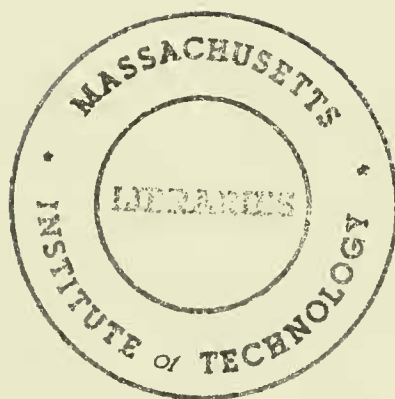


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MARKET SHARE REWARDS TO PIONEERING BRANDS:
AN EMPIRICAL ANALYSIS AND STRATEGIC IMPLICATIONS

Glen L. Urban*
Theresa Carter**
Zofia Mucha***

Sloan School of Management
Working Paper No. 1454-83
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INTRODUCTION

One strategy for new product development is based on innovation and the creation of new markets. It is expensive and risky (Urban and Hauser, 1980). The costs of development are often large and the first firm in a market must allocate funds to make consumers aware of its product and convince them to buy it. The risk of failure is high because the potential demand is not known with certainty. An alternative strategy is based on being the second (or later) entrant into the market. The costs may be lower since the innovator has created the primary demand and the basic product design exists; the risk also may be less because a proven demand exists. If an equal market share can be gained, this strategy could be more profitable. If, on the other hand, as a result of being the first entrant in a market, a dominant market share is achieved and maintained, the innovation strategy may be superior. The purpose of this paper is to investigate the market share effects of being a pioneering brand.

If the market grants a long-run market share reward to early entrants, this would encourage innovation. From a public policy point of view, this would serve a similar function to that of patents by providing an additional reward to innovators. Although patents sometimes provide protection, in many cases they are ineffective because of difficulties of establishing and protecting the rights and the ability of other firms to invent around the patent as technology advances (von Hippel, 1982). This difficulty of protecting an innovation is compounded by the fact that imitators generally take less time and require fewer funds to copy the innovation (Mansfield, Schwartz, and Wagner, 1981). If pioneering brands earn a long run market share advantage, the effectiveness of patent protection may be less critical in providing incentives for innovation and firms may be more willing to innovate without patent protection.

Several authors have argued on theoretical grounds that such long lived advantages can exist. Early ideas by Bain (1956) indicated that existing products can have an advantage accruing from fundamental consumer traits that lead to stable preference patterns. Schmalensee's (1982) theoretical work is based on the fundamental notion that once buyers use the first entrant's product, they will be willing to pay more for it, if it works, because they are not certain the second product will work. Based on a number of assumptions (e.g., products either work or do not work, second entrant objectively equal to first, no response by pioneer to new entrant, and no advertising effects) he shows that a long run price advantage can persist for the pioneering brand. In this model, the second entrant must offer a price reduction to persuade consumers to try and learn about the product. This can imply higher profits for the pioneer. Lane and Wiggins (1981) similarly assume that consumers only know the exact quality of the products they have used. Their model is similar to Schmalensee's but includes advertising and some response by the pioneer to later entrants. After examining profit maximizing strategies they find "even with entry, the first entrant's advantage persist in the form of higher demand and profitability" (p. 3).

Hauser and Shugan (1983) have formulated a defensive strategy model which uses the product positioning of the new entrant to determine share. In this model, the persistence of the sales levels of pioneering brands depends on how well the pioneer designed the product attributes to meet heterogeneous consumer preferences. If the "best" positioning was chosen by the first firm, later entrants may have lower market shares because, if they want to differentiate, they must adopt an inferior position. However, if the first brand to enter did not fully understand consumer preferences, the second entrant could get a preferential positioning advantage and earn a greater share.

These theoretical models show the possibility of long run market share rewards for pioneering brands and indicate these rewards will be a function of the product positioning and pricing strategies of the new and old products.

A limited amount of empirical analysis on the benefits of early entry has been reported. Biggadike (1976), studied 40 product entries into new markets conducted by large firms in the PIMS project. He found that after four years the average share of these entrants was 15 percent and the share of the largest existing competitor in each of the 40 businesses decreased from 47 percent to 28 percent after the new entrant came on the market. These data suggest that although the share of the pioneering brand decreases as the results of subsequent entry, shares may not equalize.

Two industry studies have been conducted which have information relevant to entry effects. The first is by Bond and Lean (1977) and reflects a study of two related prescription drugs (diuretics and antiaginals). A historical review and time series regression analysis of the sales, entry and promotion in each of these led the authors to conclude for these prescription drugs that "the first firm to offer and promote a new type of product received a substantial and enduring sales advantage" (p. vi). Neither heavy promotional outlays nor low price dislodged the pioneers. However, later entrants that offered therapeutic novelty did achieve substantial sales volumes when backed by heavy promotional expenditures. They found that "large scale promotion of brands that offer nothing new is likely to go unrewarded" (p. vi).

Another interpretative study of trends in seven cigarette submarkets by Whitten (1979) led to the finding that the "first entry brand received a substantial and enduring sales advantage" in six of the seven cigarette market segments (p. 41). She found, however, that later entry brands which were early in a growing market or which were significantly differentiated could gain a substantial share in the market or even dislodge the first entry brand

from its dominant position.

These theoretical and empirical analyses suggest order of entry may affect the market share potential of later entries and that this effect is mediated by the entrant's positioning, pricing, and advertising strategy. The purpose of this paper is to enlarge the body of empirical analysis and testing of these theoretical propositions on the effects of order of entry on market share. In contrast to the two industry studies, our work reflects a cross product analysis over many (24) categories of frequently purchased brands of consumer goods. It includes effects of entry as well as advertising and positioning variables. We begin by describing the data base. Next we specify the statistical model, describe its fit to an initial data base of 38 brands, assess its predicative ability to a new sample of 44 brands and present a re-estimation of the model parameters based on the pooled data. We consider the strategic implications of our findings and close with a discussion of future research needs.

DATA

Pre-test market assessment procedures have been widely used in the markets for frequently purchased brands of consumer products. One such system, called ASSESSOR (Silk and Urban, 1978) provides a rich data base for the study of order of entry effects. In this procedure, data on existing products is collected first and then new product response is measured. We are concerned here with only the data on existing products (all brands that had been on the market at least three years). In each category studied, 300 (or more) respondents are interviewed to determine their evoked set of brands,¹ their

¹Based on positive unaided response to one of the following conditions: now using, ever used, on hand, would consider using, or would not consider using. Over 90% of evoking is associated with use experience.

preferences for these brands (constant sum paired comparisons across each consumer's evoked set), the last brand they purchased, and ratings of selected evoked brands on product attribute scales. These data allow market shares to be estimated by the fraction of the sample which last purchased the brand. The preference and ratings data are the basis of determining product position and differentiation. An initial sample of 15 categories was selected for exploratory analysis. 38 major brands existed across these categories. One year later, nine new and different categories (44 brands) were made available for study. This second sample became the data for predictive testing. After the collection and analysis of the initial sample, new studies were available and a request was made for more data and some categories with more than three brands. Both samples represent tightly defined categories of frequently purchased goods (e.g., liquid detergent, instant freeze dried coffee, fabric softener, anti-dandruff shampoo), but the first sample has three or fewer major brands in each category, while the second sample has an average of almost five. These data were supplemented by advertising expenditures obtained from the Leading National Advertisers published media audits. Although these audits may not report one hundred percent of each brand's spending, they are useful in comparing relative advertising expenditures if we assume any biases are systematic across brands. Since all brands considered had been on the market at least three years, these spending levels represent sustaining expenditures.

