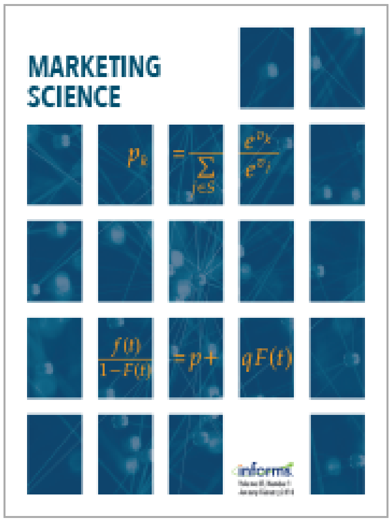

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Growing, Growing, Gone: Cascades, Diffusion, and Turning Points in the Product Life Cycle

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Research on the product life cycle (PLC) has focused primarily on the role of diffusion. This study takes a broader theoretical perspective on the PLC by incorporating informational cascades and developing and testing many new hypotheses based on this theory. On average, across 30 product categories, the authors find that: (i) New consumer durables have a typical pattern of rapid growth of 45% per year over 8 years. (ii) This period of growth is followed by a slowdown when sales decline by 15% and stay below those of the previous peak for 5 years. (iii) Slowdown occurs at 34% population penetration and about 50% of ultimate market penetration. (iv) Products with large sales increases at takeoff tend to have larger sales declines at slowdown. (v) Leisure-enhancing products tend to have higher growth rates and shorter growth stages than nonleisure-enhancing products. Time-saving products tend to have lower growth rates and longer growth stages than nontime-saving products. (vi) Lower probability of slowdown is associated with steeper price reductions, lower penetration, and higher economic growth. (vii) A hazard model can provide reasonable predictions of the slowdown as early as the takeoff.

The authors discuss the implications of these findings.

Key words: product life cycles; sales takeoff; cascades; new product growth; innovation; product management; diffusion; high-tech marketing
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1. Introduction

The product life cycle (PLC) is a vitally important phenomenon in marketing for at least three reasons. First, pressure on managers varies dramatically before and after the turning points in the life cycle. During the introduction (prior to takeoff) pessimism abounds and managers are under increasing pressure to pull the plug on new products. During the growth stage (prior to slowdown) optimism abounds and managers are eager to meet the apparently insatiable demand with fresh capacity and expanded marketing. Predicting the turning points of takeoff and slowdown are essential to avoid premature withdrawal or excessive investments. Second, the level and growth of sales vary dramatically across stages of the life cycle. Managers need to know these changes to appropriately plan the corresponding levels of production, inventory, sales staff, distribution, marketing, and advertising. Third, costs and prices decline substantially over the life cycle, especially during the early stages. In contrast, consumers' sensitivity to price increases over the stages of the life cycle. Managers must understand the sales patterns and change their strategy accordingly. Because of its critical impact on marketing strategy, the PLC has become a central, enduring framework in marketing. Its intuitive appeal has spread to other disciplines where the concept is used routinely.

In marketing, two streams of literature address the PLC. One stream of rigorous research initiated by Bass (1969) has attempted to model the pattern of sales during the growth stage relying on a social theory of adoption and imitation (e.g., Bass et al. 1994; Gatignon et al. 1989; Horsky and Simon 1983; Mahajan et al. 1990, 2000; Putsis et al. 1997; Talukdar et al. 2002; Van den Bulte 2000). A second stream of exploratory research has sought to ascertain the generalizability of the PLC across different industries (e.g., Polli and Cook 1969, Tellis and Crawford 1981). While this research stream has identified some patterns of the PLC (e.g., Tellis and Fornell 1988), it has neither explored all the theories for these patterns nor described the characteristics of the marketing mix over the PLC (Day 1981, Rink and Swan 1979).

A review of these streams of research suggests the following areas that can benefit from further research. First, the PLC lacks clear metrics for the turning points that define the various stages. In the absence of such metrics, the concept lacks predictive validity and empirical meaning. In particular, managers need such metrics to determine whether they should persevere or quit, build or hold. Second, the PLC lacks a comprehensive description of economic and market variables during its various stages. Such a description would help to further identify the stage in which a product may fall and the strategy managers should adopt. Third, PLC research has not considered the potential impact of informational cascades on new product sales.

Our study seeks to address these limitations. It contributes to the literature in four ways:

- We define specific metrics for the two key turning points in the PLC, takeoff and slowdown.
- We broaden the theory of the PLC by incorporating informational cascades.
- We develop a hazard model for the duration of the growth stage. The model can be used to predict slowdown, as early as takeoff.
- We test hypotheses and present new statistics about the PLC. These results suggest emerging regularities about the PLC.

The rest of this paper is organized as follows. Section 2 presents our definitions and development of hypotheses. Sections 3 and 4 propose a model of the growth stage followed by a discussion of our data and operational measures. Section 5 presents our results, and §6 concludes with a discussion of the key findings, their implications, and directions for future research.

2. Broadening the Theory of the Product Life Cycle

We begin this section by defining the key events and stages of the PLC. Then, we describe the theory of informational cascades (Bikhchandani et al. 1992, 1998) and derive nine hypotheses based on this theory. We also derive two additional hypotheses based on diffusion theory (Rogers 1995).

Definitions

We define a product category as a group of products that are close substitutes and fulfill a distinct need from the consumer's viewpoint (e.g., refrigerators, CD players, and camcorders). Our analysis of product categories is the same as nearly all previous research on the sales growth of consumer durables (e.g., Bass 1969, Sultan et al. 1990).

