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Author(s): Rolando Polli and Victor Cook
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VALIDITY OF THE PRODUCT LIFE CYCLE*

ROLANDO POLLI† AND VICTOR COOK‡

THE concept of a "product life cycle" has been widely discussed during the last decade but has not been systematically tested as a model of sales behavior. This might be the result of a tendency not to take the concept of the model very seriously—a tendency which would be consistent with its known degree of validity. But several writers have used the product life cycle as a basis for recommendations about the content of marketing programs at different stages of the life cycle.[1] Recommendations made by some of these authors concerning the level of advertising weight, nature of distribution, pricing strategy, and so forth, rest on the assumption that the product life cycle is largely independent of the firm's marketing activities. It *may* be true that changes in advertising, for example, will not significantly affect a product's life cycle, but this ought to be clearly established before it is accepted as a basis for planning.

The purposes of this paper[2] are (1) to develop an operational model of the product life cycle consistent with the assumptions underlying the concept, (2) to specify objective test statistics with which to evaluate the performance of the model, and (3) to present the results of tests which make use of observed sales in 140 categories of nondurable consumer products. These product categories include health and personal care (fifty-one), food (fifty-six), and tobacco (thirty-three). In short, we shall try to verify empirically the product life cycle as a descriptive model of sales behavior.

THE PRODUCT LIFE CYCLE CONCEPT

The product life cycle appears to be simply another example of a time-dependent, intermediate-term forecasting

* This research was supported by the Marketing Science Institute, Cambridge, Mass.

† Assistant professor of marketing, University of Pittsburgh.

‡ Assistant professor of marketing, University of Chicago.

[1] See, for instance, Joel Dean, "Pricing Policies for New Products," *Harvard Business Review* 28, no. 6 (November-December 1950): 45–54; Jay W. Forrester, "Advertising: A Problem in Industrial Dynamics," *Harvard Business Review* 37, no. 2 (March-April 1959): 100–111; Arch Parron, "Top Management's Stake in the Product Life Cycle," *Management Review* 18, no. 6 (June 1959): 9–15; Theodore Levitt, "Exploit the Product Life Cycle," *Harvard Business Review* 43, no. 6 (November-December 1965): 81–94; Donald K. Clifford, Jr., "Leverage in the Product Life Cycle," *Dun's Review of Modern Industry*, May 1965, pp. 62–70.

[2] The research summarized here is reported in more detail in Rolando Polli, *A Test of the Classical Product Life Cycle by Means of Actual Sales Histories* (Ann Arbor, Mich.: University Microfilms, 1968), and in Rolando Polli and Victor Cook, "A Test of the Product Life Cycle as a Model of Sales Behavior" (Marketing Science Institute working paper, Philadelphia, November 1967).

model, based on an inept biological analogy. But this view is misleading. First, it has not been utilized primarily for forecasting. Instead, it has been considered an aid in planning and policy formulation.[3] For example, the identification of a stage in the life cycle is thought useful because it permits evaluation of a series of tactical and strategic considerations bearing on product policy. Second, the characteristic life cycle curve (see fig. 1, *A*) finds strong theoretical support in Rogers's theory of the diffusion and adoption of innovations.[4] Essentially, the concept implies that a product finds initial resistance to widespread acceptance of some new way of behaving and is purchased by only a limited segment of the buying population. Later, as the product's performance and value are known and communicated, a larger segment of buyers adopt it, and sales begin to increase at a faster pace. Eventually, the rate of growth decreases as the proportion of adopters gets closer and closer to a maximum, with most sales representing repeat purchases. The rate of adoption remains constant throughout the maturity phase and diminishes in the decline phase. The link between Rogers's theory and the life cycle concept becomes obvious if one considers that the logistic curve usually employed to represent the life cycle is the cumulative equivalent of the normal density function, which is precisely the shape of Rogers's adoption function.[5]

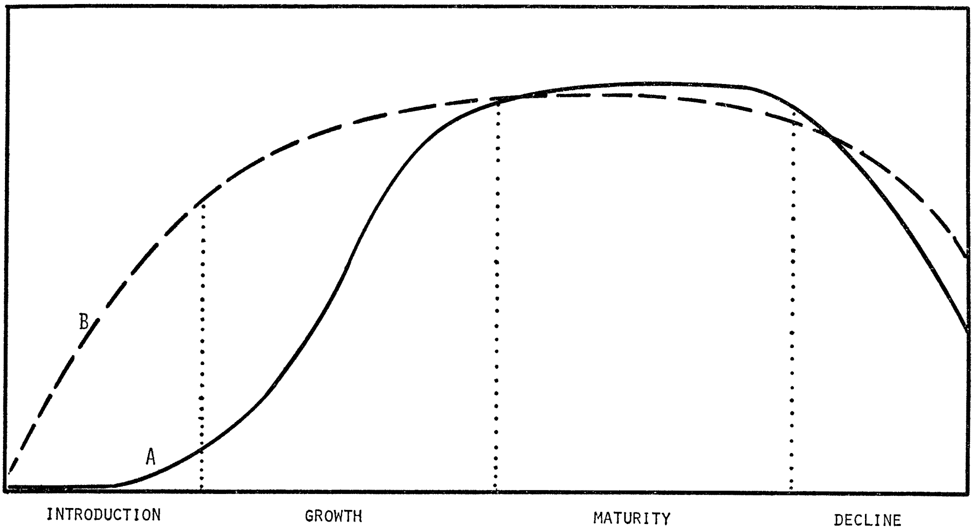

FIG. 1.—Two frequently hypothesized life cycle patterns

While the relationship between the life cycle and the theory of adoption provides a plausible rationale for the life cycle model, the choice of a logistic curve between the introductory and early maturity periods is an unnecessary restric-

[3] Yet, some attempts have been made to use the life cycle for predictive purposes. See Philip Kotler, "Computer Simulation in the Analysis of New Products Decisions" (Purdue University, 1966).

[4] Everett Rogers, *The Diffusion of Innovations* (Glencoe, Ill.: Free Press, 1962).

[5] For a more complete discussion of the ties between product life cycle and diffusion theory, see Thomas S. Robertson, *Innovation and the Consumer* (New York: Holt, Rinehart & Winston, in press) chap. 2.

tion. The diffusion of many new products resembles an exponential curve (fig. 1, *B*), especially if the item is not a dramatic innovation and if its entry into the market is supported by adequate promotion.