The order of entry was determined by identifying the time of national introduction for each brand. This was done by personally calling the firms who market each of these products and determining when it was introduced. In the few cases where the firms were not willing to provide this data, at least two competitors were asked to provide an estimate of the entry time.

These data provided a cross sectional data base for the investigation of order effects. At the time of each study, the shares for the existing brands, the year of each product's entry into the market, the brand's recent advertising spending, and the relative product preferences are known.

STATISTICAL MODEL

The dependent variable in this study is the ratio of the market share of the n^{th} (second, third, fourth ...) brand to enter the market to that of the first product to enter. Since the number of brands in each category varies, the absolute shares also vary; the ratio allows a meaningful comparison of relative relationships of brands within and across categories. Brands are included in the analysis if they were advertised at a significant level (greater than one million dollars per year in LNA) and a reasonable share estimate could be obtained (at least 30 respondents reporting them as last brand purchased.)

The order of entry (first, second, third ...) is used as an independent variable. This variable can empirically reflect the theoretical long lived share advantages of pioneering brands argued by Schmalensee (1983) and Lane and Wiggins (1981). If, as theorized, the early entrant becomes the standard of comparison and subsequent brands require consumers to make additional investments in learning, the order of entry variable will be negatively correlated to the share index. This variable is supplemented by another which is defined as the number of years between the n^{th} entry and the one which immediately preceded it. Being the second brand in the category is likely to have a different share effect if the lag between the pioneer is one year rather than two, three, or four years. Whitten (1979) stressed the importance of a firm being early after a new trend is established. Advertising is

represented by the total advertising expenditure over the last three years by the n^{th} brand to enter the category divided by that of the pioneering brand. This variable reflects the sustaining level of advertising spending and allows the order of entry effect to be mediated by the application of marketing resources.

Differential product positioning has been identified as another mediator of the effect of order of entry. The Bond and Lean (1977) and Whitten (1979) studies stress its significance. Hauser and Shugan (1983) also argue for its importance. One method of constructing a positioning variable is by combining the product attribute ratings to estimate the utility for a brand. (See Urban and Hauser (1980) or, Srinivasan and Shocker (1979) for a review.) Many procedures exist and they usually reproduce stated preferences or choices well. Another method is to use stated preferences directly. This has the advantage of avoiding variance due to lack of fits between the attributes and preferences, but has the disadvantage of not linking the attributes to preference. Because our primary purpose is to use the positioning variable as a covariate of order of entry in explaining share rather than supporting the design of new products, we choose to use preference to construct the positioning variable. The constant sum preferences supplied by each respondent over their evoked set reflect their overall evaluations of the brand's price and features. After scaling the preferences by least square procedures (see Silk and Urban, 1978), we obtain a preference for a brand value for each evoked brand j , respondent i and category c (V_{ijc}). We define a relative preference for a brand for each consumer and average over all individuals:

$$R_{jc} = \frac{1}{I_{jc}} \sum_i \left[\frac{V_{ijc}^{\beta_c}}{\sum_j V_{ijc}} \right] \quad (1)$$

- V_{ijc} = preference value for respondent i and brand j in category c
 I_{jc} = number of respondents in category c who evoke brand j
 β_c = scale parameter for category c
 R_{jc} = relative preference of brand j in category c

The value of R_{jc} reflects the consumers' evaluation of the products given that it is evoked. In most cases this means after having used the brand. If it performs well and price is low, R_{jc} will be high; if it does not perform well and price is high, R_{jc} will be low. The scale parameter β_c is estimated by logit procedures (see Silk and Urban, 1978, for details) and it empirically has values in the range of 1 to 3 with a median of about 2. This scaling of preferences results in R_{jc} approximating the probability of purchase of the brand given that it is evoked. The driving forces behind R_{jc} are the measured preferences across the evoked set, but this scaling must be remembered when the statistical analysis is interpreted (see below).

Another aspect to emphasize is that R_{jc} is conditioned by evoking. The same market share (e.g., 10%) for a brand could be due to high preference conditioned on evoking and low evoking (e.g., 50% preference given evoking and 20% evoking), low conditioned preference and high evoking (e.g., 20% preference and 50% evoking) or moderate levels of both (e.g., 33% preference and 33% evoking). The variable R_{jc} is not necessarily correlated to share. Before 1974, TYLENOL had a low share, but pre-test market evaluations indicated high preference by those who had used it. After TYLENOL advertised and promoted its product, its share increased dramatically as the fraction of the population evoking it increased.

The positioning variable R_{jc} reflects consumers' preference for their evoked brand. It is scaled to approximate the probability of purchase conditioned by the fact that the brand is evoked. In our model we are

interested in the positioning quality of later entrants relative to the pioneer, so we define the ratio of R_{jc} for the n^{th} brand to R_{1c} for the first brand to enter as the variable to represent the relative preference given evoking. If the later entrant is superior, the ratio is greater than one, and if less desirable, the ratio is less than one.

The form of the model is non-linear to reflect the hypothesis that the impact of the second brand to enter on the pioneer will be greater than the third or fourth brand. Considerable precedent exists for modeling a non-linear response to advertising (Little, 1979). Bond and Lean (1977) indicate an interaction between order, position, and marketing promotion. We choose a log-linear form to reflect interactions and non-linearities.

Formally for brand n ($n > 1$) in category c :

$$S_{nc} = \alpha_0 + \alpha_1 E_{nc} + \alpha_2 P_{nc} + \alpha_3 A_{nc} + \alpha_4 L_{nc} \quad (2)$$

S_{nc} = log of ratio of the market shares of the n^{th} brand to enter category c to the market share of the first brand to enter the category

E_{nc} = log of order to entry of n^{th} brand in category c ($n = 1, 2, 3, 4, \dots$)

P_{nc} = log of ratio of preference for given evoking for n^{th} brand to preference for first brand given evoking

$$P_{nc} = \frac{R_{nc}}{R_{1c}}$$

where R_{jc} = preference for j^{th} brand in category c conditioned by evoking
(see Equation 1)

A_{nc} = log of the ratio of the last 3 years advertising for n^{th} brand to enter to three year advertising for first brand

L_{nc} = log of number of years between n and $n-1$ brand entry.

This model captures the major theoretical phenomena. If α_1 is negative and significant, it supports the notion of an enduring share advantage for early entrants. If α_2 is positive and significant, it confirms the notion that the order of entry effect can be moderated by a product which is perceived as superior in price and features by those who have it in their evoked set. If α_3 is positive and significant, it suggests advertising may mediate the order effect. If α_4 is negative and significant it would indicate a penalty for the n^{th} entrant, the later arrival in the market.

