Will It Ever Fly? Modeling the Takeoff of Really New Consumer Durables

Peter N. Golder • Gerard J. Tellis
Stern School of Business, New York University, MEC 8-79, 44 West Fourth Street, New York, New York 10012-1126
Marshall School of Business, University of Southern California, Los Angeles, California 90089

Abstract

A consistent pattern observed for really new household consumer durables is a takeoff or dramatic increase in sales early in their history. The takeoff tends to appear as an elbow-shaped discontinuity in the sales curve showing an average sales increase of over 400%. In contrast, most marketing textbooks as well as diffusion models generally depict the growth of new consumer durables as a smooth sales curve.

Our discussions with managers indicate that they have little idea about the takeoff and its associated characteristics. Many managers did not even know that most successful new consumer durables had a distinct takeoff. Their sales forecasts tend to show linear growth. Yet, knowledge about the takeoff is crucial for managers to decide whether to maintain, increase, or withdraw support of new products. It is equally important for industry analysts who advise investors and manufacturers of complementary and substitute products.

Although previous studies have urged researchers to examine the takeoff, no research has addressed this critical event. While diffusion models are commonly used to study new product sales growth, they do not explicitly consider a new product's takeoff in sales. Indeed, diffusion researchers frequently use data only from the point of takeoff. Therefore, nothing is known about the takeoff or models appropriate for this event. Our study provides the first analysis of the takeoff. In particular, we address three key questions: (i) How much time does a newly introduced product need to takeoff? (ii) Does the takeoff have any systematic patterns? (iii) Can we predict the takeoff?

We begin our study by developing an operational measure to determine when the takeoff occurs. We found that when the base level of sales is small, a relatively large percentage increase could occur without signaling the takeoff. Conversely, when the base level of sales is large, the takeoff sometimes occurs with a relatively small percentage increase in sales. Therefore, we developed a "threshold for takeoff." This is a plot of percentage sales growth relative to a base level of sales, common across all categories. We define the takeoff as the first year in which an individual category's growth rate relative to base sales crosses this threshold. The threshold measure correctly identifies the takeoff in over 90% of our categories.

We model the takeoff with a hazard model because of its advantages for analyzing time-based events. We consider three primary independent variables: price, year of introduction, and market penetration, as well as several control variables. The hazard model fits the pattern of takeoffs very well, with price and market penetration being strong correlates of takeoff.

Our results provide potential generalizations about the time to takeoff and the price reduction, nominal price, and penetration at takeoff. In particular, we found that:

- On average for 16 post-World War II categories:
  - —the price at takeoff is 63% of the introductory price;
  - —the time to takeoff from introduction is six years;
  - —the penetration at takeoff is 1.7%.
- The time to takeoff is decreasing for more recent categories. For example, the time to takeoff is 18 years for categories introduced before World War II, but only six years for those introduced after World War II.
- Many of the products in our sample had a takeoff near three specific price points (in nominal dollars): $1000, $500 and $100.

In addition, we show how the hazard model can be used to predict the takeoff. The model predicts takeoff one year ahead with an expected average error of 1.2 years. It predicts takeoff at a product's introduction with an expected average error of 1.9 years. Even against the simple mean time to takeoff of six years for recent categories, the model's performance represents a tremendous improvement in prediction. It represents an immeasurable improvement in prediction for managers who currently have no idea about how long it takes for a new product to takeoff. The threshold rule for determining takeoff can be used to distinguish between a large increase in sales and a real takeoff.

Some limitations of this study could provide fruitful areas for future research. Our independent variables suffer from endogeneity bias, so alternative variables or methods could address this limitation. Also, the takeoff may be related to additional variables such as relative advantage over substitutes and the presence of complementary products. Finally, examination of sales from takeoff to their leveling off could be done with an integrated model of takeoff and sales growth or with the hazard model we propose. Generalizations about this period of sales growth could also be of tremendous importance to managers of new products.

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Introduction

One of the most consistent patterns about the sales of new consumer durables that have now become household products is a dramatic increase in sales that took place sometime early in their history (Golder 1994). Marketing textbooks refer to this point as the transition between the introduction and growth stages of new products. We refer to this point as the *takeoff* of the new product. Products that enjoy this dramatic increase in sales first become desirable products, then popular products, and ultimately household necessities. During the year of takeoff, average sales increase over 400% from the previous year (see Figure 1 for examples).

The takeoff in sales is a critical issue for industry analysts and managers. The rapid increase in sales requires enormous resources in terms of manufacturing, inventory, distribution, and sales staff. Firms need to know when to invest in these resources. In addition, they have to decide whether to invest in further product or process research, or in advertising and promotion. For managers handling the new product, the takeoff is the sign that wins continued interest and support of senior managers. For senior managers, the absence of a takeoff may be the sign to cut short further support for the product and invest in alternate products. In spite of its enormous significance, our informal discussions with managers indicate that they have little idea as to what drives the takeoff. Some managers did not even know that most successful new consumer durables had a distinct takeoff. None had any idea as to how long a product needed for takeoff. Many managers of new products develop plans that assume a linear pattern of growth for the new product without any price reduction. Both assumptions run directly counter to the phenomenon of a takeoff.

Aside from its managerial significance, the takeoff is an interesting phenomenon in its own right. In particular, the phenomenon raises several questions:

- How much time does a new product need to takeoff?
- Does the takeoff have any systematic patterns?
- Can we predict the takeoff?