The interpretation of the life cycle as having four main stages and a sales pattern like that of figure 1, *A* or 1, *B* is far from universal.[6] There have been attempts by some to develop a taxonomy of different life cycles. William E. Cox, in a study of 258 ethical-drug brands, identified six patterns and found that for over 50 percent of these, a fourth-degree polynomial (fig. 2) best fit the historical data.[7] His results are very similar to those of J. Hinkle of the A. C. Nielsen Company, who identified a "recycle" pattern for brands in different product categories.[8] Buzzell,[9] in his investigation of the food industry, obtained results more consistent with the concept described earlier; but even so he ventures to distinguish among "innovative," "growth," and "stable" maturity stages.

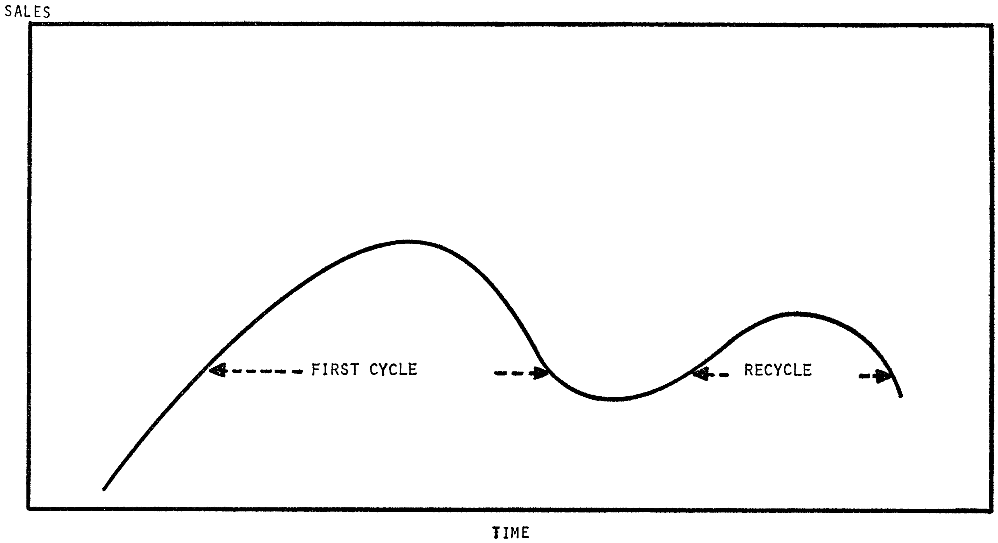

FIG. 2.—The Nielson-Cox recycle

These empirical approaches to the life cycle leave much to be desired. If we consider *any* sales pattern as a "life cycle" and concentrate upon the type of function that best approximates the observed data, without providing a theoretical rationale for the observed pat-

[6] Several different approaches to definition and use of the product life cycle are found in: Hugh M. Beville, "The Product Life Cycle Theory Applied to Color Television" (M.A. thesis, New York University, 1966); Robert D. Buzzell and R. E. Nourse, "The Product Life Cycle," in *Grocery Manufacturing in the United States*, ed. Gary A. Marple and Harry B. Wissman (New York: Frederick A. Praeger, Inc., 1968), pp. 39–83; Victor J. Cook and Thomas F. Schutte, *Brand Policy Determination* (Boston; Allyn & Bacon, 1967), pp. 49–58; Leonard I. Rothman, "Measurement and Description of Product Life Cycles" (M.B.A. thesis, University of Pennsylvania, 1967); Robert B. Stobaugh, Jr., "The Product Life Cycle, U.S. Exports, and International Investments" (Ph.D. diss., Harvard Business School, 1968).

[7] William E. Cox, Jr., "Product Life Cycles as Marketing Models," *Journal of Business* 40 (October 1967): 375–384.

[8] J. Hinkle, *Life Cycles* (New York: A. C. Nielsen Co., 1966.

[9] Buzzell and Nourse.

terns, the result is likely to be a fairly sterile exercise in taxonomy.

SOURCES OF CHANGE IN SALES PATTERNS

The varied, sometimes conflicting, results of earlier studies are due in part to the fact that many complex interacting forces affect sales. Some of these, such as seasonal sales fluctuations, are irrelevant to the life cycle model. Others, such as rapid declines in the dollar's value through inflation, may cause changes which *appear* to reflect life cycle patterns but are in fact quite independent of them. Accordingly, we adjusted all sales data, prior to testing, to allow for (1) population growth, (2) change in the level of personal consumption, and (3) price changes.[10]

DEFINITION OF "PRODUCTS"

Changes in sales of a "product" vary not only because of the factors named above but also according to the very definition of a product. Many different levels of aggregation may be used in definition. Both "cars" and "mentholated filter cigarettes" are products. Yet, the former category includes objects far more heterogeneous among themselves than the latter. Account must be taken of this general problem in order to avoid confusion and error.

We found it meaningful here to distinguish among *product classes*, *product forms*, and *brands*. An illustration of these definitions in the cigarette category appears in fig. 3.

It is difficult to provide unassailable general rules to define these three categories, though it is easy to partition specific markets along these lines. Theoretically, items which belong in different product classes should have near-zero demand cross-elasticity. Thus, *product classes* include all those objects that, despite differences in shapes, sizes and technical characteristics, are essentially substitutes for the same needs. The need must be fairly specific. Cars, airplanes, trains, and bicycles all satisfy a need for transportation. Only cars, however, satisfy the need for enclosed, fast, multi-passenger, overland transportation. There are, indeed, many more needs an automobile may fulfill than those mentioned, and they differ as their owners do. All that can be said is that need specification can most easily be undertaken with a specific problem in view and must entail some personal judgments.

Product forms are finer partitions of a product class. They include objects that, though not identical, are technically quite homogeneous. All objects within a product form can be meaningfully added in physical units. A product class may be partitioned in various product forms along different criteria; for example, cigarettes may be distinguished by the presence of a filter, by their length, and by menthol in the tobacco.

Brands within a product form are "unique," apart from package differences. A brand is completely specified technically and is, of course, further identified by the trademark of the manufacturer or distributor.

Given these definitions, we may now propose a verifiable model of the product life cycle.