We define the four stages of a PLC as follows:

1. *Introduction* is the period from a new product's commercialization until takeoff.
2. *Growth* is the period from a new product's takeoff until its slowdown in sales.
3. *Maturity* is the period from a product's slowdown until sales begin a steady decline.
4. *Decline* is the period of steadily decreasing sales until a product's demise.

These stages occur due to well-defined events in the history of a new product. We define three of these events, which mark the beginning and end of the first two stages.

1. *Commercialization* is the point at which a new product category is first sold to consumers.
2. *Takeoff* is the point of transition from the introduction to the growth stage of the PLC. It is the first dramatic and sustained increase in product category sales.
3. *Slowdown* is the point of transition from the growth stage to the maturity stage of the PLC. The slowdown signals the beginning of a period of level, slowly increasing, or temporarily decreasing product category sales. A later section proposes a specific operational measure for the slowdown.

Informational Cascades

Informational cascades describe how people converge on adopting a behavior with increasing momentum and declining individual evaluation of the merits of the behavior, due to their tendency to derive information from the behavior of prior adopters (Bikhchandani et al. 1992, 1998). The essence of informational cascades is that even though individuals make decisions based on their own private information, their decisions are influenced by other people's decisions, too.

As people adopt a new product based on its merits, their adoption provides a signal to nonadopters. Some of these nonadopters go on to adopt the new product, at least partly influenced by the behavior of the previous adopters. As the number of adopters increases, they provide an increasingly strong signal to the nonadopters, who then adopt in increasing numbers. Once information derived from the decisions of others begins to outweigh an individual's private valuation, the process begins to increase in momentum or cascade toward conformance in the behavior of more and more buyers.

At this point, new adopters reveal no additional private information to the market. Thus, the mass conformance or cascade to a particular behavior is based on the initial decisions of a small number of adopters, rather than the cumulative decisions of all adopters. This feature makes a cascade quite fragile. It is easily triggered or reversed by new information that affects the decisions of a small number of people. Therefore, cascades can depress pre-takeoff sales, sharpen the takeoff of new products, exaggerate product growth, and reverse sales growth when maturity first sets in. We elaborate on these points.

Because most individuals do not purchase a new product during the introduction stage, most consumers use this information to decide likewise. This decision may occur even when, for some individuals, private information alone would have led to purchasing the new product. As a result, early sales of a new product could be depressed or time-to-takeoff could be longer than seems justified by the potential utility of the new product (Golder and Tellis 1997, Tellis et al. 2003).

On the other hand, once a sizable segment of consumers adopts the new product, other consumers use this information to decide to purchase the new product as well. These purchases occur even when their own private valuation would have meant they should not purchase the new product. In such a positive cascade, more consumers buy than might be expected on a strict cost-benefit analysis.

This cascade of consumers to adopt a new product is likely to end somewhere. Potential triggers include a decline in the growth rate of the new product's benefits, the announcement of a rival technology, or a change in the economic environment, such as an increase in interest rates or the onset of a recession. Any of these may be small shocks to the system. However, in the presence of a cascade in favor of the new product, any of them might be enough to reverse the trend. Some informed consumers might decide to wait before purchasing the new product. Other consumers may have already bought before their private valuations justified such a purchase. Once some consumers delay their purchases and other consumers become aware of these decisions, a negative cascade begins. As a result, the slowdown in market sales might not be a gradual flattening of the sales curve, but a drop in sales at the onset of maturity.

This theory of informational cascades together with standard economic theory and diffusion theory suggest 11 testable hypotheses about the PLC of new consumer durables. The first nine hypotheses help us to evaluate the role of informational cascades; the last two hypotheses are predictions derived from diffusion theory, which have not been evaluated in previous research.

As discussed above, one potential trigger of a negative cascade is a decline in GNP at the onset of a recession. Thus, we hypothesize:

Hypothesis 1. *Declines in GNP shorten the duration of the growth stage.*

However, economic theory offers a simpler, alternative explanation for the impact of changes in GNP: the shortening of the growth stage could be due to problems of affordability when GNP declines (Golder and Tellis 1998). How can we distinguish this economic explanation from the one based on informational cascades presented in Hypothesis 1?

When GNP declines, disposable incomes also decline, likely prompting consumers to cut back on adopting new products. If consumer adoptions are driven primarily by the economic explanation of consumer's private utility, then declines in GNP should be proportionate to declines in sales at slowdown. Similarly, increases in GNP should have a proportional impact on sales increases at takeoff. Thus, we hypothesize:

Hypothesis 2. *Sales declines at slowdown are proportional to changes in GNP.*

Hypothesis 3. *Sales increases at takeoff are proportional to changes in GNP.*

Note that Hypothesis 1 (based on informational cascades) and Hypotheses 2 and 3 (based on standard economic theory) are competing hypotheses. If Hypotheses 2 and 3 are supported and Hypothesis 1 is not, it would imply that the role of GNP is primarily economic. Alternatively, if Hypothesis 1 is confirmed and Hypotheses 2 and 3 are not, that would support the theory of informational cascades. Finally, rejection or confirmation of all three hypotheses would not help in resolving these competing explanations.