To the best of our knowledge, no empirical study has addressed these questions. The closest single study has been a recent one by Kohli et al. (1995) that analyzes the impact of what they call the incubation time on the subsequent diffusion of a new product. The *incubation time* includes the product development period prior to introduction and some of the introductory period. The focus of our study is the period from *market introduction to takeoff.* Study on the diffusion of new products using the Bass model is a research area that is also closely related to that of the takeoff. An excellent review of the diffusion literature, however, concludes that diffusion research has not addressed this important area (Mahajan et al. 1990):

> Not all new products are accepted by consumers at the time of their introduction. Some products are much slower than others in being accepted by potential adopters. That is, they differ in terms of how long it takes them to "take-off." The "take-off" phenomenon is not considered explicitly in the Bass model. The Bass model assumes the presence of a certain number of consumers before "take-off" (i.e., pm). (p. 21)

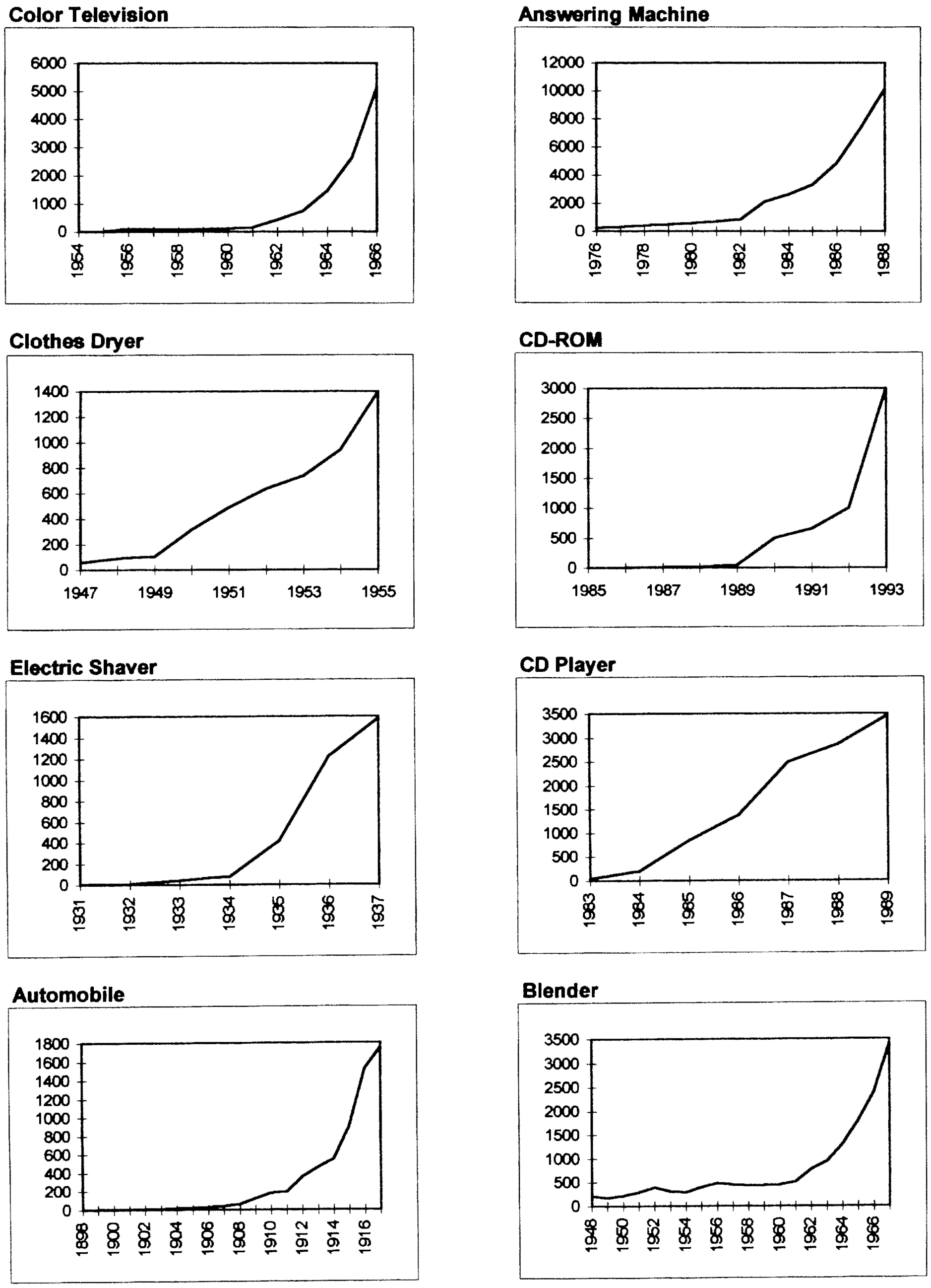
Indeed, researchers using the Bass model frequently include data only from the point of takeoff. The importance of understanding really new products and the paucity of research on the takeoff have prompted the Marketing Science Institute to list this topic among its highest priorities (Marketing Science Institute 1995). Our study is a first attempt to understand the takeoff in sales of new consumer durables. In particular, it seeks to answer the questions raised above.

The second section of the paper discusses the measurement of takeoff. The third section presents our model of the takeoff. The fourth section presents the data collected for the estimation of our model. The fifth section presents the results of the estimation and the predictive ability of the model. The final section discusses the implications and limitations of the model.

Measuring Takeoff

Although no definition of takeoff exists in the literature, the name itself suggests the beginning of a new phase in the sales history of a product, marked by rapid growth. Therefore, our conceptual definition of *takeoff* is the point of transition from the introductory stage to the growth stage of the product life cycle. For most new products, the start of the growth stage is dramatic and clear. Therefore, the point of takeoff is

Figure 1 Early Sales History of Really New Consumer Durables (unit sales in thousands)

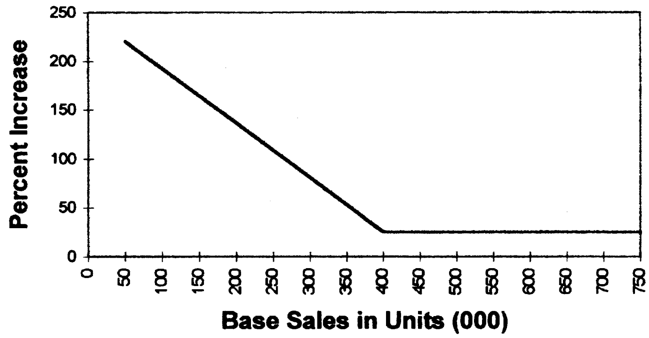


characterized by the first large increase in sales in the new category.