AN OPERATIONAL MODEL OF THE PRODUCT LIFE CYCLE

As we interpret it, the product life cycle is a time-dependent model of sales which has a relevant theoretical foundation. The model hypothesizes that sales follow a consistent sequence of stages,

[10] Cigarette sales were in units and did not need a price adjustment.

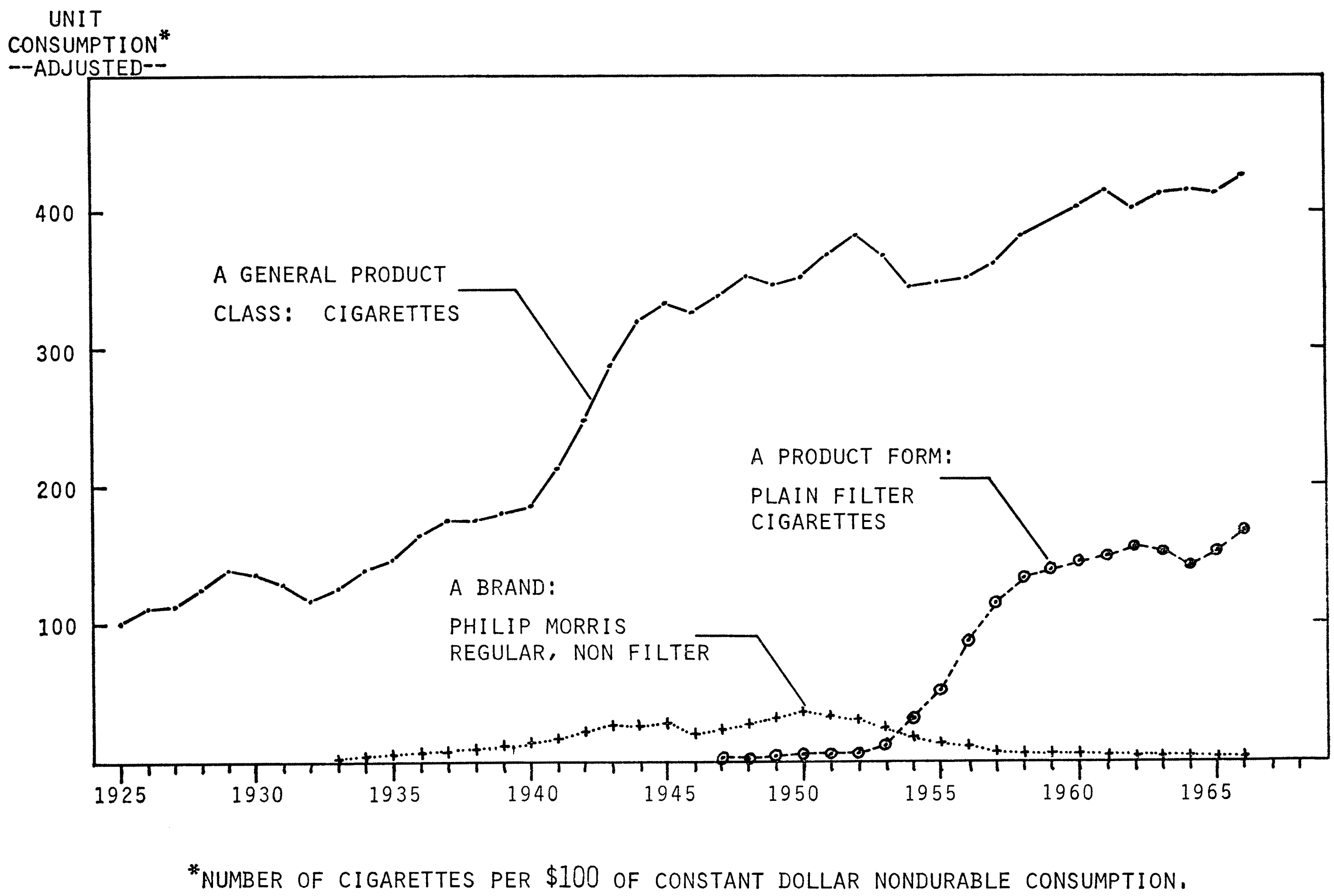

FIG. 3.—Illustration of product definition

beginning with introduction and proceeding to growth, then to maturity, and eventually into decline. Since the principal components of this model are (1) changes in sales, (2) stage identification, and (3) sequential sales behavior, these three factors were given operational meaning in the following way.

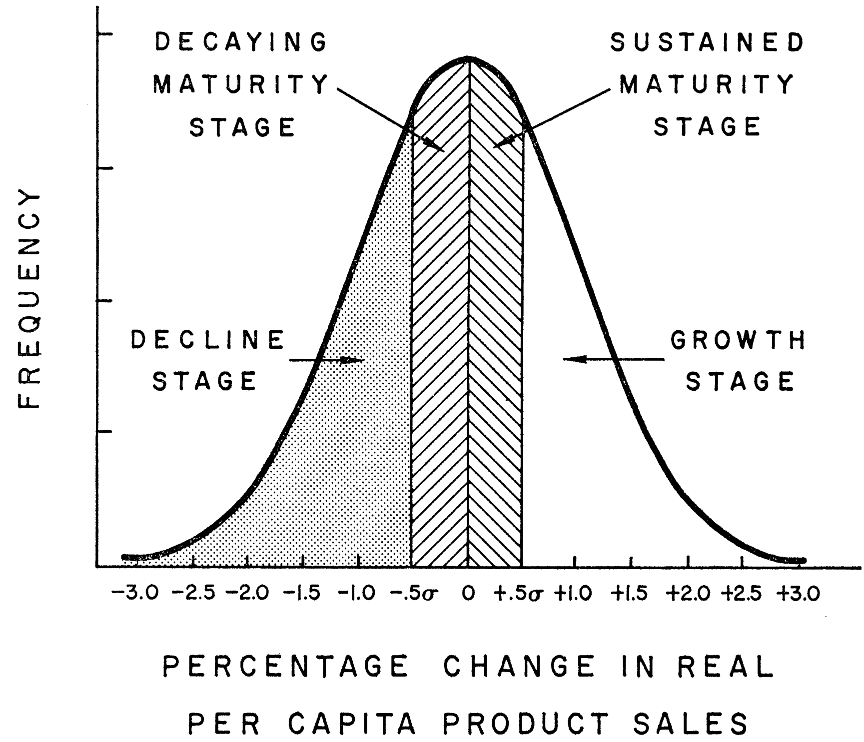

FIG. 4.—How product life cycle stages were identified

SALES CHANGE AND STAGE IDENTIFICATION

Suppose we have unit sales data for all products of a certain class of goods sold in some well-defined market, like the United States, and suppose for any two years, say 1967 and 1968, these data are adjusted for population growth and changes in general business activity. From these sales observations we can calculate the percentage change in real sales for each product. We would expect the percentage changes to vary among these products, ranging from sharply negative to very large positive values. If the percentage changes are plotted, we might expect the distribution to be near normal with mean zero.