Differences by Product. Because an informational cascade is driven by observing the purchases of other consumers, its strength is likely to vary across products. In particular, products with a sharp increase in sales at takeoff are more likely to have a sharper decline in sales at slowdown. The reason is that products that are susceptible to an upward momentum will be equally susceptible to a downward momentum. Indeed, it is the intrinsic nature of cascades that positive momentum will be followed by corresponding negative momentum when sales move lower. Thus, we hypothesize:

Hypothesis 4. *Products with large sales increases at takeoff will have larger sales declines at slowdown.*

During an informational cascade, more people buy a new product than would buy it based on their own private valuation. When the cascade reverses, fewer people are available to buy the new product. Thus, due to informational cascades, high growth rates will be followed by sharp declines in sales at slowdown. Thus, we hypothesize:

Hypothesis 5. *Products with high growth rates during the growth stage will have larger sales declines at slowdown.*

Informational cascades are likely to be stronger for products that are more visible to consumers. Horsky (1990) proposed that new products can be usefully classified into time-saving products (e.g., microwave ovens) or leisure-enhancing products (e.g., VCRs). We expect that leisure-enhancing products will be affected more strongly by informational cascades than time-saving products. Leisure-enhancing products such as TVs, radios, and CD players are more likely to be seen and discussed than time-saving products like disposers and clothes dryers. This difference in the strength of cascades should affect the growth rates of new product sales. Thus, we hypothesize:

Hypothesis 6. *Leisure-enhancing products have higher growth rates than nonleisure-enhancing products.*

Hypothesis 7. *Time-saving products have lower growth rates than nontime-saving products.*

Different growth rates will affect the speed at which the pool of potential adopters is depleted. As a result, we expect that:

Hypothesis 8. *Leisure-enhancing products have a negative effect on the duration of the growth stage.*

Hypothesis 9. *Time-saving products have a positive effect on the duration of the growth stage.*

Role of Penetration Based on Diffusion Theory

Although we focus on the impact of informational cascades, our consideration of diffusion theory leads us to propose two additional hypotheses, which have not been evaluated in previous research. A great body of research on the diffusion of innovations has found that the rate of adoptions follows a normal distribution, with a peak of adoptions at 50% penetration (Mahajan et al. 1990, Rogers 1995). However, new products differ in their ultimate market penetration. Some new products (e.g., TVs and telephones) are adopted by nearly all consumers, while others (e.g., radar detectors and electric razors) are adopted by a fraction of consumers. Because new product adoptions follow a normal distribution, a new product with very high ultimate penetration will be adopted by a higher percentage of all households at every point along the adoption curve. In contrast, a new product with a low ultimate penetration will be adopted by a lower percentage of all households at every point along the adoption curve. Thus, we hypothesize:

Hypothesis 10. *Higher penetration at takeoff is associated with higher penetration at slowdown.*

Because a decline in the rate of adoptions is expected to occur when 50% of potential adopters have already adopted the new product, penetration at slowdown should serve as a predictor of a new product's ultimate penetration. Thus, we hypothesize:

Hypothesis 11. *A product's penetration at slowdown divided by its ultimate penetration will be* 50%.

3. Modeling the Duration of the Growth Stage

Three of our hypotheses make predictions about the duration of the growth stage. To evaluate these hypotheses, we propose a model for this duration.

After takeoff, new product sales grow rapidly. However, this growth does not last forever. Indeed, our research indicates that sales of fast growing durables follow a *consistent pattern* of strong growth followed by a sudden reversal into decline. After declining for a few years, growth resumes but at a much slower rate (Goldenberg et al. 2002).

We model the time from takeoff to slowdown as a function of a baseline hazard function and independent variables.[1] We use Cox's (1972) proportional hazard model because it is not constrained by a particular distribution for the baseline hazard function and it allows time-varying independent variables. The time-to-slowdown for each category in our sample follows its own hazard function, $h_i(t)$, expressed as $h_i(t) = h(t; z_{it}) = h_0(t)\exp(z_{it}\beta)$, where $h_0(t)$ is an unspecified baseline hazard function, z_{it} is the vector of independent variables for the ith category at time t, and β is the vector of parameters to be estimated.[2] The effect of independent variables on the baseline hazard function is captured by the hazard ratio, which is defined as e^{β}. Positive β coefficients increase the hazard function or probability of slowdown and negative β coefficients decrease the hazard function. The magnitude of the effect of any independent variable increasing by one unit is $(e^{\beta} - 1) \times 100\%$. Estimation of the hazard model is done with the semiparametric partial likelihood method (Cox 1972). The partial likelihood considers the probability that one category experiences slowdown out of all categories that have not reached slowdown. We use the SAS program PHREG for the estimation.

Independent Variables

To test our hypotheses on informational cascades, we include percent change in GNP and dummy variables for time-saving products and leisure-enhancing products. Based on previous research, we include several control variables, which provide additional insights

[1] See Allison (1995), Helsen and Schmittlein (1993), and Jain and Vilcassim (1991) for details on hazard models.

[2] Similar to previous research, we do not include a term for unobserved heterogeneity (Golder and Tellis 1997, Helsen and Schmittlein 1993). This approach is appropriate when only nonrepeated events are modeled and the transition from growth to maturity occurs once for each category (Allison 1984).