FITTING

The application of the model is to the initial sample of 38 brands across 15 categories. Regression is used to estimate the parameters in Equation 2. These regression procedures are based on 23 data points because the first brand is not appropriate for inclusion in relative share formulation given in Equation 2. The F (4, 18) is 52.1 and the fit is very good. The t and F values are all significant at the one percent level (see Table 1). The order coefficient (α_1) is negative as hypothesized indicating that subsequent entrants are associated with reduced shares relative to the pioneering brand. The positioning effect (α_2) is positive, indicating good positioning is associated with larger shares. In this log-linear model the position effect increases share proportionately at each entry point. Therefore share for the n^{th} entrant is reduced by the order effect (α_1) and mediated by the positioning effect (α_2). If the positioning index is greater than one (superior price and quality), share will not decrease as much as if it is low (less than one or inferior positioning). It is possible for the n^{th} entrant to earn a dominant share when its positioning is sufficiently superior to overcome the order effect penalty. The relative advertising coefficient

TABLE 1: STATISTICAL FITTING RESULTS

<u>Variable</u>	<u>Parameter</u>	<u>Value</u>	<u>t Statistic*</u>
Constant	α_0	1.31	3.28
Order of Entry (E)	α_1	-1.30	-3.04
Position (P)	α_2	1.62	9.07
Advertising (A)	α_3	-.34	6.28
Lag Between Entry (L)	α_4	-.20	3.19

*All values significant at 1% level. Critical value with 18 degrees of freedom and two tail test is $t = 2.88$.

(α_3) is also positive and reflects another correlate to increased share when a brand is a late entrant. Superior positioning and aggressive advertising spending would be the most likely correlates of dominance in a category by a later entrant. The parameter reflecting the time between entry (α_4) is negative and indicates if one is a late entrant ($E=n$), it is better to be only one year behind ($L=1$) the previous entrant ($E=n-1$) than two or three years ($L=2$ or $L=3$).

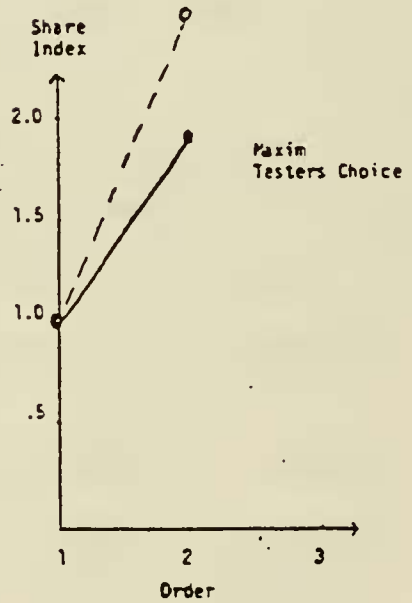
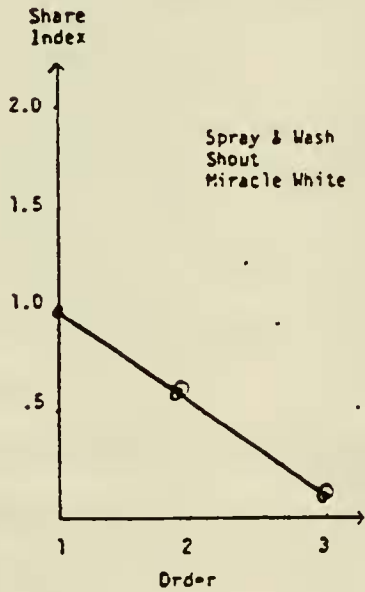
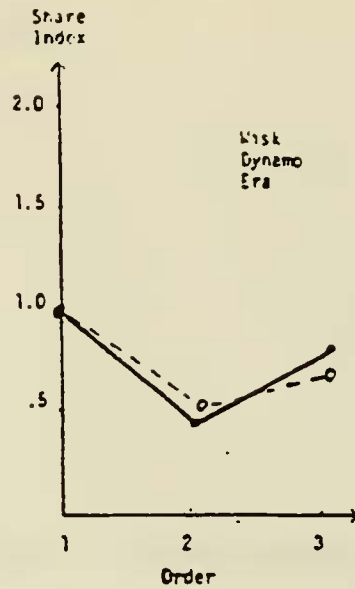
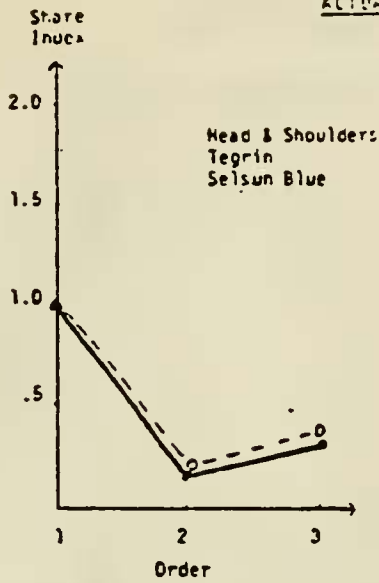
Figure 1 shows the actual and predicted values for the share indexes plotted versus the order of entry variable. Recall the predictions are obtained from our multivariate model so any deviation from the negative effect of order of entry (α_1 and α_4) reflects positioning and/or advertising effects. For example the third entry in the liquid detergent market (Era) achieved a predicted share higher than the second entrant due to a higher advertising value (A_{nc} of 1.1 vs. .6). This more than compensated for the order of entry decline and the resulting predicted share is above that of Dynamo.

In assessing these fits, we calculate R^2 at 92 percent. Another measure of goodness of fit is to determine the proportion of the cases where the model prediction corresponds to the turns in the actual data shown in Figure 1. There are 23 turns and the direction of actual and predicted agree for 22 turns or 96 percent of them.

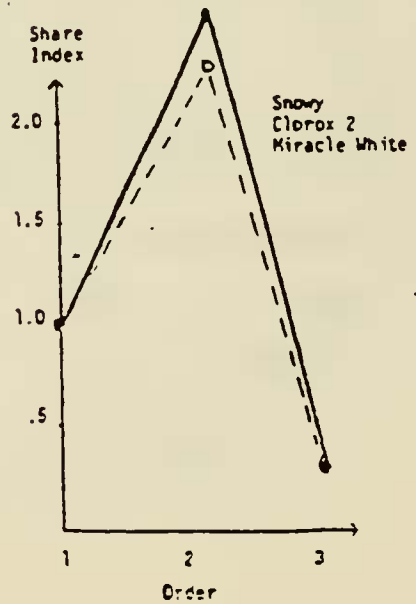
Multicollinearity among the independent variables is low. Five out of six of the pairwise correlations are less than .11 and the sixth is only .31 (see Table 2).