We assigned boundaries to this theoretical distribution of percentage changes (see fig. 4), as follows: values lower than $-\frac{1}{2}\sigma$ were considered to represent significant "declines" in real adjusted sales; values greater than $+\frac{1}{2}\sigma$ were considered to represent significant "growth" in real adjusted sales; and values in the range of $\pm\frac{1}{2}\sigma$ were considered to be stable, corresponding to the "maturity" stage. The maturity phase was subdivided into three substages: sustained maturity for positive, but small, percentage changes; decaying maturity for negative, but small, changes; and stable maturity for no significant changes. The introduction stage was defined as that time period when annual sales were less than 5 percent of the observed peak level, which could be the real maximum sales level, or some observation en route to it. These stage identification criteria, applied to food and to health and personal care products, are listed in table 1.

One important property of this method is that it identified major stages in a product life cycle (except introduction) without knowing what came before or after any pair of sales observations.

The results reported here are based on three classes of consumer products: (1) health and personal care; (2) foods, and (3) cigarettes. Since sales changes for all items in these product categories were unknown, relevant parameters were estimated from the sample of products at hand. The actual stage-boundary criteria for food and for health and personal care products was ±5 percent, and cigarette products ±7 percent, as the standard deviations of the observed distributions (four of these are shown in fig. 5) were approximately 0.10 and 0.15, respectively. Furthermore, the limits agreed with our judgment as to what constitutes the limits of stability. They would change significantly with different data. For example, if deseasonalized monthly data for a single brand were used, the standard deviation, and hence limits of maturity, would likely be much larger.

Table 2 shows the observed frequency of occurrence for each stage in the three product categories.

The rules adopted for stage identification are by no means flawless. However, they seem reasonable for analysis of the incomplete sales histories normally available.

EXPECTED SALES SEQUENCES

Given the unit of measure and stage-identification criteria, formulation of the model was completed in a way which seemed consistent with the major assumptions about the product life cycle. There are two principal assumptions in the model.

At the very least, the product life cycle leads us to expect the following sequence of sales behavior: once introduced, products may undergo a period of relatively limited acceptance and, therefore, low sales compared with their eventual peak

TABLE 1

CRITERIA FOR STAGE IDENTIFICATION IN THE FOOD AND THE HEALTH AND PERSONAL CARE CATEGORIES

Symbols: S_i = Yearly sales of nondurable i divided by sales of all nondurables
S_i^* = Yearly percentage changes in S_i

Introduction	S_i less than 5% of peak sales
Growth	S_i^* greater than +.05
Sustained maturity	S_i^* in the +.05 to +.01 range
Maturity	S_i^* = +.01 to −.01
Declining maturity	S_i^* in the −.01 to −.05 range
Decline	S_i^* greater than −.05

sales level. After this, sales enter a period of sustained growth, until a peak is reached, very likely including an initial period of rapid growth, followed by a period of diminishing growth with decreasing increments. When the rate of growth approaches zero, a period of stability or maturity is reached and maintained until sales begin to decline. The product will be withdrawn when sufficiently low levels of use and sales are reached to make it unprofitable for all sellers.

Not all sequences of stages occurring in actual sales histories are consistent with this expected sequence. Table 3 defines in detail all "consistent sequences."

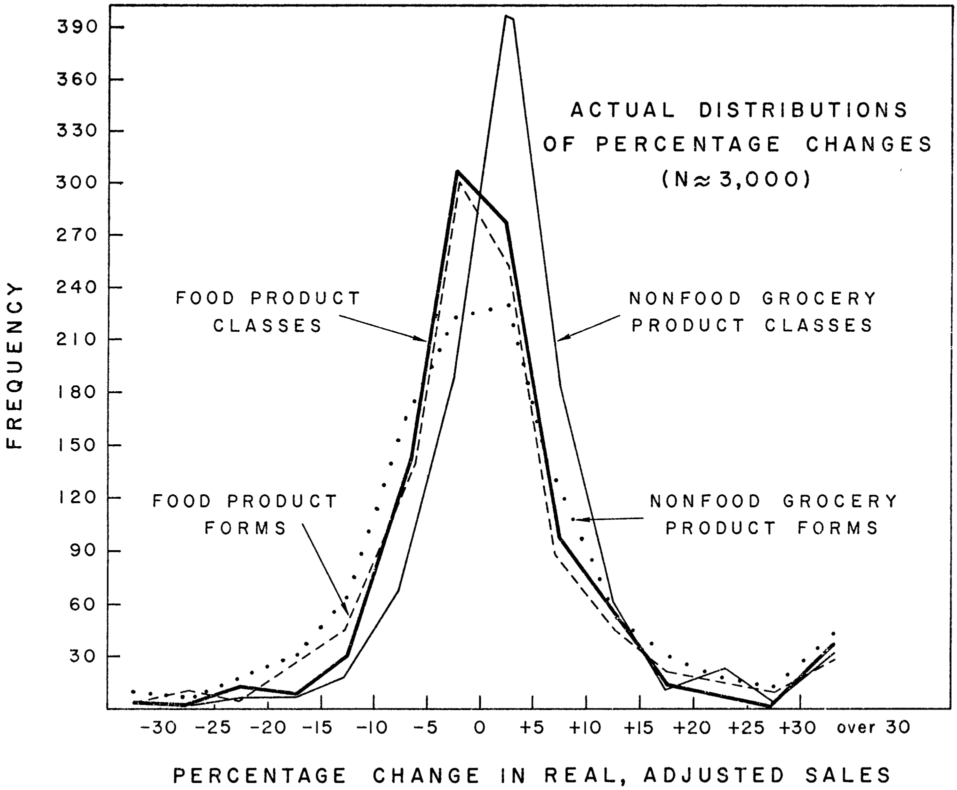

FIG. 5

TABLE 2

OBSERVED FREQUENCY OF OCCURRENCE FOR EACH LIFE CYCLE STAGE

Growth	Cigarette Brands Total (%)		Health and Personal Care Total (%)		Food Total (%)	
Growth	37.0		26.0		18.0	
Sustained maturity	16.0	36.0	30.0	56.0	23.0	60.0
Maturity	2.0		5.0		5.0	
Declining maturity	18.0		21.0		32.0	
Decline	27.0		18.0		22.0	
Total	100.0		100.0		100.0	

