DETERMINING MANUFACTURERS' COUPONING STRATEGIES

by

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ABSTRACT

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Increasing competition and changing consumer behavior have put pressure on manufacturers to protect their market shares via aggressive marketing actions. Hence, the ability to predict sales as a function of marketing control variables such as price, promotion, and couponing, is becoming more important for determining manufacturers' strategies.

In this thesis, a quantitative consumer response model is developed which utilizes Universal Product Code (UPC) scanner data on individual purchase observations for particular customers. A logit model of purchase probabilities is then calibrated and used to predict market shares under different conditions. The model developed tracks well across time, population, and stores.

A further study is done on a specific marketing tool which has recently gained popularity - couponing by manufacturers. Couponing is evaluated using the model by comparing actual vs. predicted market shares. Significant positive effects on market share are found. The results are similar to those found in a controlled field experiment.

Two separate coupon programs are evaluated and show different effects with different strategy implications. Thus, one coupon gained incremental sales by drawing broadly from all other brands, whereas the other coupon drew heavily from another brand of the same manufacturer.

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I dedicate this thesis to my parents without whose love and support neither I nor this thesis would exist.

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CHAPTER 1:   INTRODUCTION

The ability to predict sales as a function of marketing control variables such as advertising, price, promotion, and couponing aids a manufacturer in planning marketing strategy. Thus, measuring consumer response to various marketing tools is an important area for research. This desire to measure consumer response has led to attempts at modelling the market place. In particular, many quantitative sales response models have been developed and tested (e.g., BRANDAID (Little (1975)), and SPRINTER (Urban (1970))).

However, calibrating such models for a specific market environment is often a problem because of insufficient data. In the past, only very aggregate sales data have generally been available (e.g., monthly store audits or warehouse withdrawals).   Data   collection   procedures   have   been inaccurate, time-consuming, and costly.   Knowledge of a customer's actual series of purchases over time has usually been absent.

With the advent of Universal Product Code (UPC) scanner technology, massive amounts of data are now available, potentially on almost any level of detail desired.   Sales

could be tracked on a weekly, and conceivably daily or hourly basis. Effects of individual promotional activities such as temporary store initiated price cuts or manufacturers' off-label discounts can be observed in individual store environments. Consumer panel data can be collected more easily and objectively than before.

In this thesis, a model is developed which uses the insights available through scanner data by combining individual purchase observations for particular customers with the market environment in which the purchase takes place. In this way, individual probabilities of purchasing a particular product are estimated.

Once parameters for the model are estimated, a further study is done on a specific promotional tool - couponing by manufacturers. A coupon experiment designed and executed by Management Decision Systems (MDS) allows assessment of couponing impact on market share. Furthermore, differential effects of individual coupons can be analyzed. Possible long-run effects can be investigated. In addition, cost versus benefit issues can be addressed. Most of all, potential couponing strategies for manufacturers can be developed.

CHAPTER 2:   RATIONALE AND METHODOLOGY

Increasing competition and changing consumer behavior have not only put pressure on manufacturers to protect their market shares via aggressive marketing, but also have provided incentives for increasing new product development. One marketing tool which has gained tremendous popularity recently is couponing; the A.C. Nielsen Co. estimates that distribution of manufacturers' cents-off coupons in 1974 was 29.8 billion and grew to 90 billion in 1980 - an increase of 202%.

There are many reasons for such explosive growth in couponing. Manufacturers are motivated to:

1. maintain market share,

2. encourage new product trials,

3. support market and product development,

4. combat competition,

5. encourage retailers to carry more product,

6. reduce excessive inventories, and

7. promote switching behavior to their brand.

In addition, the retailer receives benefits from coupons: a low-price image is reinforced in the consumer, traffic through the store increases, product movement increases, and sales increases occur even after the promotion period.

However, there are other considerations which partially offset perceived selling benefits from couponing. At high frequency of use, coupons constitute an almost permanent price cut for the consumer. At the same time, manufacturers must reimburse the retailer $0.05 per coupon for handling. Ward and Davis have found that during periods of rising prices, coupon programs generally cost more to implement so that the program becomes a less effective marketing tool. Hence, the net results benefit the consumer but reduce retailer and manufacturer revenues. Therefore, a major question becomes, "What is the effect of coupons?"

