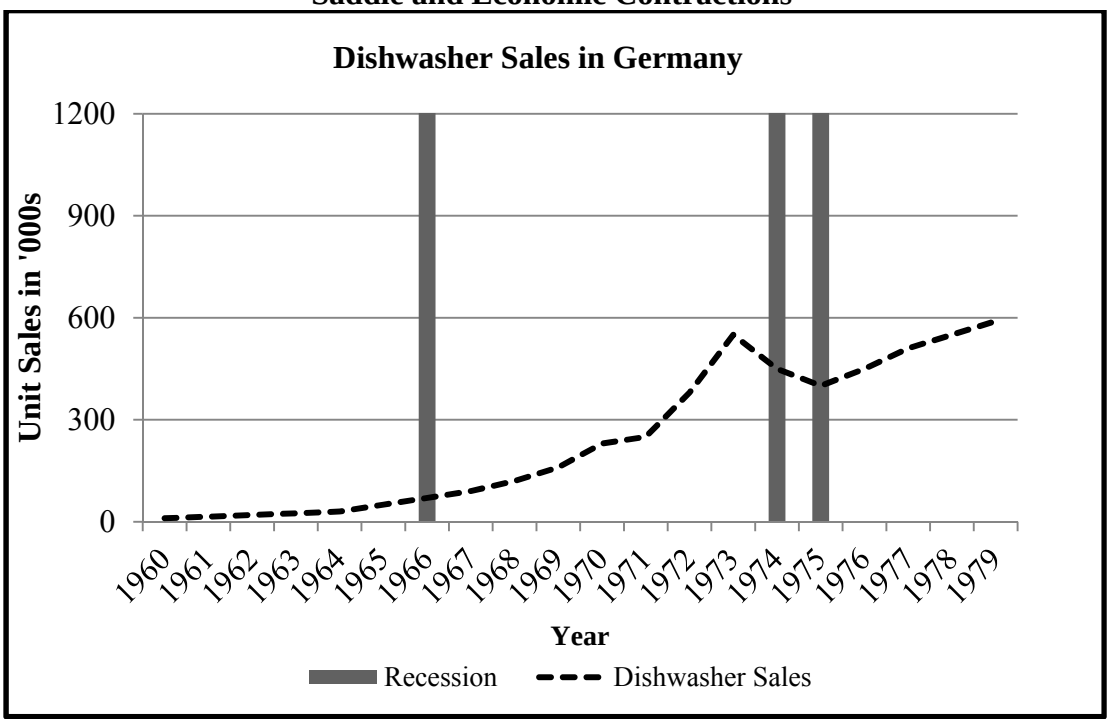
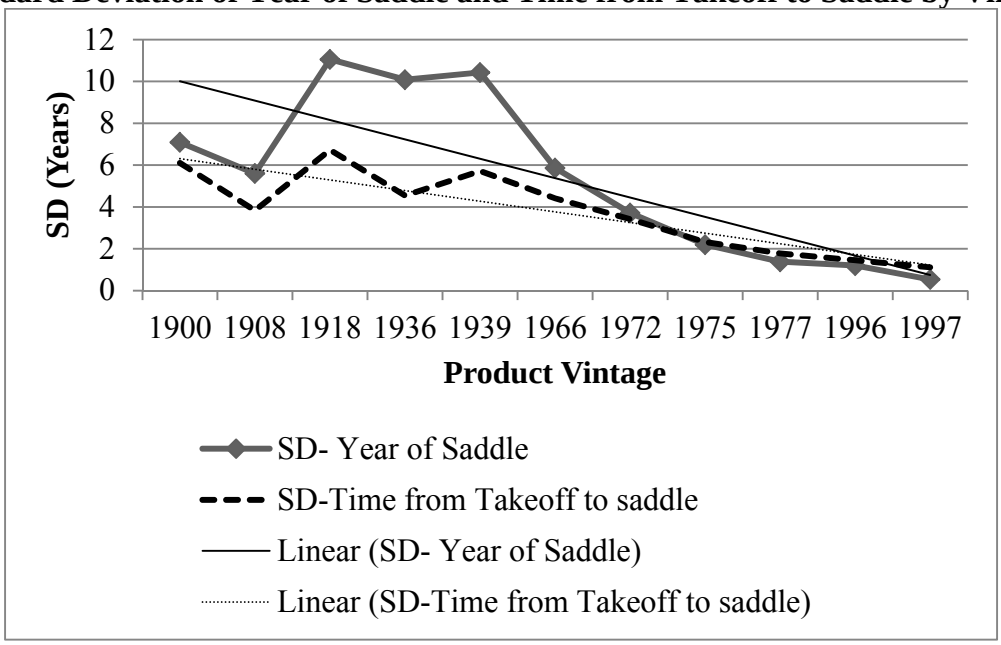