TABLE 3

STAGE SEQUENCES CONSISTENT WITH THE LIFE CYCLE

May Be Preceded by	Period	May Be Followed by
I, *G*	*G*	*G*, *M*+, *M*, M−, *D*
G, *M*+, *M*, *M*−	*M*+, *M*, *M*−	*M*+, *M*, *M*−, *D*
G, *M*+, *M*, *M*−, *D*	*D*	*D*
G, *M*+, *M*, *M*−, *D*	*DD**	*D*, *M*−
G, *M*+, *M*, *M*−, *D*	*DDD*†	*D*, *M*−, *M*

NOTE—*I* =introduction, *G* =growth, *M*+ =sustained maturity, *M* =maturity, *M*− =decaying maturity, *D* =decline.
* Two *consecutive* decline periods.
† Three *consecutive* decline periods.

It may be noted that we have allowed for periods of declining or simple maturity to follow three consecutive decline phases. Decline is seldom discussed in the life cycle literature, and it is not clear whether it must be a time of *steadily* declining sales. As table 3 indicates, we have adopted the view that some pauses in the decline phase are permissible.

The life cycle pattern suggests, in addition to this *expected sequence,* an *expected time pattern* for the stages. The expected time pattern, while extremely important, is often dismissed with the thought that it depends on the product in question. No doubt this is true. Yet, most graphic representations of the life cycle ignore the decline stage and give the impression that the introductory and growth periods combined account for at least half (possibly more) of the product's life. Furthermore, we are often left with the implication that the life cycle curve is symmetrical around the midpoint in a growth stage and might best be forecast by a logistic growth curve. The implication of this statement is that the time spent in the introductory and rapid-growth stages is equal to that spent in the periods of slow growth and maturity.

We concluded that the expected sequence of changes in sales beginning with introduction, proceeding to rapid growth and then to reduced growth, and reaching stability, with the possibility of decline, represents the *weak assumption* of the product life cycle model. This expected sequence plus the expected proportion of time spent in each stage represents the *strong assumption* of the product life cycle model.

By the designation of "weak" and "strong" assumptions, we do not suggest that the weak assumptions of the model are unimportant or obvious, for they are neither. This research attempted to test the validity of the weak assumption and develop a better understanding of the proportion of time spent in each stage.

To summarize, the model which we tested against observed sales data included three main elements: (1) a unit of measurement—percentage change in real, adjusted sales data; (2) stage identification criteria—percentage change rates consistent with "growth," "maturity," and "decline"; and (3) a weak assumption—the expectation of an orderly time path in sales proceeding from introduction to growth to maturity to decline, as illustrated in figure 6.

TEST AIMS AND PROCEDURES

Since the primary goal of the research was to assess the consistency of the life cycle model with observed sales histories, in the nondurables field, tests were needed to determine, for any product, the degree of consistency between sales records and life cycle.

The test chosen is a comparison between the number of *inconsistent observations*—that is, stages that deviate from the expected sequence of the life cycle model—of an actual sales history and the average number of inconsistent observations found in 100 *simulated sequences* of equal length. A simulated sequence, as the name implies, is a series of stages generated by a chance process. The probabilities of occurrence of each stage were made equal to their relative frequencies in the product category to which the specific product belonged (see table 2).

Runs of 100 simulated sequences were generated for time periods with lengths corresponding to those of the products analyzed. The mean and standard deviations of inconsistent observations were computed.[11] It was thus possible to construct confidence limits which have the same meaning as those employed in statistical hypothesis testing. For example, suppose that in a sequence of 18 S_i^*, two inconsistent observations were found. Further, suppose that the mean of inconsistent observations of 100 simulated sequences is 7 and $\sigma = 1.4$. We will conclude that the inconsistent observations in the actual series are significantly different from chance if they are less than $\bar{x} - 2.56\sigma$, at the 1 percent confidence level. In this specific case, this happens to be true, as $7 - (2.56 \times 1.4) = 3.436 > 2$. Figure 7 outlines the test procedure, and table 4 shows the values of $\bar{x}$ and σ and the limits at the 5 percent and 1 percent confidence levels, for simulated sequences of different lengths.

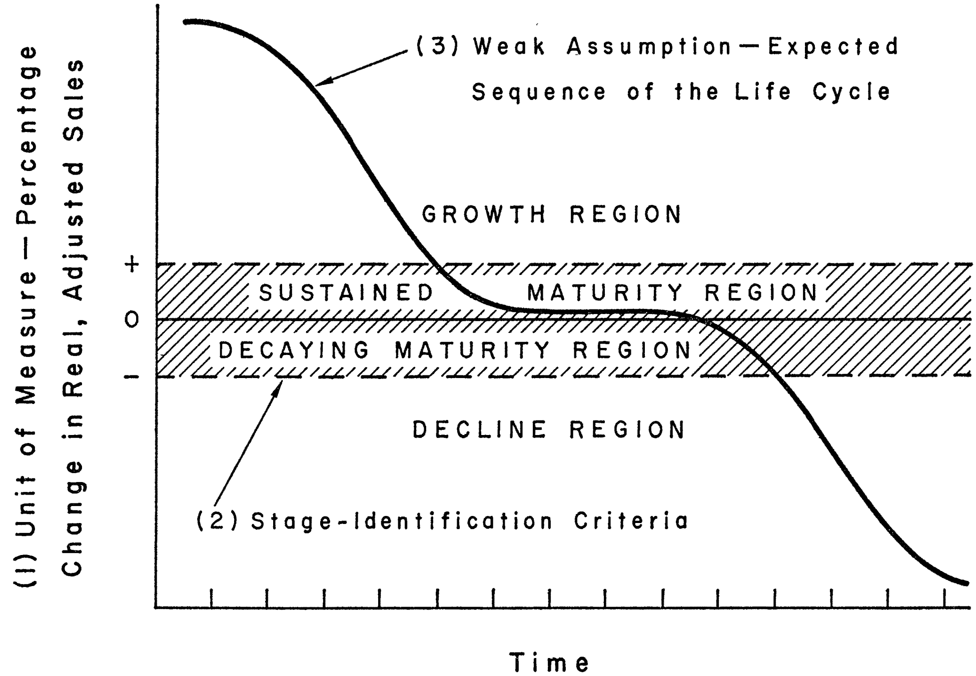

FIG. 6.—Verifiable model of the product life cycle

THE DATA

Sales histories used in our analysis were for product classes and product forms in the food and health and personal care categories and for product forms and brands in the cigarette category. For data reported here, all sales histories are expressed in annual terms and vary in series length from a maximum of forty-one to a minimum of six years. Most, however, are more than ten years in length.