We need one operational definition of takeoff that is consistent with the conceptual definition and can be used as a heuristic across all categories. We found that when the base level of sales was small, a relatively large percentage increase sometimes occurred without signaling the takeoff. Conversely, when the base level of sales was large, the takeoff sometimes occurred with a relatively small percentage increase in sales. So we developed an operational rule or threshold for takeoff that varied by the base level of sales (see Figure 2). Formally, we define the *threshold for takeoff* as a plot of the percentage increase in sales relative to its base sales that demarcates the takeoff. We define a product's *relative growth rate* as the plot of its annual growth in sales relative to its base sales for that year. We then define a *takeoff* as the first year a product's relative growth crosses the threshold in Figure 2.[1] We define the *time to takeoff* as the number of years a new product category is sold up to and including the year of takeoff.

Surprisingly, this simple rule for takeoff fits a visual identification of the takeoff for all but three (over 90%) of the 31 product categories studied. For two product categories, visual inspection suggests a takeoff the second and third times, respectively, each product's growth rate crosses the threshold. For one product category, visual inspection suggests a takeoff at a point at which its growth rate comes very close to but does not cross the threshold. In conclusion, the threshold in Figure 2 provides a simple, generalizable heuristic to define takeoff with few errors.[2]

Figure 2 Threshold for Takeoff



Modeling Takeoff

Findings from the management of technology literature provide support for our concept of takeoff (Foster 1986, Utterback 1994). These researchers argue that really new products are introduced on waves of technological innovation. Initially such innovations are not commercially significant; however, as these products become less expensive relative to the benefits offered, they trigger a massive increase in demand. The authors suggest a discontinuity in the growth of sales of the new product. We call this point the takeoff.

Thus, the takeoff is a time-dependent binary event. The nonoccurrence of the event in the past influences the likelihood of its occurrence in the present. In particular, given favorable conditions, the probability of takeoff increases with the length of time it has not occurred. This phenomenon can be modeled best by the hazard function (Allison 1984, 1995; Cox 1972; Heckman and Singer 1984; Helsen and Schmittlein 1993; Jain and Vilcassim 1991; Kalbfleisch and Prentice 1980; Lawless 1982). For analyzing duration times, the hazard model has several advantages. It can identify cross-sectional and longitudinal effects. It can handle sample selection biases such as censoring. It need not be restricted to a given time horizon when inferring or predicting the duration time process. Helsen and Schmittlein (1993) present an excellent discussion of these benefits.

Hazard Model

We model the rate at which takeoff occurs as a function of (i) a baseline hazard function that captures the effect of time since introduction and (ii) independent variables. The baseline hazard function specifies the probability of takeoff given that no takeoff has occurred up to time t.

We use Cox's (1972) proportional hazard model for two main reasons. First, it is not constrained by a particular distribution for the baseline hazard function. Second, it allows us to use time-dependent independent variables. Therefore, the time to takeoff for each category in our sample follows its own hazard function, $h_i(t)$, expressed as:

$$h_i(t) = h(t; z_{it}) = h_0(t)e^{(z_{it}\beta)}, \qquad (1)$$

where $h_0(t)$ is an unspecified baseline hazard function, z_{it} is the vector of independent variables for the ith

[1] We concede that this is an instrumental definition that is based on the data. However, it is inspired by the conceptual definition and the most plausible given our resources. Our approach is similar to that of Guadagni and Little's (1983) definition of a promotional event based on the pattern of sales. Note from Figure 2 that base sales must be at least 50,000 units. Large percentage increases from a smaller base level of sales were not a reliable indicator of takeoff.

[2] In the appendix, we consider two alternative measures of takeoff to assess the robustness of using the threshold rule to define takeoff.

category, and β is the vector of unknown parameters. β is the same for all categories.

An interpretation of (1) is that the baseline hazard function is adjusted by the independent variables of each individual category at each time period. This adjustment occurs by the hazard ratio, which is defined as e^{β}. Positive β coefficients increase the hazard function or probability of takeoff and negative β coefficients decrease the hazard function. The magnitude of the effect of any independent variable increasing by one unit is $(e^{\beta} - 1) \times 100\%$.

Similar to Helsen and Schmittlein (1993) but unlike Jain and Vilcassim (1991), we do not include a term for unobserved heterogeneity. Omitting unobserved heterogeneity does not have serious consequences when only nonrepeated events are modeled (Allison 1984). For example, Jain and Vilcassim (1991) found that not including unobserved heterogeneity caused multiple interpurchase times coming from the same household to be treated as coming from different households. Since the takeoff can occur only once for each category, our approach seems reasonable. In addition, considering unobserved heterogeneity would not be helpful when using our model for predicting takeoff.

Estimation

We estimate the hazard model with a semiparametric partial likelihood method (see Helsen and Schmittlein 1993 and Allison 1995 for details). The partial likelihood considers the probability that one category experiences the takeoff out of all categories that have not had a takeoff. Using this approach, the baseline hazard function cancels out leaving,

$$PL_i = \frac{e^{z_{it}\beta}}{\sum_{k=i}^{n(t)} e^{z_{kt}\beta}}. \qquad (2)$$

Therefore, the partial likelihood estimate of β is the maximum of the product of (2) over all observed takeoff times. We use the PHREG procedure in SAS for the estimation.

Independent Variables

We examine two classes of independent variables: First, a set of three primary variables that are likely to impact the takeoff: price, year of introduction, and market penetration of the new product; second, a set of control variables that characterize the product category and the state of the economy, and could affect the product's takeoff. We briefly discuss the role of these variables.

Price. Price is probably the single most important factor determining the takeoff of new durables. Most new durables are introduced as soon as it is technically feasible at relatively high prices. Their high price hinders immediate wide market acceptance (Tellis and Golder 1996). For example, when initially introduced, color televisions sold for around \$3,000 and cellular phones and microwave ovens for around \$2,000.[3] Although these products represented radical technological breakthroughs with substantial benefits, consumers did not purchase them en masse because of their high prices. However, the prices of new products drop steadily especially in the first few years. At some point in the price decline, the new product crosses a critical point of affordability. At that point, sales take off dramatically (Foster 1986, Utterback 1994). For example, the introduction of Henry Ford's Model T led to a dramatic increase in the number of automobiles sold. During the 1970s, Texas Instruments' low price strategy in calculators led to exponential sales growth. In fact, Texas Instruments was so aggressive in lowering prices that some analysts wondered "why TI dropped prices when there is a shortage of some components, and there is no pressure on prices at the retail level" (*Business Week* 1972, p. 28). Texas Instruments' management felt that prices needed to be lowered to less than half of their introductory price before calculators would become a "widespread consumer item" (*Business Week* 1972, p. 28).