ACTUAL/PREDICTED

FIGURE 1:
FITTING PROCEDURE -
ACTUAL AND FITTED
RESULTS*

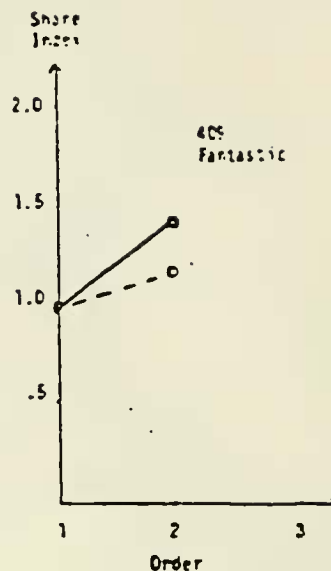
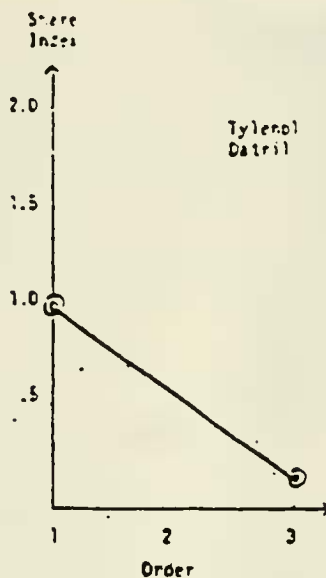
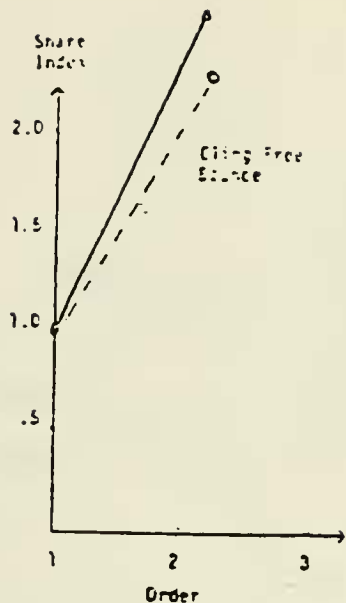


ACTUAL/PREDICTED



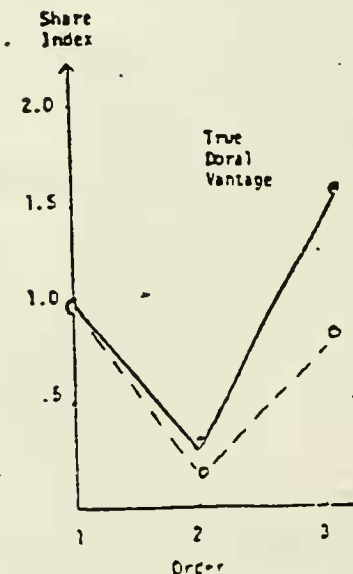
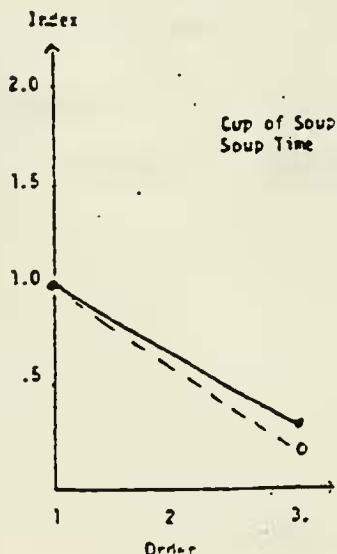
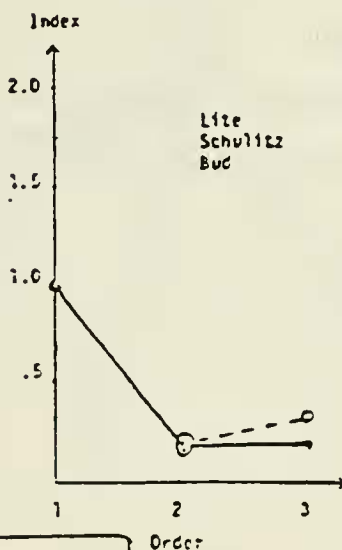
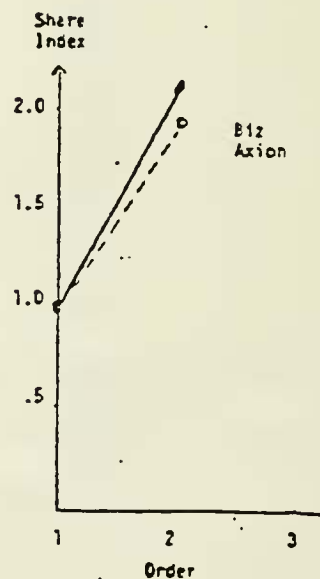
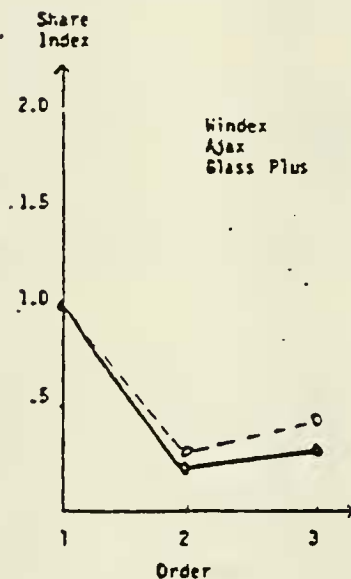
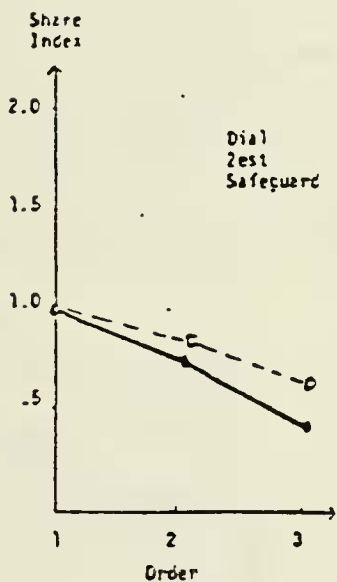
* 0---0 is Predicted
— is Actual

FIGURE 1: FITTING PROCEDURE -
ACTUAL AND FITTED RESULTS* (Cont.)



ACTUAL

PREDICTED



o---o is Predicted

TABLE 2: CORRELATIONS AMONG VARIABLES

	<u>E</u>	<u>P</u>	<u>A</u>	<u>L</u>
E				
P	-.08			
A	.02	.31		
L	-.01	-.10	-.04	

The parameter estimates are stable as variables are added to the regression. The order effect parameter is -1.57 ($t=1.15$) when it is the only independent variable, -1.13 ($t=-1.44$) when the positioning variable (P) is added, -1.21 ($t=-2.45$) when the advertising variable (A) also is appended, and -1.30 ($t=-3.04$) with all the variables.

The estimates have been reviewed for adverse effects from leverage (Belsley, Kuh and Welsh, 1980). Two variables were identified as having high leverage (Tegrin and Datril), but when they were removed, the parameters (α 's) change less than five percent from their original values and all t 's remain significant.

A number of alternative forms (e.g., linear and exponential) and variable specifications (e.g., advertising as a percentage of category spending), were evaluated in the statistical analysis, but none were superior to the results reported here.

In reviewing the regression results, we find all variables are significant. The positioning variable is most significant followed by advertising and the order of entry parameters. In a step wise regression, the positioning variable was the first to be included and explained 67 percent of the variation. Adding advertising increased the R^2 to 84 percent and the order of entry (E) and number of years between entry (Y) variables raised it to 92 percent. In each case the incremental variance explained was

significant at the 10 percent level and all variables are significant when the full model is considered (Table 1).