All the data for food and for health and personal care products were taken

[11] We are indebted to Mrs. Ada Scott for setting up a computer program that generates the chance sequences, identifies inconsistent observations, and computes mean and standard deviation. The hardest task is the identification of inconsistent observations. As the complete scanning of all consistent sequences is too laborious even for the computer, the program is based on a few heuristics. After various attempts, it now identifies the correct number of inconsistent observations in over 90 percent of the series to which it is applied.

from *Food Topics* and *Drug Topics*;[12] for cigarettes in the postwar period, the Wotten-Maxwell, Jr., reports published in *Printers' Ink*;[13] and for cigarettes in the prewar period, Nichols's *Price Policies in the Cigarette Industry*.[14] For several of the food and health and personal care categories, independent sales estimates were available. Cross-checking revealed consistent downward biases in the data, though changes were comparable. Independent checks were not available for the

[12] Annual Consumer Expenditure Study, *Food Topics* and *Food Field Reporter* (1947–65); *Drugs Topics* and *Drugs Trade News*.

[13] Wotten report, *Printers' Ink* (December or January issue, 1941–61); Maxwell, Jr., report, *Printers' Ink* (usually December issue, 1963–66.

[14] William H. Nicholls, *Price Policies in the Cigarette Industry* (Nashville, Tenn.: Vanderbilt University Press, 1951).

TABLE 4

MEAN AND STANDARD DEVIATION OF INCONSISTENT OBSERVATIONS FROM 100 SIMULATED SEQUENCES OF LENGTH t

Sequence Length (t)	$\bar{x}$	σ	$x-1.96\sigma$	$x-2.56\sigma$
Health and Personal Care Product Forms:				
18	7.12	1.46	4.26	3.37
13	4.69	1.37	2.02	1.18
11	3.61	1.26	1.13	0.36
10	3.45	1.43	1.20	0.50
9	3.01	0.95	1.08	0.47
6	1.70	0.85	0.03	*
Health and Personal Care Product Classes:				
18	5.92	1.48	3.00	2.09
15	4.91	1.41	2.15	1.29
13	3.85	1.34	1.22	0.39
Food Product Forms and Classes:				
18	5.59	1.78	2.11	1.01
15	4.71	1.49	1.80	0.89
14	3.82	1.55	0.79	*
13	3.64	1.44	0.82	*
11	3.14	1.30	0.60	*
8	2.25	..01	0.24	*
Cigarette Brands:				
41	19.18	2.22	14.82	13.45
39	18.31	2.25	13.90	12.52
37	16.74	2.16	12.50	11.17
34	15.33	2.16	11.52	10.19
33	15.21	2.11	11.08	9.78
31	13.97	1.80	10.44	9.33
27	12.04	1.76	8.60	7.52
26	11.36	1.63	8.17	7.17
22	9.44	1.66	6.19	5.17
20	8.38	1.70	5.06	4.01
19	7.79	1.65	4.57	3.55
18	7.56	1.56	4.51	3.55
17	6.92	1.47	4.04	3.14
16	6.48	1.42	3.70	2.83
14	5.47	1.28	2.95	2.16
13	5.06	1.30	2.51	1.71
12	4.49	1.32	1.91	1.10
11	3.96	1.08	1.85	1.19
10	3.44	1.02	1.43	0.81
9	3.06	1.14	0.83	0.13

* Negative limit.

cigarette series, but we believe them to be accurate and reliable.

THE RESULTS

The results divide naturally into two areas: first, the performance, in statistical terms, of the life cycle model compared with actual data; second, the management implications of this performance.

STATISTICAL RESULTS

Tables 5 and 6 summarize the results of the tests of 140 products, including product classes, product forms, and brands. The brand data are limited to to cigarettes.

TABLE 5

OVERALL RESULTS OF LIFE CYCLE MODEL COMPARED WITH CHANCE MODEL

Result	All Products
Percentage of observed sequences significantly different from chance:	
At .01 confidence level	34%
At .05 confidence level	44%
Percentage of observed sequences with *no* inconsistent observations	12%
Percentage of observed sequences with fewer inconsistent observations than expected from chance	92%

Compared with the chance model, the life cycle model gave significantly different results in 34 percent of the observed series at a .01 confidence level, and in 44 percent of the cases at the .05 level.

An illustration of the results in one category is shown in figure 8. For cigarettes the results were significantly different from chance in a majority of cases. For example, in the entire forty-one years of observed sales changes in the general product class, there were only six reversals, or observed changes in adjusted sales outside the boundaries of maturity, and four of these occurred during the war years from 1941 to 1945. Also, the product form "plain filters" followed the expected sequence closely with only one reversal (1966), as did the brand "Philip Morris" in its rush from growth to maturity to decline—where it has remained since 1952.