The total effect of coupons can be broken into an information effect and a price effect. If the price effect equals the total effect, then there is no information effect on the consumer. The underlying hypothesis here is that mass media advertising is intended to inform and persuade the consumer by changing preferences, whereas couponing is intended to convey a good buy. In the first case, information effects should be dominant. In the latter case, price effects should dominate. The logit model and coupon experiment should help identify different effects more objectively and credibly.

In addition, the effect of coupons is a function of:

1. size of the coupon drop (i.e., number of coupons distributed),

2. method of distribution/media characteristics,

3. monetary value of coupon,

4. size of purchase required for redemption,

5. level of general advertising and promotion,

6. product usage rates and consumer attitudes,

7. product availablity,

8. elapsed time since coupon distribution, and

9. level of competitive activity.

For example, Ward and Davis, assuming that (5) through (7) above stay relatively constant, concluded that direct mail was the most effective medium for coupon redemption, given a 30-million, $0.10 coupon drop.

Clearly, couponing as a marketing tool deserves further study. With so many factors impacting the effectiveness of coupons, choosing the appropriate combination is very difficult. Most factors are constantly changing, which makes evaluating the effectiveness of coupon campaigns even harder. Thus, a modeling technique which can readily adapt to a dynamic marketplace would be a very valuable tool for managers. With such a model, expensive, time-consuming controlled experimentation could be unnecessary. This thesis attempts to shed more light on the coupon marketing tool while developing the logit modeling technique.

The Data

Selling Areas Marketing, Inc. (SAMI), a subsidiary of Time, Inc., collected the data over a 65-week period (July 25, 1979 to October 15, 1980) from the UPC scanner systems of six supermarkets in Kansas City. Consumers indicating loyalty to one of the six stores were recruited to form a panel of 2313 customers, ranging from 200 to 600 people per store. These customers were given identification cards which were presented to the cashier at each purchase occasion. The cashier then entered the customer's number, allowing the scanner system to retain relevant purchase information for that consumer by week, UPC, and store.

Individual UPC information such as price, brand, size, and manufacturer, is also available by store. This study of a household cleaner category involves 17 brands, 4 sizes, 7 manufacturers and 88 UPC's. Thus, every purchase is associated with a customer, store, brand, size, price, and week.

All these data are available courtesy of SAMI. Since the data are proprietary, all brands are referred to by a letter and all sizes are coded by a number.

MDS provided the computer time-sharing decision support system called EXPRESS for data manipulation.

The Coupon Experiment

MDS mailed package of assorted coupons to randomly selected panel customers on May 5, 1980. Some customers (Group 1) received a package containing a $0.35 coupon for any size purchase of Brand B household cleaner. A second set of customers (Group 2) received a package containing a $0.35 coupon for any size purchase of Brand C household cleaner. The remaining panel members (Group 3) received a package containing no coupon for household cleaner. Thus, three "test cells" of consumers are available for comparative study, and consumer response for each customer group can be tracked.

The Multinomial Logit Model

The multinomial logit model is a probability of choice model which can take advantage of UPC scanner data. Prior studies have shown this model to be useful for estimating brand choice behavior. (McFadden (1973), Jones and Zufryden (1978), Gensch and Recker (1979), Levin (1980), Guadagni (1980), Novich (1981))

The model itself is a cumulative logistic probability function. It can be derived by assuming individuals wish to choose purchases that give them the greatest amount of satisfaction, i.e., maximize their utility (McFadden (1973)). It can be calibrated using a maximum-likelihood procedure.