Some care must be exercised in interpretation of the advertising and positioning coefficients. Although the advertising index (A) correlates highly with the share index, this may not be due to advertising causing share changes. In fact if advertising budgets were set by a rule such as "advertising equals X% of sales," the causative relationship is one of advertising being dependent on sales. Although the interpretation of the advertising coefficient must be cautious, this does not affect the interpretation of the order of entry coefficient (α_2), the variables have small intercorrelations (see Table 2) and one can consider α_2 as a significant explanatory variable of the residual variance.

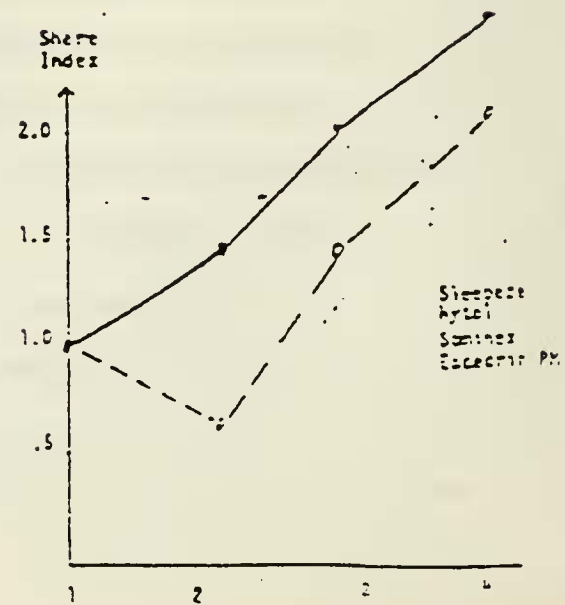
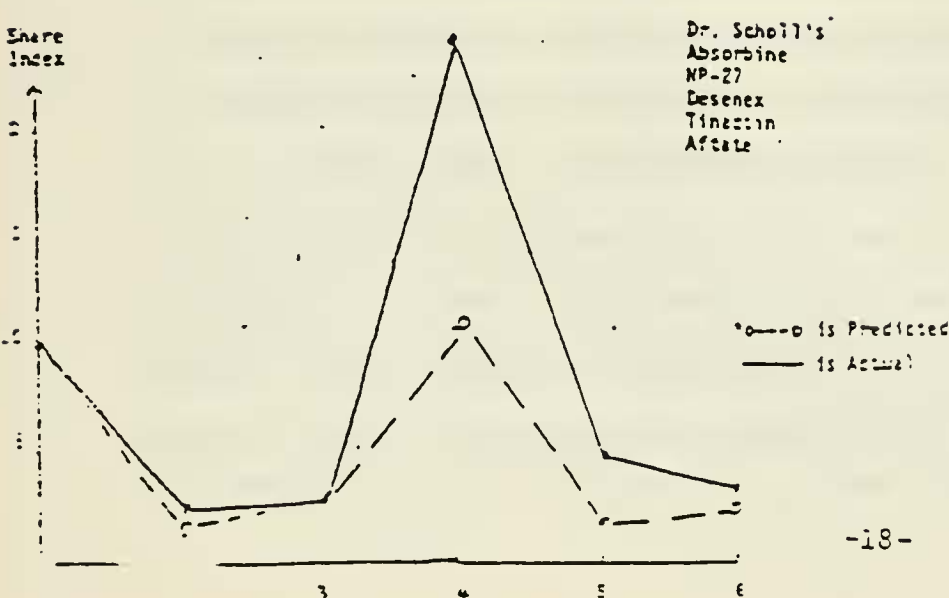
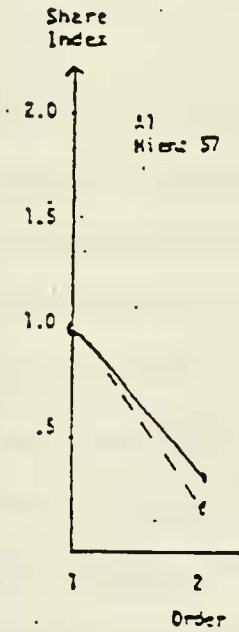
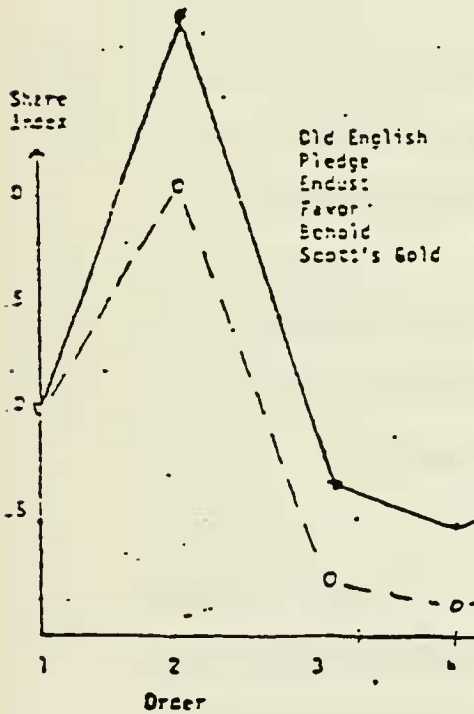
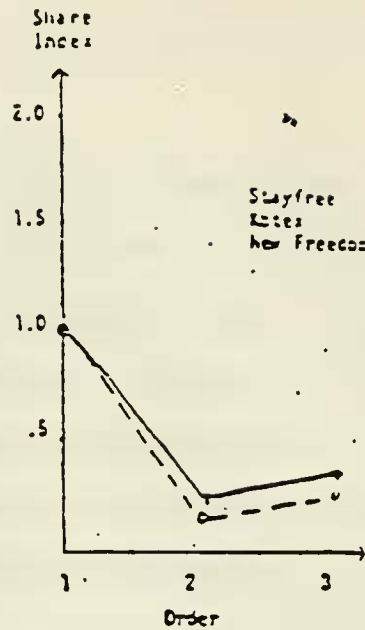
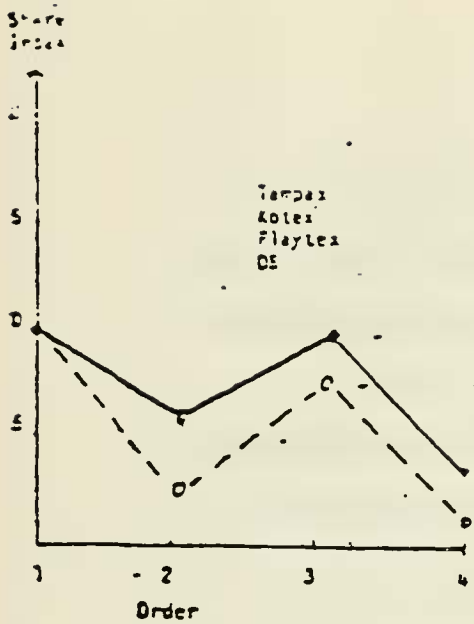
The positioning variable reflects the relative preference of brands given they were evoked. Such relative preferences when scaled by β through logit procedures provide good estimates of the probability of purchase conditioned by evoking (see Equation 2). Since past choices among evoked brands are used to estimate β and the market shares are estimated based on the unconditional fractions of past practices, there is a danger that the correlation would be inflated. However, this threat would be greater if the scaling parameter β were fit along with the α 's in Equation 2 by non-linear estimation procedures. The conservative position is to consider the positioning variable as removing a component of the variance due to correlation of unconditioned market share and probability of purchase conditioned by evoking. The positioning variable (P) is virtually independent of the order variable (see Table 2), so the threat to the construct validity of the order effects (α_2 and α_4) is low. The overall interpretation we draw from the fitting is that the order of entry effect is significant after considering the mediating effects of advertising and product positioning.