Returning to the overall results, we

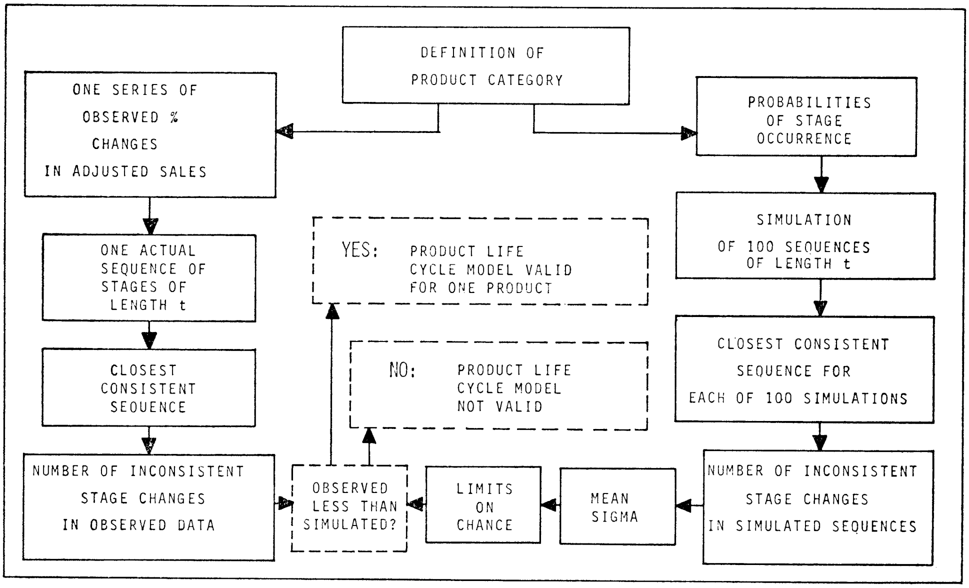

FIG. 7.—Test procedure for validating product life cycle

hypothesized that the life cycle model would be a better descriptor of sales behavior of health and personal care products than of food items, as the latter are more subject to supply conditions because of their dependence on climate, crop results, etc. The life cycle is closely related to the theory of adoption and is essentially a demand model, while actual sales depend on both demand and supply. Hence, the life cycle applies best to those products where sales are not significantly affected by variations in supply conditions.

Our findings strongly support this hypothesis. A χ^2 test was used to determine whether the consistency of the life cycle was significantly greater for the health and personal care than for the food products. For 1 degree of freedom χ^2 was 18.943, far greater than the value of the cumulative χ^2 distribution for $\alpha = .01$.

We also thought that the model would be a more appropriate interpretation of the life of product forms than of product classes.[15] The adoption process is more likely to occur at an uninterrupted pace for specific product forms like "aluminum foils," "stick deodorants," and "plain filter cigarettes" than for aggregate categories like "hair spray," "toilet water and cologne," and "soft drinks," where the introduction of new product forms may induce entry into the market by previous nonbuyers.

TABLE 6

RESULTS OF THE COMPARISON BETWEEN THE LIFE CYCLE AND CHANCE MODELS FOR DIFFERENT PRODUCT CATEGORIES AND LEVELS OF AGGREGATION

	No. of Sales Sequences	Percentage of Observed Sequences Significantly Different from Chance — Confidence Level .05	Percentage of Observed Sequences Significantly Different from Chance — Confidence Level .01	Ratio between Sequences Significantly Different at .05 Confidence Level and Sequences Not Significantly Different
Health and personal care:				
Product classes	20	50.0	25.0	1.00
Product forms	31	67.7	35.5	2.10
Total	51	60.8	31.3	1.55
Food:				
Product classes	16	18.8	....	0.23
Product forms	40	20.0	10.0	0.25
Total	56	19.6	7.1	0.24
Cigarettes:				
Product class	1	....	....	....
Product forms	5	....	....	....
Brands	27	55.5	51.9	1.25
Total	33	60.6	51.5	1.54
Product forms total	76	43.4	22.4	0.75
Product classes total	37	40.5	16.3	0.60

Although product forms, on the whole, were more consistent with the life cycle model than were product classes, the difference in performance was not sig-

[15] No test could be performed for brands, as only cigarette brands have been processed so far.