Table 1 Key Years in Category Histories

Product category	Commercialization	Takeoff	Slowdown
Direct broadcast satellite	1990	1995	No slowdown in data
CD-ROM	1985	1990	No slowdown in data
Camcorder	1984	1985	1991
Compact disk (CD) player	1983	1985	No slowdown in data
Cellular phone	1983	1986	No slowdown in data
Cordless phone	1979	1982	1985
Food processor	1973	1977	1982
Home VCR	1972	1980	1987
Video game	1972	1976	1978
Answering machine	1972	1983	No slowdown in data
Digital watch	1972	1973	1984
Radar detector	1972	1984	1991
Calculator	1971	1972	1986
Microwave oven	1966	1972	1988
Can opener	1956	1959	1970
Color television	1954	1962	1969
Home freezer	1939	1947	1953
Black-and-white TV	1939	1948	1951
Blender	1938	1962	1970
Steam iron	1936	1950	1957
Clothes dryer (spin)	1936	1950	1957
Electric blanket	1936	1955	1964
Disposer	1935	1955	1974
Automatic coffee maker	1934	1948	1957
Power lawn mower	1933	1949	1960
Electric razor	1931	1935	1938
Room air conditioner	1929	1953	1957
Radio	1920	1923	1930
Refrigerator	1918	1926	1938
Dishwasher	1900	1959	1974

on the PLC. First, we include price. To standardize the impact of price reduction across categories, our measure is the price during each year in the growth stage divided by price at takeoff. All price data are adjusted for inflation. Second, we include the calendar year of takeoff to evaluate whether the duration of the growth stage has been decreasing over time (Qualls et al. 1981, Bayus 1994). Third, we include market penetration to capture the impact of cumulative adopters (Bass 1969, Golder and Tellis 1997). We measure market penetration as the percentage of households that own each product in each year.

4. Data

This section describes our data, discusses our operational measures of takeoff and slowdown, and presents some descriptive results on new product sales.

We use the historical method to collect data (Golder 2000, Golder and Tellis 1993). Our sampling frame consists of consumer durables with information on sales, price, penetration, and other related variables. Our main sources are *Dealerscope Merchandising*, *Merchandising Week*, *Electrical Merchandising*, the Electronic Industries Association, *Business Week*, *Advertising Age*, the *Statistical Abstracts of the United States*, and other Department of Commerce publications.

Operational Measures

The three key events in a new product's sales are commercialization, takeoff, and slowdown. Commercialization is the first year in which a new product is sold to consumers. Following Golder and Tellis (1997), takeoff is the first year in which a product's growth rate relative to its previous year's unit sales is higher than a predetermined threshold for takeoff. No formal measure of slowdown is available in the literature. Thus, we operationalize slowdown as the first year, of two consecutive years after takeoff, in which sales are lower than the highest previous sales. Our measure of slowdown matches a visual inspection of the sales curve in 96% of our categories.[3] Table 1 presents the

[3] Five of our 30 categories have not reached slowdown, based on available data. For two of the remaining categories, we have only one year of data after the growth stage. Because sales are lower in this year, we use this year as the slowdown. For one category, we have two years of sales after the growth stage. The first year of sales is lower while the second year is somewhat higher. We use the first year of lower sales as the slowdown, so this is the only category that does not fit our rule. Therefore, our classification rule fits 22 of the 23 cases (96%) where we have at least two years of sales data

Table 2 Growth Rate (%)

	Introduction[1]	Takeoff	Growth	Slowdown	Early maturity[2]	Late maturity
Total sample	31	428	45	−15	−25	3.7
Standard deviation	39	995	39	13	15	5.7
Median	15	207	32	−12	−22	2.9
10th–90th percentile	6–74	33–491	15–92	−33–(−4)	−42–(−9)	−2.2–10.9
Sample size	9	30	30	25	25	19
Pre-WWII	19	181[3]	39	−14	−29	3.2
Standard deviation	24	154	44	11	10	5.8
Median	12	182	23	−14	−28	2.5
10th–90th percentile	5–42	31–429	14–79	−25–(−5)	−42–(−17)	−2.7–8.5
Sample size	5	14	14	14	14	14
Post-WWII	45	645[3]	50	−15	−21	5.0
Standard deviation	52	1,337	34	15	19	5.9
Median	22	249	44	−9	−14	4.4
10th–90th percentile	17–93	84–907	18–81	−37–(−4)	−36–(−5)	−0.1–11.1
Sample size	4	16	16	11	11	5

[1] Nine categories with sales data for three years before takeoff and base sales of at least 15,000 units.
[2] Minimum sales after slowdown relative to sales at local peak.
[3] A t-test for difference in means statistically significant ($p < 0.10$).

years of commercialization, takeoff, and slowdown for the 30 categories.

Characterization of Stages

The three key events enable us to demarcate the stages of new product sales and present descriptive results on growth rates and unit sales. Our analysis of sales after slowdown leads us to divide the maturity stage into two substages—early maturity and late maturity. Early maturity begins with the year of sales slowdown and continues until sales grow to the previous local peak. Late maturity begins with the first year sales are higher than the local peak and continues until a product's sales begin to fall steadily during the decline stage. Only a few of our categories have reached the decline stage, so we do not report findings for this stage. Because some of our older categories have been in the maturity stage for many decades (e.g., radios and refrigerators), we present statistics about the late maturity stage that are based on the first 10 years of late maturity in all categories. Thus, our results on late maturity apply only to this period of category sales. On average, the period we describe represents nearly the first 35 years of a new category's history.

Table 2 contains the growth rates during the stages and at the key events of the PLC. We measure growth rate as annual percentage change in unit sales. Growth rates vary dramatically over the PLC. While growth is high during the introduction, the base is relatively small so these percentages do not represent substantial increases in unit sales.[4] However, at takeoff the market for these new products changes dramatically with an average sales increase of over 400%. During the growth stage, sales increase at 45% per year on average. In addition, the higher base of sales after takeoff means that increases in unit sales are quite substantial.