PREDICTIVE TESTING

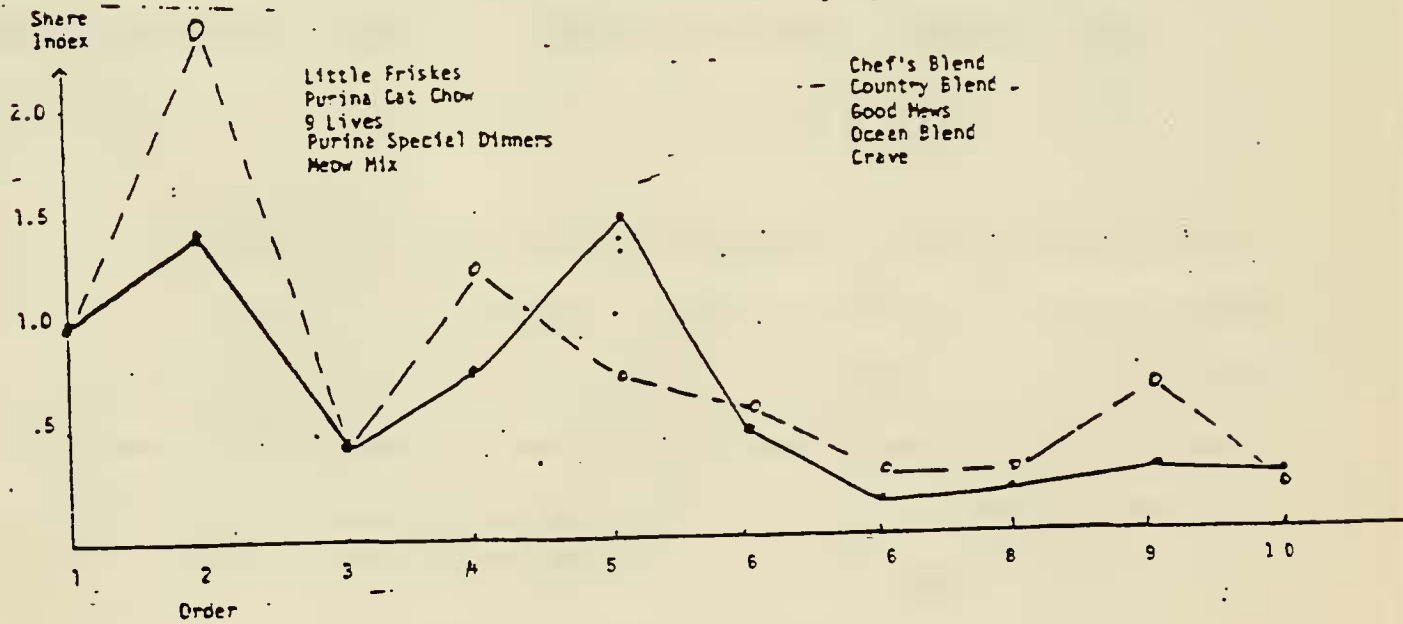
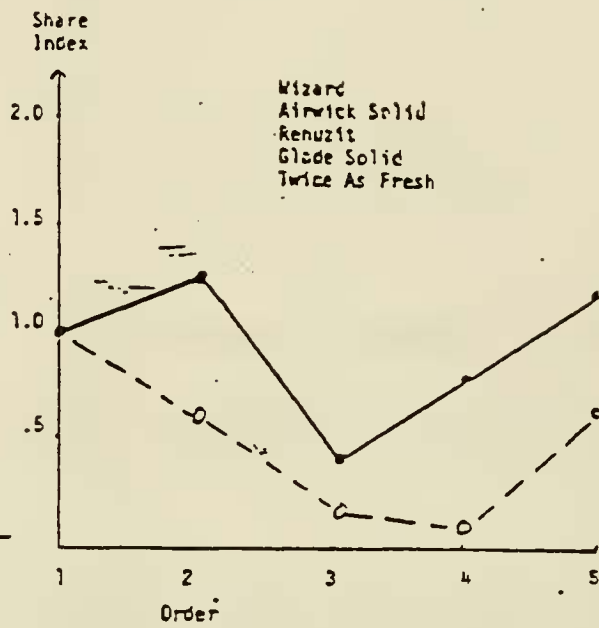
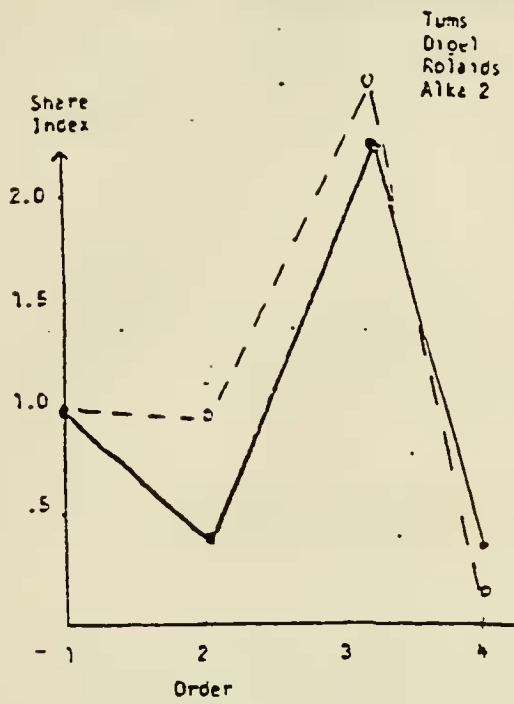
The above results are impressive, but they were viewed with some caution by the authors because many regressions were run to find them and the sample is small. In order to gain more confidence in these results, predictions were made on a new sample of data that became available after the fitting analysis. This data set contained 45 new brands across nine new and different categories. The average number of brands per category in the new data was five. This is substantially more than the 2.5 brands per category in the fitting data. The predictive test reflects not only prediction on a new data set, but also extends the order of entry variable outside the range used in the fitting. The solid line in Figure Two shows the actual data. Note in seven of the categories more than three brands exist, and in the cat food category there are ten brands.

The parameters (α 's) reported in Table 1 and the observed independent variables for the new sample are used in Equation 2 to predict the new share ratios. Figure 2 shows the actual and predicted share ratios. Visual inspection indicates that the predictive accuracy is encouraging. The correlation between actual and predicted values from equation 2 is .76 (the corresponding value in the fitting is .96). The predicted turns correspond with 83 percent of the actual turns (the corresponding value in the fitting is 88). The root mean squared error in the raw data shown in Figure 2 is .90 and the corresponding value in the fitting is .42. The ninety percent confidence intervals for the prediction of the share indices were calculated (Theil, 1971, p. 122-23, 134-36) and they contained the actual values in 60 percent of the cases. The differences between predicted and actual value are frequently greater than would be expected by random errors based on equation two. This result casts doubt on the predictive adequacy of the model, but before reaching this conclusion we should examine the structure of the differences in actual and predicted values.