To standardize our measure of price across categories, we divide the price of each product in each period by that product's initial price. While we use this measure primarily for standardization, the effect is to measure price relative to the introductory price serving as a reference point. There is strong support for incorporating price relative to reference prices in econometric models (Kalyanaram and Winer 1995, Rajendran and Tellis 1994).

[3]These values are in 1995 dollars. Model estimation and results are done in constant (1987) dollars.

Year of Introduction. Bayus (1994) posits that product life cycles have not shortened over time. He argues that shorter times to bring innovations to market and an increasing number of new product introductions have been misinterpreted as evidence of shorter product life cycles. In contrast, we posit that the introductory stage of the product life cycle is shorter and the takeoff occurs earlier than in the past for several reasons. First, today's communications promote faster awareness of new products. Second, increased travel enhances the rate of information dissemination about new products. Third, the growth of national and multinational manufacturers and the simultaneous growth of huge retailer networks make it more likely that new products will be available to a national market right away. Fourth, consumer incomes have risen dramatically over time. Therefore, in recent years more consumers can afford new products sooner after they are introduced, rather than having to wait for prices to come down substantially. Scattered empirical research (e.g., Qualls et al. 1981) supports our position.

Thus we expect that the year of introduction of a new product is likely to be positively correlated with takeoff. We measure *year of introduction* by the calendar year of introduction of each product.

Market Penetration. We define *market penetration* as the percentage of households that have purchased a new product. Rogers' (1983) research on diffusion of innovations finds that markets for new products tend to cross a threshold from innovators to more of a mass market at about 2.5% penetration. Similarly, a meta-analysis on diffusion models finds that the average coefficient of innovation was 0.03 (Sultan et al. 1990). This finding means that the average intercept (which is meant to coincide with the takeoff) is the point at which sales are 3% of market potential. While this measure and Rogers' measure are not exactly the same, they both suggest that penetration may be an important correlate of takeoff. Another reason that market penetration may be correlated with takeoff is that important complementary products are made available once ownership reaches a certain percentage.

Control Variables. While we posit that these three variables are the primary correlates of takeoff, other variables might also affect the takeoff and need to be controlled. These control variables can be broken down into two groups: product-specific variables and economic variables. The product-specific variables include unit sales, and several characteristics of the product category such as whether it is a leisure, time-saving, electronic or white good, and whether its sales depend on externalities such as software or programming. We measure these characteristics with dummy variables. Economic variables include GNP, number of households, and consumer sentiment. We use standard economic measures of the latter.

Problem of Causality. As with econometric models in general, specification of independent variables does not imply causal impact on the dependent variable. This is especially true of price and market penetration, which are probably codetermined with sales and takeoff of the same year and are at least partly endogenous. Thus, our model must be interpreted primarily as a descriptive model of the factors associated with takeoff. In a subsequent section, however, we show how this model can help in predicting takeoff in a manner that would be useful to mangers. The predictive approach uses only information that would have been available at the time predictions are made about future takeoffs.

Data

The unavailability of suitable data has been a major hurdle that has hindered possible research efforts on the takeoff of new durables. To overcome this hurdle, we carried out a major search of the academic and business literature on the history of new durables (Golder and Tellis 1993). This section explains the sampling and data collection aspects of this search.

Sampling

We selected three sequential samples of product categories. Sample 1 consists of 11 consumer durables that have been analyzed frequently in diffusion research. To enhance the external validity of the findings and have a sample large enough to test our model, we selected a second sample of 10 consumer durables emphasizing products introduced more recently. A third sample of 10 categories was added during the review process to support the generalizability of our findings. Overall, Samples 1, 2, and 3 contain 31 product categories (see Table 1).

Data Collection

Sales data before takeoff are difficult to collect because statistics are usually reported only for categories that reach a threshold sales level. Therefore, we had to use multiple sources for collecting data, including *Merchandising, Merchandising Week, Electrical Merchandising, Business Week, Advertising Age,* the *Statistical Abstract of the United States,* other Department of Commerce publications, and Electronic Industries Association publications. We collected these data at the Library of Congress in Washington, D.C., the Conference Board and the Survey Research Center at the University of Michigan, in addition to local city and university libraries. We collected data on the following variables for every category in every year of interest where it was available: sales (in units), price (average price per year), market penetration, year of first sales in product category, GNP, disposable income per capita, price indexes, consumer confidence, consumer expectations, and consumer sentiment.

Table 1 presents the year of introduction for the 31 categories and the year of takeoff as determined by the threshold rule. To assess the robustness of our results to this measure of takeoff, we determine year of takeoff and reestimate the model based on two alternate measures (see Appendix A).

Table 1 Key Years in Category Histories

Product Category	Introduction	Takeoff
Direct Broadcast Satellite	1990	1995
CD-ROM	1985	1990
Camcorder	1984	1985
Compact Disk (CD) Player	1983	1985
Cellular Phone	1983	1986
Cordless Phone	1979	1982
Food Processor	1973	1977
Home VCR	1972	1980
Video Game	1972	1976
Answering Machine	1972	1983
Digital Watch	1972	1973
Radar Detector	1972	1984
Calculator	1971	1972
Microwave Oven	1966	1972
Can Opener	1956	1959
Color Television	1954	1962
Home Freezer	1939	1947
Black and White TV	1939	1948
Blender	1938	1962
Steam Iron	1936	1950
Clothes Dryer (spin)	1936	1950
Electric Blanket	1936	1955
Disposer	1935	1955
Automatic Coffee Maker	1934	1948
Power Lawn Mower	1933	1949
Electric Shaver	1931	1935
Room Air Conditioner	1929	1953
Radio	1920	1923
Refrigerator	1918	1926
Dishwasher	1900	1959
Automobile	1898	1912

Model Results

Table 2 summarizes results of estimating the hazard model. We discuss these results in terms of the key covariates of takeoff.