FIGURE 6
Standard Deviation of Year of Saddle and Time from Takeoff to Saddle by Vintage



WEB APPENDIX
APPENDIX W1
OVERVIEW OF EMPIRICAL LITERATURE ON NEW PRODUCT DIFFUSION

Authors	Sales/Adoption	Variable(s) of Interest	Method	Products	Countries	Product-Country Combinations
Libai, Muller and Peres (2009a)	Subscribers	Diffusion parameters, churn rate	Seemingly unrelated, nonlinear least squares	4 service categories (Note: multiple firms considered)	USA/Belgium/S. Korea	7
Stremersch et al (2007)	Sales	Takeoff	Growth model	9 categories	USA/ UK/Japan	9
Ganesh and Kumar (1996)	Individual store level adoption	Learning coefficient	NLS estimation of learning model.	1 industrial product	10 European countries, USA and Japan	10
Golder and Tellis (1998)	Sales	New product growth	Affordability model	10 categories	USA	10
Van den Bulte and Lilien (1997)	Penetration	Bass model parameters	NLS estimation of Bass model	12 innovations	USA	12
Bemmaor and Lee (2002)	Penetration	Parameters of G/SG model	Bass model; G/SG model	12 innovations	USA	12
Van den Bulte and Joshi (2007)	Sales or penetration	Two-segment Bass model parameters	Two segment model of new product growth	Four sets of data- antibiotic tetracycline; Music CDs; 5 high tech products; 8 misc data series	USA	<=15
Desiraju et al	Sales	Diffusion speed, penetration potential	Hierarchical Bayesian estimation of logistic diffusion model	1 pharmaceutical drug category	15 countries	15
Libai, Muller and Peres (2009b)	Number of subscribers	Takeoff time, within-brand and cross-brand influence	Bass-type diffusion model	1 category – cellular phones (Note: Diffusion of brands within this category considered)	16 Western European countries	16
Deleersnyder et al (2004)	Sales	Cyclical sensitivity and asymmetry	Band pass filter and test statistics	24 consumer durables	USA	24
Agarwal and Bayus (2002)	Sales	Time-to-takeoff	Proportional hazard model	30 innovations	USA	30
Golder and Tellis (2004)	Sales	Time to saddle	Proportional hazard model	30 products	USA	30
Van Everdingen et al.(2005)	Penetration	Social system size, long run penetration ceiling	Cross-population, adaptive diffusion model	2 products- Internet access, mobile telephony	15 EU countries	30
Golder and Tellis (1997)	Sales	Time-to-takeoff	Proportional hazard model	31 categories- consumer durables and electronics	USA	31
Van den Bulte (2000)	Adoption	Diffusion speed	Logistic distribution	31 electrical products	USA	31
Kohli, Lehmann and Pae (1999)	Sales	Incubation time	Bass model with NLS	32 appliances, house wares and electronics	USA	32

Goldenberg, Libai and Muller (2002)	Sales	Prevalence, depth and duration of saddle	Cellular automata	32 categories- electronics only	USA	32
Takada and Jain (1991)	Sales	Coefficient of imitation	Bass with NLS	8 consumer durables	4 Pacific Rim countries	32
Helsen, Jedidi and DeSarbo (1993)	Sales	Country segmentation	Latent-structure methodology	3 consumer durables	12 countries- Western Europe, US and Japan	36
Ganesh, Kumar and Subramaniam (1997)	Sales	Learning coefficient	Non-linear least squares; Simultaneous generalized least squares	4 consumer durables	16 European countries	<=64
Kumar, Ganesh and Echambadi (1998)	Sales	Bass model parameters	Simultaneous estimation of diffusion model parameters with covariates, using GLS	5 consumer durables	14 European countries	<=70
Gatignon, Eliashberg and Robertson (1989)	Penetration	Diffusion parameters	Simultaneous generalized least squares approach	6 consumer durables	14 European countries	84
Tellis, Stremersch and Yin (2003)	Sales and penetration	Time-to-takeoff	Parametric hazard model	10 products	16 European countries	137
This study	**Sales and penetration**	**Start and end of saddle**	**Discrete time hazard model with split population duration**	**10 categories- consumer durables and consumer electronics**	**19 countries- Western Europe, US, Japan and Canada**	**156**
Stremersch and Tellis (2004)	Sales and penetration	Duration and growth rate of growth stage	Parametric hazard model	10 products	16 European countries	160
Dekimpe, Parker and Sarvary (2000)	Duration	Transition rate	Coupled hazard approach	1 service	160 countries	160
Talukdar, Sudhir, Ainslie (2002)	Sales only	Parameters of Bass model p, q and m	Nonlinear Bass model with Hierarchical Bayesian estimation	6 consumer durables	31 developing and developed countries	Up to 186
Dekimpe, Parker, Sarvary (1998)	Penetration	Social system ceiling	Staged estimation procedure	1 category- cell phone	184 countries	184
Van Everdingen, Stremersch and Fok (2009)	Penetration	Takeoff	Discrete-time duration model	8 products	55 countries	308
Chandrasekaran and Tellis (2008)	Penetration	Time to takeoff	Accelerated failure time hazard model	16 categories- consumer durables and electronics	31 developing and developed countries	430
Stremersch and Lemmens (2009)	Sales	Drug sales growth	Time-varying coefficient model	15 new molecules	34 countries	510
Sood and Tellis (2009)	Penetration	Market penetration	Functional regression	20 categories	Multiple countries	760