FIGURE 2: PREDICTIVE TEST*



PREDICTIVE TEST



o---o is Predicted
— is Actual

We can gain insight into the nature of the errors in prediction by examining Theil's U^2 measure (Theil 1966, p. 28, Bliemel, 1973):

$$U^2 = \frac{\sum_i (P_i - A_i)^2}{\sum_i A_i^2} \quad (3)$$

where P_i = predicted observation i .

A_i = actual observation i .

U^2 represents the sum of the squared deviations as a proportion of the sum of squares of the actual values. In this application it has an additional interpretation. Consider a revised U^2 where P_0 reflects the null hypothesis of no order of entry effects or a share index of 1.0:

$$U^2 = \frac{\sum_i (P_i - A_i)^2}{\sum_i (P_0 - A_i)^2} \quad (3A)$$

Recall we are using log transforms for all values and note for $P_0 = \ln(1.0) = 0$. Equation 3A reduces to Equation 3 in this case. Therefore, we can interpret the U^2 in Equation 3 as the sum of squares of the error in prediction as a fraction of the sum of squares of the deviation of the new data from the null hypothesis values reflecting no order of entry effect. In our application the value is .51.

Theil (1966, p.33-35) decomposes the mean squared deviations of predicted (P_i) and actual (A_i) into three components to reflect sources of error in the predictions. The first component reflects the differences in the means of the sample.

$$U^M = \frac{(\bar{P} - \bar{A})^2}{\frac{1}{n} \sum_i (P_i - A_i)^2} \quad (4)$$

\bar{P} = mean of predicted values

\bar{A} = mean of actual values

In our application $U^M = .29$ or thirty percent of the mean squared error is due to the bias in the predicted mean. This is evident in Figure 2 where in 24 of 44 cases, the predicted value is less than actual.

The second component of the mean squared error is the regression proportion:

$$U^R = \frac{(S_P - rS_A)^2}{\frac{1}{n} \sum_i (P_i - A_i)^2} \quad (5)$$

where S_P = variance in predicted values = $\frac{1}{n} \sum_i (P_i - \bar{P})^2$

S_A = variance in actual values = $\frac{1}{n} \sum_i (A_i - \bar{A})^2$

r = correlation of actual and predicted values

In our case $U^R = .22$ and indicates a systematic error due to failure of the regression of actual or predicted values to have a slope of one (in this data slope = .63). The third component in Theil's decomposition in the disturbance term:

$$U^D = \frac{(1 - r^2) S_A^2}{\frac{1}{n} \sum_i (P_i - A_i)^2} \quad (6)$$

Its value is .49 in our test and indicates about 50 percent of mean squared deviation is unaccounted for by the mean and regression errors.

Recall the fitting was done before a new set of data became available for prediction. The errors reflected in the mean (U^M) and regression (U^R) terms of Thiel's statistic indicate a substantial difference in the samples. This is true particularly in terms of the number of brands per category. The order of entry variable is significantly different in the two samples ($F = 17.1$). This is also evident when the parameters of the model (Equation 2) are fit by a regression on the predictive data. The parameters are significantly different from those obtained by regression in the original data ($F(5,48) = 4.63$ for Chow test). The failure of the actual values to fall in the confidence intervals as often as expected is due in part to the differences in the fit and prediction subsamples resulting from the sequential data availability.

It would have been more desirable to have had all the data before the fitting began, randomly split the sample into a fitting and prediction subsample, and calculated the predictive statistics. In order to determine the effect on predictive accuracy of the sequential analysis reported here,

we combined the data and repeated the predictive test based on a random splitting of the 24 categories into two subsamples. Categories were divided into strata determined by the number of brands in each category and assigned to one of the subsamples by equally likely random sampling within strata. The first subsample with 11 categories and 35 brands comprised the data for estimation of the parameters of equation 2. These parameters then were used to predict the share indices for the second subsample of 47 brands in the remaining 13 categories.

This new predictive test resulted in a U^M of .05 (versus .25 for the original predictions) which indicates the error due to the differences of means in the new subsamples was made. The Chow test was just insignificant at the 10% level ($F(5,48) = 2.0$). The two subsamples are more similar than the original fitting and prediction samples. The new predictive accuracy was similar to the original results: the new correlation for actual and predicted was .75 (versus .76 for the original analysis) RMS of .95 (versus .90), percent of turns 79% (versus 83%) and $U^2 = .4$ (versus .51 -- recall low values are improved accuracy). When ninety percent confidence intervals for prediction were calculated (Theil, 1971, p. 122-23. 134-36), the actual values were in the interval in 79% of the cases (versus 60% in the original analysis). This is a much more acceptable result.²

The re-examination of the predictive characteristics of our model based on a random selection of subsamples indicates improved results. Our assessment of the predictive testing reported here is that the model performs well and the predictive accuracy supports the argument for a relationship between order of entry and share.

²When the role of the random subsamples was reversed and the second subsample ($n_2 = 34$) was used to predict the first ($n_1 = 24$), 96% of the predictions were in the ninety percent confidence intervals. The average value is 88 percent $[(96 + 79)/2]$ for the cross predictions between the subsamples.

POOLED DATA ANALYSIS

To reflect the total information in our data, we pooled both samples and re-estimated Equation 2 over the 24 categories and 82 brands. The fits were again good: $F(4,53) = 31.3$, $R^2 = 70.3$ percent. 89 percent of the turns matched by the predictions, and the root mean square error was .61. The parameter values are given in Table 3 with their associated t statistics. All of them are significant at the one percent level except the coefficient for the variable reflecting the number of years between entries (α_4) which is significant at the 20 percent level (two tailed test). The order of entry parameter (α_1) is more significant and lower in magnitude in the pooled data than in the fitting data. This is consistent with the systematic downward bias observed in the predictive testing. The value coefficient of α_2 is -.97 in the pooled data versus -1.3 in the initial sample.

TABLE 3: STATISTICAL RESULTS FOR POOLED DATA

<u>variable</u>	<u>parameter</u>	<u>coefficient value (α)</u>	<u>t statistic*</u>
Constant	α_0	.89	2.73
Order of Entry (E)	α_1	-.97	-4.69
Position (P)	α_2	1.23	7.63
Advertising (A)	α_3	.29	6.23
Log Between Entry (L)	α_4	1.26	-1.43

The standardized regression coefficients (β) are shown in Table 4. The positioning variable has the greatest impact on share, followed by advertising and order of entry. The caveats on interpretation outlined above continue to apply. Although not the largest effect, order of entry continues to be a significant explanatory variable for relative market share.