Price

As expected, price reduction appears to be an important factor associated with the takeoff. Its effect is large and significant at the 0.01 level. The coefficient of -0.043 in the hazard model implies that every 1% decrease in price is associated with a 4.2% increase in the probability of takeoff. This effect mirrors that which we noticed when reviewing the early history of these products. Table 3 gives some additional insights about the role of price. On average, the price at takeoff is 70% that at introduction. However, we found a statistically significant difference in this ratio before and after World War II.[4]

[4]Initial Price or first available price. A possible reason for the higher percentage in pre-World War II categories is that data were not available as early as in post-World War II categories. For the newer categories, our data are complete from introduction to takeoff for nine categories. Concern about the missing data is mitigated by the fact that prices typically show marginal reductions in the early years when sales are very low. For the nine post-World War II categories with complete data, price at takeoff/initial price is 0.65.

Table 2 Estimates of the Hazard Model (Standard Errors in Parentheses)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price Relative to Introductory Price	−0.048***			−0.039***	−0.053***		−0.043***
	(0.012)			(0.013)	(0.014)		(0.015)
Year of Introduction		0.042***			NS	NS	NS
		(0.011)					
Penetration			0.442***	0.219*		0.410***	0.217*
			(0.144)	(0.135)		(0.144)	(0.137)
Log likelihood	−29.9	−54.5	−33.8	−28.4	−29.7	−33.4	−28.2
U^2	0.270	0.143	0.176	0.308	0.276	0.186	0.312

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$, NS = not significant.

Another finding about price is that takeoffs often occur at specific price points. Based on nominal dollars, we found that 16 of 31 categories took off around either $1,000, $500, or $100 (see Table 4). These price points probably reflect acceptable points for mass adoption of new consumer durables. Informal analysis of price surveys of *Consumer Reports* indicates that such price points may persist for certain categories, even though product quality and disposable income improve substantially over time. For example, the most popular television sets have long sold for under $500, while the most popular answering machines have long sold for under $100.

Market Penetration

The coefficient for market penetration is large and significant at the 0.06 level. The coefficient of 0.22 implies that every 1% increase in penetration is associated with a 24% increase in the probability of takeoff. Further analysis supports the importance of penetration as a covariate of takeoff (see Table 5). For our categories, penetration at takeoff tends to be lower for newer categories, perhaps reflecting the shorter time to takeoff. Overall, our estimate of penetration at takeoff tends to be consistent with Rogers' (1983) estimate that innovators make up 2.5% of the population.

The standard deviation of penetration at takeoff is much lower after World War II than before.[5] One possible explanation for this effect is that consumer affluence and disposable incomes have risen substantially

[5]If we could correct for the small number of sales in the early years

Table 3 Price at Takeoff/Initial Price By Time Period (Standard Deviations in Parentheses)

Class	Number	Mean	Median	Range
Total	31	0.70 (0.20)	0.74	0.34–1.00
Pre-WW II	15	0.79 (0.18)**	0.82	0.40–1.00
Post-WW II	16	0.63 (0.20)**	0.64	0.34–0.96

**t test for difference in means statistically significant ($p < 0.05$).

Table 4 Product Categories by Price Point at Takeoff (Nominal Dollars)

$1000	$500	$100
Home VCR	Color TV	Calculator
Camcorder	CD Player	Answering Machine
Automobile	CD-ROM	Disposer
Cellular Telephone	Black and White TV	Coffee Maker
Direct Broadcast Satellite		Digital Watch
		Food Processor
		Video Game

Table 5 Penetration (%) at Takeoff by Time Period (Standard Deviations in Parentheses)

Class	Number	Mean	Median	Range
Total	31	2.9 (3.4)	1.5	0.3–15.0
Pre-WW II	15	4.3 (4.2)**	2.8	0.9–15.0
Post-WW II	16	1.7 (1.7)**	1.1	0.3–5.6

**t-test for difference in means statistically significant ($p < 0.05$).

and been more uniformly distributed after World War II. Similarly, the availability of credit cards and other forms of credit have made the purchase of durables much easier. Thus, after World War II products may begin to both takeoff earlier and with less variance across categories.

Year of Introduction

The bivariate analyses in Tables 3, 5, and 6 suggest that some descriptive statistics vary significantly in the economy before and after World War II. In particular, more recent categories (after the war) take off an average 5.8 years after introduction, whereas older categories did so after nearly 18 years (see Table 6).[6] These differences can also be explained by the greater availability of credit and the greater disposable income after World War II.

The coefficient for year of introduction, measured continuously or as a dummy, is not significant in the hazard model, however. Thus, the year of introduction may not affect the likelihood of takeoff after controlling for other variables. Interactions of year of introduction with the other independent variables were also not significant. The lack of significance may be due to multicollinearity or causal relationships between the year of introduction and the other two independent variables. For example, the steeper drop in prices after World War II may cause earlier takeoffs for products introduced after World War II. Another explanation may be that enhanced communications after World War II increased the rate of market penetration and possibly increased the rate of price reductions.[7]

Control Variables

With the exception of unit sales,[8] none of our control variables was significant. Category characteristics such as the product being an appliance, electronic item, or a white good did not affect the probability of takeoff. Similarly, the need for a complementary product (VCRs needing videos) also did not affect the probability of takeoff. Our measure of this need was a dummy variable that remained constant for each category, however. Economic characteristics such as consumer sentiment, GNP, or number of households did not affect the probability of takeoff. One explanation for these findings may be that when the primary conditions for a takeoff are satisfied, these forces are so great that even a weak economy cannot stall the takeoff. For example, the personal computer took off during the depths of recession in the early 1980s.

Model Performance

The consistency of the model's estimates with the hypotheses provides some support for its validity. In addition, we can directly assess the performance of the model by two criteria: 1) the reduction in uncertainty associated with modeling the probability of takeoff, and 2) the ability of the model to predict takeoff.

Analyzing Reduction in Uncertainty

We use the U^2 measure (Hauser 1978) to assess reduction in uncertainty. This measure reflects the relative increase in fit from including independent variables. It is analogous to the R^2 of multiple regression, although lower U^2 values are associated with excellent fits. For our model, U^2 is 0.31. This value is reasonable when compared to the U^2 of 0.48 obtained by Guadagni and Little (1983) who modeled brand choice using seven

for categories in which we do not have complete data, penetration at takeoff would be slightly higher. However, for the nine post-World War II categories with complete data, penetration at takeoff is actually lower at 0.92%.