Note: Meta-analytic studies are excluded from these comparisons

APPENDIX W2

CORRELATION MATRIX

Variables	Event	Product Vintage	Product Age	Economic Contraction	Dispersion	Prior Saddles
Information/Entertainment Products						
Event	1.00					
Product vintage	-.01	1.00				
Product age	.19	-.10	1.00			
Economic contraction	.03	.14	.00	1.00		
Dispersion	-.16	.61	-.24	.17	1.00	
Prior saddles	.25	-.02	.22	-.05	-.29	1.00
Weighted patent counts	.19	-.09	.10	.05	-.41	.32
Kitchen/Laundry Products						
Event	1.00					
Product vintage	-.02	1.00				
Product age	.14	-.06	1.00			
Economic contraction	.14	-.06	.06	1.00		
Dispersion	-.08	.27	-.30	-.03	1.00	
Prior saddles	.11	.04	-.02	.03	-.00	1.00
Weighted patent counts	.07	.47	-.04	-.03	.32	.19

APPENDIX W3

ROBUSTNESS CHECKS

	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory Variables	**(I/E)**	**(K/L)**	**(I/E)**	**(K/L)**	**(I/E)**	**(K/L)**
Product age	1.375**	.087	1.950***	.038	1.930***	.043
Age square	-.041**	-.001	-.050***	-.001	-.052***	-.000
Log (product age)	-3.926	.533	-6.412***	.878	-6.049***	.882
Product vintage	.035**	-.001	.041*	-.002	.030	-.002
Economic contraction	.305	.769***			.233	.820***
Dispersion	-.059***	-.030**	-.035**	-.018	-.034*	-.017
Weighted patent counts	-.000	.001**	.0003**	.001*	.0002	.001**
Prior saddles	.077	.219***	.100	.197**	.140	.219**
Change in economic growth			. 657**	.760***		
Constant	-71.048**	-3.427	-83.576**	-1.759	-62.32	-88.62
Observations	453	620	400	727	400	727
Log likelihood	-152.0	-217.6	-124.9	-237.5	-129.6	-236.1

Notes:

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

I/E refers to Information/Entertainment products and K/L refers to Kitchen/Laundry products

APPENDIX W4

ROBUSTNESS CHECKS (CONTINUED)

	(7)	(8)	(9)	(10)	(11)	(12)
Explanatory Variables	**(I/E)[a]**	**(K/L)[a]**	**(I/E)[a]**	**(K/L)[a]**	**(I/E)**	**(K/L)**
Product vintage	.032	-.007	.035*	.001	.053**	-.002
Product age	1.278**	.125	1.853***	.149	.304***	.046***
Age square	-.029	-.002	-.047***	-.002		
Log(Product age)	-4.673**	.390	-5.868***	.350		
Economic contraction	.242	.864***	.216	.823***	.233	.811***
Dispersion	-.050***	-.013	-.033*	-.015	-.043**	-.023**
Weighted patent counts	.001**	.002**	.001**	.001	.0004**	.001**
Prior saddles	.009	.214**	.148	.212**	-.007	.228***
Constant	-63.235	7.890	-69.883*	-7.215	-108.905***	-.544
Observations	400	727	400	727	402	727
Log likelihood	-125.8	-233.3	-123.3	-232.6	-129.9	-237.2

[a] Product and regional dummies are not included

Notes:

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

I/E refers to Information/Entertainment products and K/L refers to Kitchen/Laundry products