At slowdown, the sustained period of rapid growth suddenly reverses into a 15% decline. Our theoretical discussion of informational cascades helps to shed some insight into the sales reversal at slowdown. After slowdown, sales tend to decline for a few years, reaching a minimum of 25% below the local sales peak prior to slowdown. During late maturity, sales surpass the previous local peak in sales but tend to grow at a much slower rate (3.7%). Sales growth during maturity seems to reflect increases in the total economy.

Table 3 contains the mean unit sales at three key events: commercialization, takeoff, and slowdown. These averages provide benchmarks for judging the success of today's new products.

We use our sales data to construct a "typical" or average PLC. We do this exercise for all categories and for the subset of categories introduced after World War II (see Figure 1).[5] Now, the duration of the introduction and growth stages varies across categories.

after the growth stage. In 72% of our categories, an even simpler rule classifies slowdown. This rule is that slowdown is the first year of lower sales after penetration is at least 11%. Finally, an extremely simple rule classifies slowdown for 60% of our categories. This rule is that slowdown is the first decline in sales after takeoff.

[4] Because some categories report very small sales for the first full year or partial year of sales, there can be very large percentage increases relative to these low bases. Therefore, growth rates during introduction are based on categories with a minimum base sales of 15,000 units and at least three years of available sales data before takeoff.

[5] Two categories (calculators and digital watches) are not used because of limited data availability after slowdown.

Table 3 Unit Sales (Thousands)

	Commercialization	Takeoff	Slowdown
Total sample	34	902	5,839
Standard deviation	41	754	6,904
Median	5	654	3,828
10th–90th percentile	2.9–83	317–1,690	1,296–11,496
Sample size	9	30	25
Pre-WWII	3.0[1]	728	3,243[2]
Standard deviation		414	1,700
Median		574	3,560
10th–90th percentile		349–1,336	1,266–5,300
Sample size	1	14	14
Post-WWII	38[1]	1,053	9,142[2]
Standard deviation	42	948	9,444
Median	25	802	5,000
10th–90th percentile	2.9–88	313–2,464	2,585–21,697
Sample size	8	16	11

[1] A t-test for difference in means statistically significant ($p < 0.01$).
[2] A t-test for difference in means statistically significant ($p < 0.05$).

To avoid averaging sales across different stages of the life cycle of various categories, we anchor the average PLC on the two turning points—takeoff and slowdown. We then use the average times between commercialization, takeoff, and slowdown to define the duration of the stages in the average PLC (see Table 14). Finally, we compute the average sales per year across categories, *within* stages of the life cycle, anchored on the turning points, as follows:

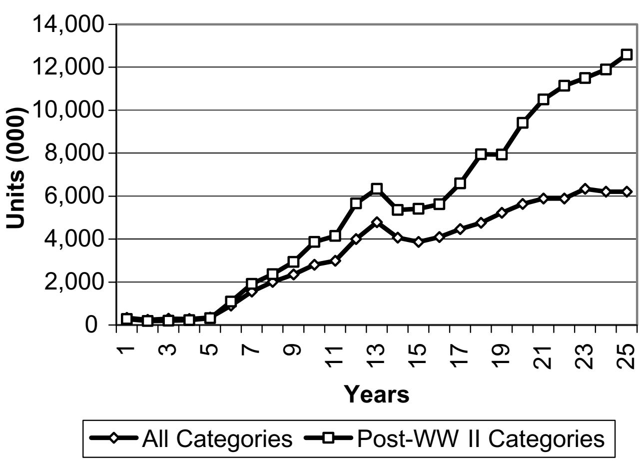
Average Sales Around Takeoff

$$\text{average sales}_{t=\text{takeoff}+j} = \frac{\sum_{i=1}^{n} \text{unit sales}_{i,\,\text{takeoff}+j}}{n}, \tag{1}$$

where takeoff = the year of takeoff in each category, $j = -5$ years to $+3$ years, and n = number of categories.

Equation (1) gives the average sales at the year of takeoff (year 6 in Figure 1), the five years prior to takeoff, and the three years after takeoff. We use

Figure 1 Average Sales History of Really New Consumer Durables



$j = -5$ years before takeoff because the average duration from commercialization to takeoff for more recent categories is six years. The longer introduction period for older categories would extend the initial period of low sales.

Average Sales Around Slowdown

$$\text{average sales}_{t=\text{slowdown}+j} = \frac{\sum_{i=1}^{n} \text{unit sales}_{i,\,\text{slowdown}+j}}{n}, \tag{2}$$

where slowdown = the year of slowdown in each category, $j = -3$ years to $+11$ years, and n = number of categories.

Equation (2) gives the average sales at the year of slowdown (year 14 in Figure 1), the three years prior to slowdown, and the 11 years after slowdown. Note that we use both Equations (1) and (2) to calculate year 10 sales, and then take the average of these two numbers. This averaging allows for a smooth merging of the two series (Equations (1) and (2)).[6]

Figure 1 confirms the importance of properly identifying takeoff and slowdown, because the average life cycle changes so distinctively at these points. In particular, after slowdown, sales take several years to surpass the previous local peak (see also Goldenberg et al. 2002).