[6]An alternate explanation for the data in Table 6 could be that products introduced more recently have not had the opportunity to takeoff yet and are therefore not part of our sample. However, even when we omit categories introduced since 1975, the average time to takeoff is still much less for more recent categories (6.8 years).

[7]Thanks to the area editor for contributing to several important points in this paragraph.

[8]At takeoff, the mean of unit sales is 884,000 and the median is 607,000.

Table 6 **Variation of Time to Takeoff by Time Period (Standard Deviations in Parentheses)**

Class	Number	Mean	Median	Range
Total	31	11.5 (11.2)	9	2–60
Pre-WW II	15	17.7 (13.4)***	15	4–60
Post-WW II	16	5.8 (3.4)***	5	2–13

***t-test for difference in means statistically significant ($p < 0.01$).

brand constants plus an additional seven independent variables.

Evaluating Predictive Ability

To estimate the predictive ability of the model, we use a type of jackknifing technique. We first hold out one target category, reestimate the model on the other 30 categories, and then use the estimated parameters to predict takeoff for the target category. In addition, we use *forecasted* and not actual values of the independent variables (price and penetration) of the target category. Thus, the prediction does not make use of any future information of the target category being predicted. It puts the forecaster in the position of the manager who would not have any foreknowledge about the takeoff or about future values of price or penetration.

Based on this principle, we make two types of forecasts, at introduction and one year ahead. The two types of forecasts differ by the method we use to forecast independent variables.

Forecast at Introduction. For the forecast at introduction, we forecast independent variables of the target category right at its introduction. These forecasts are obtained from the average values of these variables for the other categories. Thus:

$$X_i(t) = \frac{\sum_{j=1}^{n-1} X_j(t)}{n-1}, \tag{3}$$

where n is the number of categories, i represents the target category, and j stands for the other categories. Forecasted values are calculated for all time periods till the forecasted year of takeoff.

Once we have estimates of the coefficients and forecasts of the independent variables, we can determine the probability of takeoff. This probability will change over time based on changes in the underlying hazard distribution and the values of the independent variables.

One Year Ahead Forecasts. For the one year ahead forecasts, we modify the above approach for forecasting independent variables to also take into account the target category's actual past values of these variables. For the first year, the forecast of the independent variables is done just as above. For subsequent years, the forecast of independent variables is anchored on the actual value of the target category in the previous year and adjusted by the average change in independent variables of the other categories. Thus:

$$X_i(t) = X_i(t-1)\left[\frac{\left(\dfrac{\sum_{j=1}^{n-1} X_j(t)}{n-1}\right)}{\left(\dfrac{\sum_{j=1}^{n-1} X_j(t-1)}{n-1}\right)}\right]. \tag{4}$$

The difference in the two approaches lies in the difference between (3) and (4). The first approach does not require the target category's annual values on the independent variables, and so can be made at the time of introduction. The latter approach is anchored on the target category's actual values on the independent variables (of the previous year), and so can be made only one year ahead.

Estimation. Because we are interested in estimating the hazard rate as a function of time, we use maximum likelihood estimation. Following Jain and Vilcassim (1991) and Helsen and Schmittlein (1993), we use the quadratic specification of the hazard model. To do so, we first separate the data for all categories into discrete observations for each category-year (Allison 1995). Then, using the complementary log-log transformation and the Genmod procedure in SAS, we obtain parameter estimates that are directly comparable to the underlying proportional hazards model (Allison 1995, Prentice and Gloeckler 1978).

We predict the takeoff to occur in the year when the probability of no takeoff (commonly referred to as the survival probability) falls below 50%. The probability of the event occurring in each year is conditional on all prior years. Therefore, the estimate for no takeoff (S) after year 1 is $S(1)$; after two years $S(1)*S(2)$; after three years $S(1)*S(2)*S(3)$; etc. (Helsen and Schmittlein 1993). Because our probability estimates are conditional on every period from the year of introduction, we forecast only for the nine post-World War II categories that have complete data: color television, calculator, digital watch, CD player, cellular phone, camcorder, food processor, cordless phone, and CD-ROM.

Results. Using the approach we have just outlined, the mean absolute error in predicting the year of takeoff one year ahead is 1.2 years. The mean absolute error in predicting the year of takeoff when predicted at introduction is not much higher: 1.9 years.[9] This long-range prediction is significant because it is made several years before the actual takeoff occurs.

Discussion

This section summarizes the key findings from our study, discusses the implications of these findings, and suggests directions for future research.

Summary of Findings

The results of our study can be summarized into five major findings:

• New durables have a typical pattern of early sales characterized by a point of rapid sales increase which we call the takeoff.

• The hazard model fits this pattern fairly well. It can also predict the year of takeoff with an expected error of 1.2 years for post-World War II categories. Perhaps more importantly, the hazard model can predict takeoff at the time of introduction with an expected error of 1.9 years for the same categories.

• Two variables seem strongly associated with takeoff across categories: price and market penetration. The takeoff does not vary significantly with other characteristics of the product category or with other economic conditions.

• On average for 16 post-World War II categories:

—the price at takeoff is 63% of the introductory price;

—the time to takeoff from introduction is six years;

—the penetration at takeoff is 1.7%.

• The time to takeoff is decreasing for more recent categories. For example, the average time to takeoff is 18 years for categories introduced before World War II, but only six years for those introduced after World War II.

Implications

One of the most important implications of the study is our finding certain characteristics of the takeoff. In particular, the average time to takeoff is six years for post-World War II categories. Thus the takeoff is not instantaneous and requires patience and careful planning on the part of managers (Golder and Tellis 1993, Tellis and Golder 1996). Firms may need to be cautious about committing too many resources at the time of introduction. Moreover, six years can be a long time in the context of quarterly financial reporting required by Wall Street. Thus, firms may need to manage expectations of investors when introducing new products to avoid pressure to prematurely withdraw support for a promising new product.