TABLE 4: STANDARDIZED REGRESSION COEFFICIENT-POOLED DATA

<u>Variable</u>	<u>Coefficient</u>	<u>Value</u>
Order of Entry (E)	β_1	.39
Position (P)	β_2	.60
Advertising (A)	β_3	.48
Lag between Entry (L)	β_4	.12

The decreases in share upon subsequent entry implied by the pooled estimates are shown in Table 5 in terms of relative and absolute shares. These values represent the case when all products are equal ($P_{nc}=1$), all later entrants spend at the same level as the pioneer ($A_{nc}=1$) and there is one year or less between each entries ($L_{nc}=1.0$). Other approximate values could be simulated with the parameters in Table 3 and Equation 2. The pioneer's share drops from 100 percent to 40.3 percent after five additional entrants, but a long run premium is evident. This is especially true with respect to later entrants with equivalent products and advertising spending. In the case of six brands the pioneer has the dominant share position and a 33.4 share point advantage over the sixth entrant. These estimates suggests that the second brand will at equilibrium earn less than half of the share of the pioneering brand if its advertising and positioning are equal. The third brand would similarly earn a share of about one third of the first brand to enter with a parity product and the fourth about one quarter. As the number of brands increases, the incremental order effect penalty decreases and advertising and positioning become the determining effect on share.

TABLE 5: ORDER OF ENTRY PENALTY*

Entry Order	Share Relative to Pioneering Brand	Shares (%)					
		1st	2nd	3rd	4th	5th	6th
First	1.0	100	--	--	--	--	--
Second	.45	68.9	31.1	--	--	--	--
Third	.31	56.8	25.7	17.6	--	--	--
Fourth	.23	50.3	22.8	15.6	11.6	--	--
Fifth	.19	45.8	20.6	14.2	10.5	8.7	--
Sixth	.16	40.3	20.6	13.7	10.5	8.1	6.9

*Note: These values are calculated based on equation 2 with $P_{nc} = 1$, $A_{nc} = 1$ and $L_{nc} = 1$ and the parameters in Table 3.

In our original model (Equation 2), we include price and positioning together in the preference variable (P_{nc}). The pooled data allowed further exploration of price effects. In eight categories, approximate price measures were available for each of 39 brands. These were based in each case on small sample audits of retail stores and managerial judgments on the relative average prices. We fit the model (Equation 2) again, but with an additional variable defined by the log of the price of the n^{th} product divided by price of the first product to enter. The value of the coefficient for this price variable was $-.61$ and the t statistic -1.7 ($df = 27$). This is significant at the 10 percent level. The correlation of the price and preference variable

was not great (-.13) and indicates the price effect may be considered relatively independent of the product positioning measured by preference. These preliminary regression and correlation results imply price may be another mediating variable on the effect of order of entry.

MANAGERIAL IMPLICATIONS

There are strategic implications from this study for both later entrants and pioneers. Later entrants should plan on achieving less share than the pioneering brand if they enter with a parity product. In Table 5, the sixth brand potential is reported as 6.9 share points if it is an equal product and advertising spending is at the level of the pioneer. In many cases the sixth firm would not find it profitable to spend at the level of the pioneer who has over six times as much share. For example, if the advertising spending is one sixth the pioneer's spending level, share potential with the advertising parameter of .29 (from Table 3) drops from 6.9 to 4.1 share points. In many cases this may not make entry attractive. The defensive strategy of the pioneer may also defer entry. If advertising increases and price cuts are matched by the innovator, the later entrant may never gain parity with the pioneer. A preferred strategy may be to develop a superior product with either unique benefit features and/or a lower price. When this is backed by aggressive advertising spending, a high share can be achieved. Our data demonstrated several cases where the later entrant dominated the pioneer (see Figures 1 and 2). Although the best level of spending is not specified by our model, the advertising and entry parameters are important inputs to a profit maximizing model (e.g., Urban (1970) or Little (1975)).

Firms aiming at developing pioneering brands should be encouraged by the availability of a long run market share reward for their innovation. Although the pioneer's share does decrease as each new firm enters, the pioneer retains

a share differential. The size of this reward depends upon the presence and strategies of later entrants. The values in Table 5 show the innovator's share dropping from 100 percent to 68.9 percent after the second brand enters, to 56.8 percent after the third entrant, and to 50.3 percent after the fourth party brand enters. This share decline will be greater if other brands can achieve a superior positioning (product features and/or price). The pioneer can minimize this risk by taking care to occupy the preferred positioning with its pioneering brand. This strategy preempts the competitor's ability to develop a superior positioning. If the pioneer does not carefully design its product and an improved product is subsequently introduced and aggressively promoted by a competitor, the market share reward for innovation may be lost. The pioneer also should consider aggressively defending its brand with advertising and thereby preventing competition from gaining an advertising dominance. The pioneer could also consider entering a second brand in the category; developing a product line may be a good defense against competitive entries.

FUTURE RESEARCH

This empirical cross category study of order of entry effects indicates the presence of an important market phenomena. Our results are consistent with those found empirically by Bond and Lean (1977) and Whitten (1979) in industry studies of pharmaceuticals and cigarettes and the theoretical work of Schmalensee (1982) and Lane and Wiggins (1981). We believe that this topic deserves additional attention from researchers.

One direction of further research is to extend our study to include an improved price variable. Price is a component of our exploratory study, but it only approximates the results from large sample audit or electronic checkout (UPC) data that would provide the best measure of this variable.

Schmalensee (1982) hypothesizes that the order of entry penalty will be greater for higher priced brands. Another variable that could be added is promotional spending. We have included advertising, but expenditures on promotion might explain more of the residual variance. Finally, introductory spending may explain some of the variation in the mature market shares analyzed here. We have only included the most current three years of advertising in our statistical analysis. An improved data base would be a time series for each brand with price, advertising, promotion (e.g., UPC or Nielson) along with survey measure of perception and preference. We are pursuing such a data base to enable a time series cross sectional analysis of the effects of order of entry.

A second line of research could be aimed at determining the behavioral and microeconomic bases for the order effects we have statistically identified. Schmalensee (1982) hypothesizes the reluctance of an individual to try a second entry if the pioneering product works as the core phenomena. It may be that the pioneer has occupied the best position-combination of benefits and price--so that later entrants who differentiate their products will not appeal to as many consumers. The pioneering product may be placed in a premier place in an individual's memory so that later entrants will suffer a memory recall and evaluation disadvantage. Superior distribution and more shelf facings are often obtained by the pioneer; these affects of in store awareness may explain some of the entry affects. The defensive strategies utilized by the innovator may create barriers to entry that penalize the share of new entrants. Research is needed to formulate and test alternative hypotheses. Historical and survey data will be useful but behavioral experiments based on information processing (Beltman 1979) may be required to obtain a definitive understanding of the micro phenomena.

Another direction for research is to test for the presence of order of entry effects in other industries. This is difficult because market share data is not widely available. However, a Ph.D. dissertation by W. Robinson at the University of Michigan is examining the effects of entry in the PIMS data. An interesting aspect of this study is the consideration of the profit as well as market share effects of entry.

Finally, we did not consider optimizing strategies in this paper. Explicit management science models could be built to maximize long run profit. Works by Hauser and Shugan (1983), Hauser and Gaskin (1983), and Lane (1981) are relevant to setting the best defensive strategy for the pioneering brand. Extending these models for order of entry, equilibrium competitive conditions, and product lines are important research needs.

The phenomena surrounding order of entry are interesting research topics and important to firms in formulating new product strategies. Our study of frequently purchased consumer brands is one step toward identifying and understanding the effects of order of entry on market share.

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