Table 4 Estimates of Hazard Model

Variable	(1)	(2)
Change in GNP	-0.196^{***}	-0.181^{***}
	(0.070)	(0.069)
Time-saving product	-1.56^{***}	
	(0.56)	
Leisure-enhancing product		1.67^{***}
		(0.60)
Relative price	0.053^{***}	0.046^{***}
	(0.016)	(0.015)
Year of takeoff	NS	NS
Market penetration	0.037^{**}	0.038^{**}
	(0.017)	(0.016)
U^2	0.23	0.24

Notes. NS = not significant. Standard errors are in parentheses.
$^{*}\ p < 0.10$.
$^{**}\ p < 0.05$.
$^{***}\ p < 0.01$.

5. Results

We present estimates of the hazard model of the duration of the growth stage in Table 4. We include time-saving products and leisure-enhancing products in separate estimations because of the high correlation between these variables. Next, we discuss model results and descriptive results on each hypothesis and the control variables.

[6] We thank reviewer B for encouraging us to formalize our determination of the "average" sales curve.

Table 5 Growth at Takeoff Relative to Change in GNP

Class[1]	Increase in GNP	Increase in sales at takeoff
Large increase in GNP	6.9% (1.5)[2]	594% (1,390)[3]
Small increase in GNP	1.6% (2.5)[2]	263% (222)[3]

[1] Median split based on change in GNP at takeoff.
[2] Difference significant at $p < 0.01$.
[3] Difference significant at $p = 0.19$.

Table 6 Decline at Slowdown Relative to Change in GNP

Class[1]	Change in GNP	Decline in sales at slowdown
Increase in GNP	4.1% (1.6)[2]	16% (15)[3]
Decrease in GNP	−2.0% (3.0)[2]	14% (11)[3]

[1] Median split based on change in GNP at slowdown.
[2] Difference significant at $p < 0.01$.
[3] Difference significant at $p = 0.34$.

Informational Cascades

Hypothesis 1 argues that due to informational cascades, declines in GNP will shorten the duration of the growth stage. The coefficient for change in GNP is large and significant at the 0.01 level. The average coefficient of −0.189 across models implies that every 1% decrease in total GNP is associated with a 17% increase in the probability of slowdown. Thus, we find support for Hypothesis 1.

Hypotheses 2 and 3 evaluate whether economic theory provides a simpler explanation for the role of GNP on the PLC. If growth rates at takeoff and slowdown are proportional to changes in GNP, then the effect of GNP is more likely to be explained by standard economic theory. Tables 5 and 6 present our results on Hypotheses 2 and 3. The effect of GNP on takeoff is directionally consistent with our hypothesis but the difference is not statistically significant. For slowdown, the result is neither statistically significant nor directionally consistent. Because these results do not confirm predictions based on economic theory, they provide some additional confirmation that change in GNP may serve as a trigger that begins an informational cascade.

Table 7 provides some additional insights about the role of GNP as a potential trigger of informational cascades. The economic growth rate is significantly higher at takeoff and significantly lower at slowdown than the mean economic growth rate during the period of our data. These results are consistent with economic conditions triggering informational cascades at the two key turning points in the PLC: takeoff and slowdown. Further support for informational cascades is the fact that changes in sales at these turning points are much greater than the changes in GNP.

We conducted one additional analysis on the impact of economic growth rate on the PLC. For each category, we consider the year after slowdown when the sales decline reverses and sales begin to increase again. For these observations, the average economic growth rate across categories is 4.5%, slightly higher than the average economic growth rate at takeoff. Consistent with informational cascades, this finding suggests that higher economic growth can serve as the trigger that also reverses sales declines.

Hypothesis 4 argues that due to informational cascades, categories with large sales increases at takeoff will also have large sales declines at slowdown. Based on the results in Table 8, we find support for Hypothesis 4.

Hypothesis 5 predicts that due to informational cascades, high growth during the growth stage will be

Table 7 Mean Economic Growth Rate (%)

	Introduction	Takeoff	Growth	Slowdown	Early maturity	Late maturity
Total sample	1.0[1]	4.3[2]	3.1	0.86[1]	2.4	3.1
Standard deviation	3.9	3.3	1.4	3.7	2.2	1.3
Median	1.9	5.3	2.9	0.1	2.6	3.0
10th–90th percentile	−3.2–4.9	−0.5–7.4	2.0–4.9	−3.5–5.6	0.7–4.0	2.0–4.4
Sample size	30	30	30	25	25	19
Pre-WWII	−1.4[1]	4.7[3]	3.1	−0.19[1]	2.3	3.3
Standard deviation	4.3	3.9	1.9	4.1	2.4	1.5
Median	−0.5	5.7	2.7	0.1	2.6	3.4
10th–90th percentile	−6.5–2.1	−1.0–8.0	1.6–4.8	−4.4–4.9	0.8–4.0	1.1–4.7
Sample size	14	14	14	14	14	14
Post-WWII	3.2	3.9[3]	3.2	2.2	2.5	2.7
Standard deviation	1.9	2.6	1.0	2.8	1.9	0.3
Median	3.0	4.4	3.0	3.0	2.6	2.6
10th–90th percentile	1.6–5.5	0.5–6.6	2.3–4.9	−0.9–5.4	0.9–3.4	2.4–3.0
Sample size	16	16	16	11	11	5

[1] Significantly different from mean economic growth rate during period of analysis ($p < 0.01$).
[2] Significantly different from mean economic growth rate during period of analysis ($p < 0.05$).
[3] Significantly different from mean economic growth rate during period of analysis ($p < 0.10$).