A second important implication is the ability of our model to predict the year of takeoff. Doing so is very important to managers of new durables who agonize over continuing to support a new durable or transferring support to alternative products with potentially equal or greater promise. For categories introduced after World War II, the mean absolute error of prediction is 1.2 years for one year ahead forecasts, and 1.9 years at the point of introduction. How valuable are these predictions? We think that these results provide a substantial improvement over the current state of the art in new product management. Our informal discussions with some new product managers indicate that they have no scientific approach for estimating the time to takeoff. Therefore, just using the mean time to takeoff of six years from our sample of post-World War II categories provides an immeasurable improvement in prediction. Using the prediction of the hazard model at introduction relative to this six-year rule of thumb, provides *an additional 26% reduction in variance* of predictions.[10] In addition, our second set of predictions highlights a critically important feature of hazard models, i.e., that predictions of takeoff can be made at *any* time prior to takeoff, including at the year of introduction. Predicting the takeoff with an expected error of only 1.9 years at the point of introduction can be

[9] Time to takeoff for the nine categories used for prediction is less than the average for all 16 post-World War II categories. These categories have a mean time to takeoff of 4.1 years with a standard deviation of 2.3 years and a median time to takeoff of 4 years.

[10] With the nine categories used for prediction, another predictor of takeoff is to use their mean or median time to takeoff of four years. This approach leads to the lowest mean absolute error for predictions made at introduction, 1.7 years.

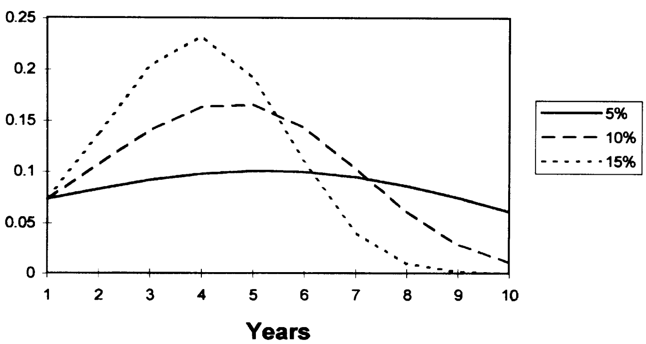
very useful to managers. In this context, the threshold rule for identifying a takeoff can be very useful too. This one simple rule accurately identified the takeoff in over 90% of the categories. The significance of the threshold rule is that managers can use it to distinguish between a large increase in sales and a real takeoff.

A third important implication is that managers can use the model results to *influence* the takeoff.[11] To show this aspect of the model, we simulated the effect of price on takeoff for a new product introduced in 1997. Figure 3 presents the marginal probabilities of takeoff over time for three rates of annual price reduction (5%, 10%, and 15%), assuming that market penetration increases from 0 to 5% over a 10-year period. Note from these curves how increasing the rate of price reduction *increases the peak probability* of takeoff in each curve, as well as *advances the time* at which the peak occurs. Similar curves can be obtained for probability as a function of penetration for fixed rates of price reduction. These curves can be used to maximize long-term profits by trading off the increased probability of takeoff or higher sales against lower prices and smaller margins.

A fourth important implication is our ability to provide a decision rule to determine whether to discontinue supporting a new product that has not taken off. Managers are often reluctant to pull the plug on unsuccessful new products, especially without predetermined stopping rules (Boulding et al. 1997). Our model can provide a useful stopping rule. For example, Figure 3 suggests a peak probability of takeoff at five years for a price reduction of 10% per year. Past that point, the marginal probability of takeoff begins to decline. If a product does not takeoff after the seventh year, the probability of it ever taking off is quite small. That would be one good point at which to pull the plug on the new product. A particular firm may determine its own stopping rule based on the chosen rate of price reduction, the expected margin per unit, and its tolerance for risk.

[11]This implication should be interpreted cautiously because of potential endogeneity bias with the independent variables.

Figure 3 Marginal Probability of Takeoff for Three Annual Price Reductions



Directions for Future Research

Our study suffers from many limitations, which may be the subject of fruitful research.

First, the independent variables suffer from endogeneity bias. Future research should attempt to measure variables that do not suffer from this bias, or adapt the hazard model to account for potential endogeneity of the independent variables.

Second, some other variables may also help explain the takeoff of new durables. Such variables include technological change, product quality, relative advantage of the new product over substitute products, availability of complementary products that increase utility of the new product, and the number of competitors. The challenge for researchers is to develop objective and meaningful measures of such independent variables and get the relevant data on them.

Third, we were unable to identify the precise explanation for the role of price in triggering the takeoff. Our analysis indicates that, on average, price at takeoff is 63% of the introductory price for recent categories. Would this figure mean that consumers retain the introductory price as a reference point, and begin to buy in large numbers when they find that prices are approaching half the introductory price? Or does the 63% reflect the point at which many consumers find the new product reflects a good buy relative to their budgets and the benefits it offers? Our data could not distinguish between these two rival explanations.

Fourth, we have not addressed the pattern of sales after the takeoff. An integrated model of takeoff and growth may be necessary for this stage. Such a model could be patterned on the hazard model developed here or, as seems especially useful to us, a multistage Tobit model (Amemiya 1985). These models could distinguish to what extent new product growth is self-perpetuating versus being driven by changes in the marketing variables.

Fifth, we have also not addressed the leveling off in sales at the end of the growth stage, as we did for the takeoff. Research could try to determine the number of years to the leveling off, the patterns if any at this point, and the factors that affect its occurrence. Current approaches such as the diffusion model may not be best suited for this purpose because they need data until the point of leveling off for estimation and parameter stability. The hazard model or its extensions could serve as a useful alternate for prediction. Any generalizations about the leveling off could also be of tremendous importance to managers of new products.[12]