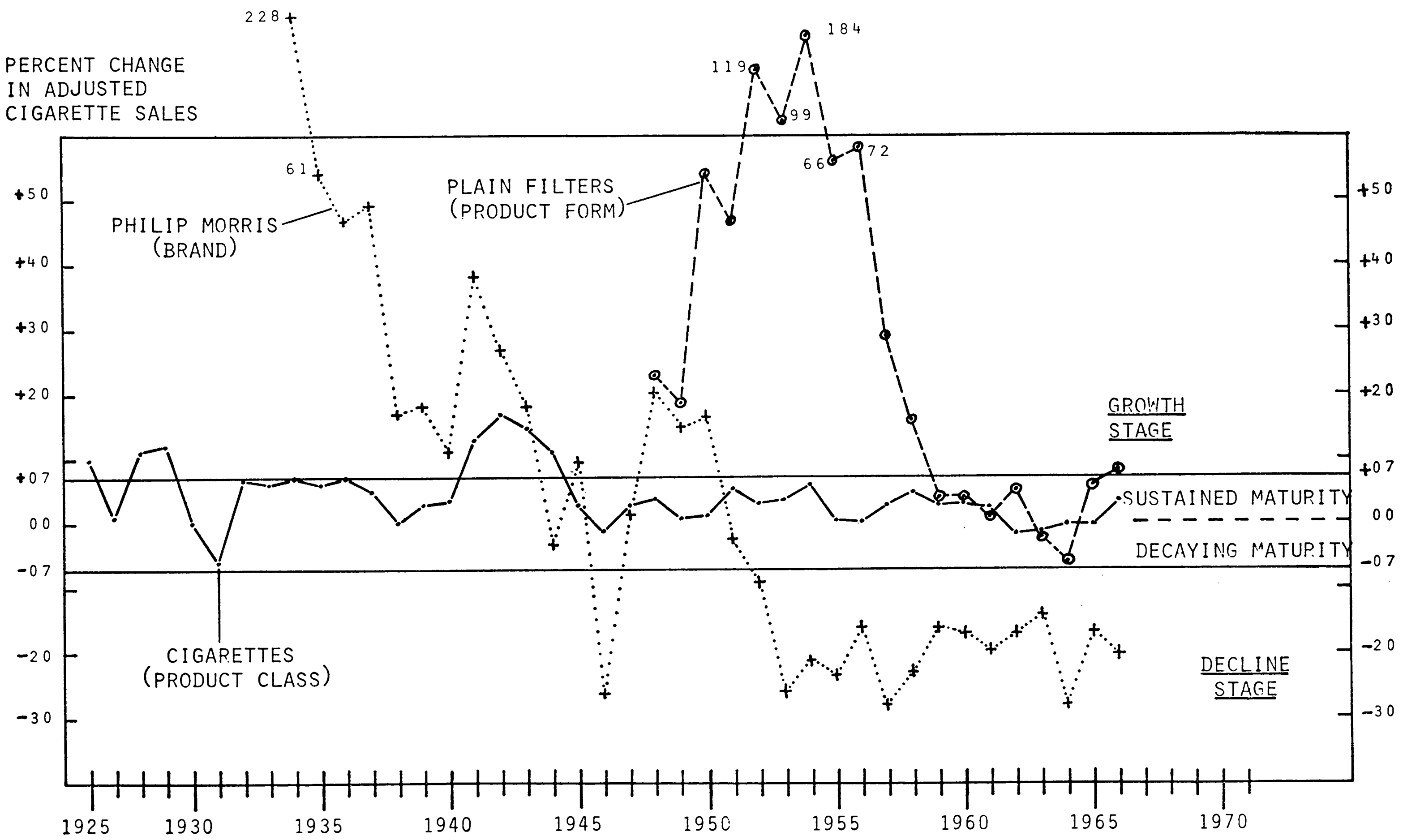

FIG. 8.—Results in one product class. Stage boundaries equal to $\frac{1}{2}\sigma$ in cigarettes are ± 7 percent. Figures are number of cigarettes per $100 of constant dollar nondurable consumption.

nificant, as the χ^2 value was 0.318, with 1 degree of freedom.[16] Our hypothesis was not, therefore, fully supported.

The results must be interpreted with caution because many of the product forms are not sufficiently detailed, especially in the food category, which comprised over half of the total and in which the findings were poorest. A product class can usually be partitioned along several criteria. The subdivision of a product class into product forms is satisfactory only when all the product and package distinctions that cause differential trends in demand are taken into account. Contrary to what the aggregate findings show, we found that whenever a market was partitioned in sufficient detail, the consistency between sales behavior of product forms and the life cycle model was usually quite good. For example, this is clear in figure 8, discussed earlier. The rate of change in real, adjusted sales for this general product class, product form, and brand were all highly consistent with the product life cycle.

Up to now, the discussion has centered on the relative goodness of fit of the life cycle in different product categories. What can be said of its absolute performance? The findings indicate that 44 percent of all products exhibited a sales behavior essentially consistent with the life cycle (at the .05 confidence level). And, they also show that for 96 percent of products, the inconsistent observations were fewer than the mean number of inconsistencies produced by our simulated sequences. Conclusions to be drawn from the results must be based on one's subjective evaluation of what constitutes a "good enough fit."

[16] Since the proportion between product classes and forms is not the same for health and personal care and for food products, although it is quite close, the two χ^2 tests based on aggregate totals may be biased. Therefore, we performed four χ^2 tests at a more disaggregate level which confirmed the overall results. There was a significant difference in performance between health and personal care and food products for both product classes and forms. There was some, but not significant, difference between product forms and classes in both the health and personal care and food categories.

MANAGEMENT IMPLICATIONS

The results suggest strongly that the life cycle concept, when tested in a given market and found valid, can be a fairly rich model of sales behavior.

STABILITY NOT NECESSARILY SATURATION

It is incorrect to infer, even from a prolonged period of sales stability in a general product class, that a ceiling sales level—or saturation—has necessarily been reached. The product life cycle model, whatever its other merits, cannot be invoked to support this inference. Saturation is reached only if new product forms are not feasible with existing technology, and if new uses cannot be found for existing forms. Either of these forces can significantly increase the level of market acceptance for a general product class, and their effects cannot be forecast from past changes in sales behavior. The maturity stage for a general product class can be interpreted as saturation only by taking as given the state of technology and applications for existing product forms within the product class.

DECLINE AS AN ADJUSTMENT PERIOD

Nor is it valid to infer, from the observation of several periods of decline after prolonged sales stability, that sales in a general product class will necessarily continue to decline. On the contrary, our findings suggest that continued decline is rare for a general product class. Though continued decline is possible, the most likely consequence of an observed decline period in a product class will be a downward shift of the sales ceiling with a renewed period of sales stability, or maturity. Decline in the acceptance of a general product class, therefore, does not identify it as a dying market opportunity.

GROWTH IS SHORT AND MATURITY PROLONGED

The results do lead to a better understanding of the proportion of time spent in each stage. A too easily forgotten tendency was identified; growth is short lived and maturity prolonged. Of all observations included in the study, barely more than 26 percent were classified in the growth stage, while over 50 percent were in the maturity stage. The management of mature products would appear to be an important, enduring problem.

MATURITY CONCEALS TURMOIL

It is sometimes suggested that the maturity stage of a product is associated with a stability of market shares within that product. In reference to the share of product forms within a general product class, this suggestion was found to be inappropiate. Changes in acceptance levels among product forms are highly significant even during prolonged maturity in the general product class. This occurred time and again in our test of the life cycle model. For example, refer back to figure 8, where plain filter cigarettes (a product form) enjoyed rapid growth to a high level of sustained demand, while the product class (cigarettes) has remained in the maturity stage for over 40 years. Obviously, a mature product class may offer important market opportunities to a new product form with distinct product advantages. The same notion of stability of shares during maturity applied to brands within a product form appears valid, though more evidence is yet to be analyzed.

DECLINE IN PRODUCT FORMS IS REAL

The validity of the life cycle model (as formulated in this paper) for product-form sales as compared with product-class sales carries strong implications for market planning. A valid life cycle model for product forms implies that the beginning of a decline period in a given form must be taken seriously, for it is likely to be irreversible. Even at the brand level of aggregation—where only cigarette sales were tested—performance of the life cycle model is strong enough to merit its use in that category and further testing in other categories.

CONCLUSIONS

The product life cycle concept, long popular in marketing, has been formulated as an explicit, verifiable model of sales behavior and tested against actual data in 140 categories of nondurable goods. While the overall performance of the model leaves some question as to its general applicability, it is clearly a good model of sales behavior in certain market situations—especially so in the case of different product forms competing for essentially the same market segment within a general class of products.

The goodness of fit found in this study depends most heavily on (1) the definition of *product* used and the relevance of product-class partitioning and (2) the relative influence of demand as compared with supply factors on sales, with the model showing its best performance where demand factors are dominant.

The intuitive appeal of the product life cycle, the existence of a theoretical foundation in the adoption process, and the results of empirical tests reported in this paper lead to the conclusion that the model is valid in many common market situations. When tested in an explicit form for given categories of goods, the product life cycle can be a useful model for marketing planning and intermediate-term sales forecasting.