Table 8 Sales Decline at Slowdown Relative to Sales Increase at Takeoff

Class[1]	Average increase at takeoff	Average decline at slowdown
Large sales increase at takeoff	750% (1,350)[2]	21% (16)[3]
Small sales increase at takeoff	100% (73)[2]	8.5% (4.6)[3]

[1] Median split based on sales increase at takeoff.
[2] Difference significant at $p < 0.05$.
[3] Difference significant at $p = 0.01$.

associated with larger sales declines at slowdown. Based on Table 9, we find directional, but not quite significant support for Hypothesis 5.

Hypothesis 6 predicts that due to informational cascades, leisure-enhancing products have higher growth rates than nonleisure-enhancing products. Hypothesis 7 predicts that due to informational cascades time-saving products have lower growth rates than nontime-saving products. Results in Table 10 support Hypotheses 6 and 7.

Hypothesis 8 predicts that leisure-enhancing products have a negative effect on the duration of the growth stage. Hypothesis 9 predicts that time-saving products have a positive effect on the duration of the growth stage. Results from the Hazard model (see Table 4) indicate that time-saving products are associated with longer growth stages and leisure-enhancing products are associated with shorter growth stages (9.6 years versus 5.5 years, $p < 0.01$). These results support Hypotheses 8 and 9.

Role of Penetration Based on Diffusion Theory

Hypothesis 10 states that higher penetration at takeoff is associated with higher penetration at slowdown. Results in Table 11 indicate directional, but not statistically significant support for Hypothesis 10.

Hypothesis 11 predicts that a product's penetration at slowdown divided by its ultimate penetration will be 50%. For the 25 categories that have reached slowdown, penetration curves over time indicate that 18 of these categories are at or near their peak penetration. For these 18 categories, penetration at slowdown divided by maximum penetration is 0.49. This result supports Hypothesis 11. Also, we now have a basis for predicting that maximum penetration will be approximately two times penetration at slowdown.

Table 9 Sales Decline at Slowdown Relative to Growth During Growth Stage

Class[1]	Average growth rate	Average decline at slowdown
High growth during growth stage	70% (42)[2]	18% (15)[3]
Low growth during growth stage	20% (6.1)[2]	12% (11)[3]

[1] Median split based on average annual growth rate during growth stage.
[2] Difference significant at $p < 0.01$.
[3] Difference significant at $p = 0.11$.

Table 10 Average Growth During Growth Stage for Leisure-Enhancing and Time-Saving Products

Class	Average growth rate
Leisure-enhancing products	62% (48)[1]
Nonleisure-enhancing products	30% (21)[1]
Time-saving products	34% (25)[2]
Nontime-saving products	65% (51)[2]

[1, 2] Differences significant at $p < 0.05$.

Control Variables

Three control variables in our model provide additional insights about the growth stage. Our first control variable, market penetration, adds to the results above. The average coefficient across models of 0.038 (Table 4) implies that every 1% increase in penetration is associated with a 3.9% increase in the probability of slowdown. Table 12 provides some additional insights about penetration. While penetration at takeoff does vary significantly between older and newer categories, average penetration at slowdown does not vary. Although the variance in penetration at slowdown is fairly high, much of this variance comes from one category, calculators. The standard deviation for post-World War II categories is 54% higher with calculators than without.

Our second control variable, relative price, indicates that higher price reductions are positively associated with the duration of the growth stage. The average coefficient of 0.05 implies that every 1% higher price is associated with a 5.1% increase in the probability of slowdown. Table 13 presents additional information about price. Larger price reductions in more recent periods may be due to stronger experience effects associated with larger national and international markets, more electronic components, and managers exploiting these experience effects more often.

The final control variable, calendar year of takeoff, is not significant in the model (Table 4). Results in Table 14 confirm that the duration of the growth stage has not been shortening over time. However, the duration of introduction and early maturity have been decreasing over time.

Table 11 Penetration at Slowdown Relative to Penetration at Takeoff

Class[1]	Average penetration at takeoff	Average penetration at slowdown
High penetration at takeoff	6.0% (3.4)[2]	37% (23)[3]
Low penetration at takeoff	1.3% (0.6)[2]	30% (17)[3]

[1] Median split based on penetration at takeoff.
[2] Difference significant at $p < 0.01$.
[3] Difference significant at $p = 0.19$.

Table 12 Market Penetration (%)

	Takeoff	Slowdown
Total sample	2.9	34.2
Standard deviation	3.4	20.3
Median	1.4	36.6
10th–90th percentile	0.4–6.8	12.0–51.0
Sample size	30	25
Pre-WWII	4.3[1]	32.5
Standard deviation	4.3	14.3
Median	2.2	36.6
10th–90th percentile	1.0–9.7	12.5–47.3
Sample size	14	14
Post-WWII	1.7[1]	36.4
Standard deviation	1.7	26.8
Median	1.1	38.2
10th–90th percentile	0.4–4.2	12.0–55.0
Sample size	16	11

[1] A t-test for difference in means statistically significant ($p < 0.05$).

Table 14 Duration of Stages (Years)

	Introduction	Growth	Early maturity
Total sample	10.4	8.4	5.5
Standard deviation	11.4	4.4	3.7
Median	8	7	5
10th–90th percentile	1.9–20	3.0–15	2.0–8.8
Sample size	30	25	19
Pre-WWII	16.9[1]	8.6	6.4[2]
Standard deviation	13.9	4.5	3.8
Median	14	7.5	5
10th–90th percentile	5.2–24.0	3.3–14.1	3.2–11.2
Sample size	14	14	13
Post-WWII	4.8[1]	8.1	3.5[2]
Standard deviation	3.4	4.4	2.7
Median	4	7	2
10th–90th percentile	1.0–9.5	3.0–14.0	1.5–7.0
Sample size	16	11	6

[1] A t-test for difference in means statistically significant ($p < 0.01$).
[2] A t-test for difference in means statistically significant ($p < 0.05$).