Table A1 **Year of Takeoff by Measure of Takeoff**

Product Category	Threshold Rule	Logistic Curve Rule	Maximum Growth Rule
Direct Broadcast Satellite	1995	1994	1995
CD-ROM	1990	1991	1990
Camcorder	1985	1986	1985
Compact Disk (CD) Player	1985	1985	1984
Cellular Phone	1986	1987	1986
Cordless Phone	1982	1981	1983
Food Processor	1977	1977	1977
Home VCR	1980	1981	1983
Video Games	1976	1975	1976
Answering Machine	1983	1983	1983
Digital Watch	1973	1976	1975
Radar Detector	1984	1979	1978
Calculator	1972	1974	1972
Microwave Oven	1972	1975	1972
Can Opener	1959	1960	1959
Color Television	1962	1963	1962
Home Freezer	1947	1946	1947
Black and White TV	1948	1949	1947
Blender	1962	1961	1962
Steam Iron	1950	1949	1950
Clothes Dryer	1950	1950	1950
Electric Blanket	1955	1952	1950
Disposer	1955	1957	1955
Automatic Coffee Maker	1948	1950	1948
Power Lawn Mower	1949	1950	1947
Electric Shaver	1935	1935	1935
Room Air Conditioner	1953	1951	1953
Radio	1923	1924	1923
Refrigerator	1926	1929	1926
Dishwasher	1959	1961	1959
Automobile	1912	1912	1912

Appendix A

This section presents the robustness of our results to two alternate definitions of takeoff: a logistic curve rule and a maximum growth rule. The results presented previously are based on the threshold rule because we believe that this approach is the most accurate and parsimonious way to measure the takeoff.

The *logistic curve rule* to measure takeoff is based on finding the first "turning point" of a logistic curve fitted to each sales series. Since the takeoff occurs with the first dramatic change in sales *growth*, the maximum of the second derivative of the logistic curve would capture this first "turning point." The *maximum growth rule* uses the largest percentage sales increase within three years of the takeoff as determined by the logistic curve rule. We next describe the identification of takeoff, descriptive statistics, and model estimates for the alternate measures of takeoff.

Identification of Takeoff

Table A1 presents the year of takeoff determined by the three measures. The table shows that the three measures often identify the same year of takeoff or differ by a very small value when they do not. In particular, the maximum growth rule is very close to the threshold rule.

Descriptive Statistics

Table A2 compares the descriptive statistics across the three measures of takeoff.

The table shows that the descriptive statistics are fairly robust to the takeoff rule that is used. The only differences close to statistically significant ($p < 0.20$) between the threshold rule and the logistic curve approach are in total and post-WW II penetration. These differences are driven by the logistic curve approach classifying takeoff as later than what seems obvious from the sales curve for several categories. The differences are particularly large for calculators and digital watches. There are no significant differences between the threshold rule and the maximum growth rule, although in some cases the highest percentage growth did occur clearly after the takeoff.

Model Estimates

Table A3 compares the estimates of the coefficients of the hazard model across the three measures of takeoff.

The table shows that the results for the three alternate measures of takeoff are quite consistent. In addition, the model's estimates are comparable.

[12]The authors thank Paul Allison, Bruce Buchanan, Rajesh Chandy, Merle Crawford, John Czepiel, Gary Frazier, Eric Greenleaf, Don Lehmann, Vijay Mahajan, Bob Shoemaker, Dave Stewart, Naufel Vilcassim, Andrew Weiss, and Fred Zufryden for their comments on this research. The study also benefited from the comments of the editor, area editor, and two reviewers, and participants at presentations at PDMA, MSI, Dartmouth College, UC Berkeley, and UC Irvine.

Table A2 Descriptive Results by Measure of Takeoff (Mean, Standard Deviation, Median, Range)

	Threshold Rule	*Logistic Curve*	*Max Sales Growth*
Years to Takeoff			
Total	11.5 (11.2) 9 2–60	11.8 (11.2) 10 3–62	11.3 (11.1) 9 2–60
Pre-WW II	17.7 (13.4) 15 4–60	17.9 (13.6) 15 5–62	17.1 (13.4) 15 4–60
Post-WW II	5.8 (3.4) 5 2–13	6.2 (2.9) 5 3–12	5.8 (3.1) 5 2–12
Price/Intro Price			
Total	0.70 (0.20) 0.74 0.34–1	0.70 (0.25) 0.76 0.27–1.3	0.73 (0.23) 0.77 0.27–1.3
Pre-WW II	0.79 (0.18) 0.82 0.4–1	0.78 (0.23) 0.79 0.27–1.3	0.84 (0.21) 0.83 0.4–1.3
Post-WW II	0.63 (0.20) 0.64 0.34–0.96	0.63 (0.25) 0.56 0.27–1	0.62 (0.21) 0.64 0.27–0.96
Penetration			
Total	2.9 (3.4) 1.5 0.3–15	4.5 (5.1) 3.2 0.2–24.7	2.8 (2.8) 1.3 0.2–10.1
Pre-WW II	4.3 (4.2) 2.8 0.9–15	4.9 (2.9) 5.0 0.3–9.1	3.4 (3.1) 1.3 0.2–10.1
Post-WW II	1.7 (1.7) 1.1 0.3–5.6	4.1 (6.6) 1.8 0.2–24.7	2.3 (2.4) 1.4 0.2–8.7

Table A3 Hazard Model Results by Measure of Takeoff (Standard Errors in Parentheses)

Variable	Threshold Rule	Logistic Curve Rule	Maximum Growth Rule
Price Relative to Introductory Price	−0.043*** (0.015)	−0.019* (0.012)	−0.024* (0.015)
Year of Introduction	NS	NS	NS
Penetration	0.217* (0.137)	0.120** (0.067)	0.519** (0.282)
Log likelihood	−28.2	−32.6	−22.5
U^2	0.312	0.218	0.339

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$, NS = not significant.

Conclusion

Which of the three measures of takeoff is the most appropriate? There are several problems with the logistic curve rule to measure takeoff. First, fitting the logistic curve requires sales *past* the takeoff. Thus, the takeoff can only be measured in hindsight. Second, the logistic curve rule is a continuous rule to measure what we believe to be a discontinuous event. Third, it involves a contradiction, in that we use a logistic model to define a point we then predict with a hazard model.

The maximum growth rule also suffers from three problems. First, the largest sales growth sometimes occurs after the takeoff has already occurred and sales are clearly in the growth phase. Second, because this rule does not establish a minimum base level of sales, large percentages sometimes occur because of a relatively small base, falsely indicating a takeoff. Third, this rule can only be applied years after the takeoff. Thus, it also involves hindsight.

In contrast, the threshold measure of takeoff does not use any future information for the new product to determine whether it has taken off. It also does not assume any model of the pattern of sales. Finally, it takes into account the base level of sales. Thus, we believe that the threshold rule is the best single rule for determining takeoff.

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