Model Robustness

We conduct three analyses to evaluate the robustness of our model results. First, we address the possible endogeneity of price and penetration by modeling the duration of the growth stage with lagged price and lagged penetration. Model results show that the same parameters remain significant.

Second, we re-estimate the model after removing the three categories (digital watch, radar detector, calculator) where data limitations led to uncertain determination of the slowdown. Again, model results show that the same parameters remain significant.

Third, we re-estimate the model after removing 10 categories where the determination of takeoff is ambiguous. Because we rely on Golder and Tellis (1997) for our determination of takeoff, we selected those categories where their threshold rule and their alternative logistic curve rule were off by more than one year. Even after deleting this much data, only penetration becomes insignificant, although it maintains its positive sign.

Table 13 Price Relative to Commercialization Price

	Takeoff	Slowdown
Total sample	0.71	0.44
Standard deviation	0.20	0.26
Median	0.76	0.44
10th–90th percentile	0.42–0.97	0.15–0.78
Sample size	30	25
Pre-WWII	0.80[1]	0.56[2]
Standard deviation	0.18	0.25
Median	0.83	0.54
10th–90th percentile	0.56–0.98	0.26–0.84
Sample size	14	14
Post-WWII	0.63[1]	0.30[2]
Standard deviation	0.20	0.19
Median	0.64	0.31
10th–90th percentile	0.41–0.85	0.05–0.50
Sample size	16	11

[1] A t-test for difference in means statistically significant ($p < 0.05$).
[2] A t-test for difference in means statistically significant ($p < 0.01$).

6. Discussion

This section summarizes our study's contributions, discusses managerial implications of the research, and outlines directions for future research.

Summary of Contributions

Our study makes four primary contributions. First, we develop a specific metric for the end of the growth stage. This metric, in combination with a previous metric for sales takeoff, enables us to determine the key events and stages of the PLC. Second, we broaden the theory of the PLC by incorporating informational cascades. Our study is the first one in marketing to fully apply this theory.[7] Third, we estimate a hazard model of the duration of the growth stage. Finally, using this model and additional analyses, we test 11 hypotheses derived from the theory of informational cascades and diffusion theory. Here are the key results.

- New consumer durables show a distinct takeoff, after which sales increase by about 45% a year. They also show a distinct slowdown when sales decline by about 15%.
- A hazard model of the duration of the growth stage shows that the probability of slowdown is positively associated with slower growth in the economy, smaller price reductions, and higher penetration.

[7] A recent paper by Elberse and Eliashberg (2003) refers to the "success-breeds-success" or bandwagon effect of informational cascades.

- Slowdown occurs at 34% penetration on average, long before the majority of households own a new product.
- The growth stage lasts a little over eight years and does not seem to shorten over time.
- Consistent with informational cascades, we find that:
  - Poor economic conditions can trigger slowdown and good economic conditions can trigger takeoff.
  - Product categories with large sales increases at takeoff tend to have larger sales declines at slowdown.
  - Leisure-enhancing products tend to have higher growth rates and shorter growth stages than nonleisure-enhancing products.
  - Time-saving products tend to have lower growth rates and longer growth stages than nontime-saving products.

Managerial Implications

Our empirical findings and their support for the theory of informational cascades lead to many implications for managers. First, we believe that consumer durables have a common sales pattern. While the period of rapid growth is well known, the slowdown and period of stagnant or even declining sales during early maturity are not well known. Managers need to anticipate the slowdown and prepare for it, because growth is not perpetual and the depth of decline may mirror the steepness of growth. Second, our results suggest that managers might be able to extend the duration of the growth stage by lowering prices. Third, our model can be used to predict the slowdown as early as the takeoff. By applying the same process as Golder and Tellis (1997) with price and penetration as the predictor variables, our model predicts slowdown *at takeoff* with a mean absolute error of 3.4 years. These predictions can warn managers who might otherwise overreact to exploding demand and overinvest in manufacturing, sales force, inventory, and marketing. Fourth, managers of new products can compare their product's sales with the successful new products in our study. Such comparisons can inform managers about expected growth rates, duration of stages, and market penetration at different points in the PLC. Finally, our findings based on informational cascades enable managers to form different expectations about category performance depending on the type of product they are managing or the initial market response to the category. In particular, both sharp takeoffs and faster growth may signal steeper slowdowns. Leisure goods are likely to grow more quickly, while time-saving goods are likely to grow more slowly. Also, general economic conditions may have not only a short-term impact on sales, but could also be the start of a positive or negative informational cascade, thus having a longer-term impact on sales.

Directions for Future Research

Our study's findings as well as its limitations provide several opportunities for future research. First, future researchers could collect measures of purchase influence to evaluate the role of informational cascades at the individual level. Informational cascades may be relevant to other phenomena in marketing, such as popularity of celebrities, marketing returns of financial products, or managing buzz around new product introductions. Second, analytical models can benefit from incorporating informational cascades. Third, future research should test the generalizability of our findings in other categories. Fourth, future research could explore whether the slowdown is caused by gaps in adoption time across segments of the population (e.g., Goldenberg et al. 2002). All of these directions will require large data collection efforts, but the results are likely to provide additional insights on this important phenomenon in marketing.

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