The standard model takes the form

$$P(k) = \exp(d(k)) / \sum_j \exp(d(j))$$

where

P(k) = probability of an individual choosing alternative k when a purchase is made

d(k) = estimated deterministic component of a person's total utility for alternative k

$$= \sum_i b(i)x(i,k) + b(0,k)y(0,k)$$

where

b(i) = coefficient estimated by the model which weights the importance of attribute i to the purchase choice

x(i,j) = observed value of attribute i for alternative j

b(0,j) = coefficient estimated by the model which weights the strength of alternative j's core franchise (i.e., average market share)

y(0,j) = dummy attribute

= 1 if alternative j
    0 otherwise

Thus, the model allows us to express the probability of purchasing a particular alternative as a function not only of the attributes of the chosen alternative, but also the attributes of all other alternatives. The use of dummy variables captures a customer's underlying preference for a product independent of other attributes such as price, promotion, or loyalty. All these measures provide managers a useful method of assessing consumer response to different marketing mix variables. More details on model derivation

and properties can be found in McFadden (1973).

Measuring Logit Performance

Hauser (1978) defines three statistics (prior entropy, expected information, and observed information) to assess the usefulness of the logit model. The usefulness measure, U-squared (U-SQRD), compares the test model to a null model. The null model can be defined in various ways. For example, the maximum-likelihood model finds parameters for the alternatives most likely to occur, given the sample observations. A market share model uses an alternative's observed proportion of choices as the initial base case. An equally-likely model assumes alternatives initially have a share of 1 divided by the number of alternatives. Similar to an R-squared in regression analysis, U-squared equals zero if the test model does not explain any uncertainty relative to the null model (i.e., predicted probabilities of the test model are exactly equal to the null model's probabilities). U-squared equals one if the test model predicts with a probability of 1 the alternative that was chosen. So U-squared close to 1 is desirable, but rare.

Hauser also shows that

$$U\text{-squared} = 1 - (l(t)/l(n))$$

where

$l(t)$ = log likelihood of test model

$l(n)$ = log likelihood of null model

Since log likelihoods are standard output from logit programs, this formulation is very convenient. More details can be found in Guadagni (1980).

For purposes of this thesis, the null model is defined to be the equally-likely model. (i.e., Each alternative's probability of being chosen is 1/(number of alternatives).) All U-squareds presented in this study will be calculated relative to this null model unless otherwise indicated.

Setting Up the Logit Model

A. Alternatives

The first step in setting up the logit model is to choose a set of alternatives for the consumer. Ideally, one would like to define a set of alternatives which includes all possible choices presented to a consumer. Unfortunately, because of the logit's massive data needs, computation time and computer resource requirements are limiting factors. Hence, at any one time, a model using a maximum of only 15 alternatives and 1200 observations can be reasonably calibrated.

So, in choosing an alternative set, one has to consider the following:

1. Should alternatives be brand choice only?

2. Should alternatives be size choice only?

3. Should alternatives be brand-size combinations?

4. If brand (with 17 alternatives) or brand-size combinations (with 39 alternatives) is chosen, which 15 should be included in the model?

Since this category exhibits brand-size specific promotional activity (e.g., a newspaper ad of a Size 1 package of Brand A for $0.89),   brand-size   combinations   were   used   as alternatives.

Prior work in a different category (Guadagni (1980)) also   lends   credence   to   choosing   brand-size combinations. Guadagni discovered that the choice process involved separate brand and size preferences. That is, brand loyalty and size loyalty were two distinct components of a purchase decision. So, even though in a different category (i.e., in household cleaners rather than coffee), similar choice processes were hypothesized to exist.

The   remaining   question   is   which   15   brand-size combinations   should   be   included   in the model.   One way to decide is to pick the 15 combinations which account for the highest   percentage of total store sales.   The 15 top combinations, in fact, comprise over 80% of total store sales.   However,   the   primary   purpose of this study is to evaluate the   coupon   marketing   variable   and,   in general, coupons are applicable to any size in a brand. Picking the

top 15 brand-size combinations would not include some of the

less popular sizes in a brand. So, analysis using the top 15

combinations   would   be   an   incomplete way of evaluating the

variable. Because of this completeness argument, 4 brands

were   considered: the 2 brands involved in the   coupon

experiment and 2 other brands which had high market   share.

These 4 brands account for about 54% of total sales.

Further refinements were required, however, because 4

brands, each with 4 sizes, yields 16 alternatives. So, the

brand-size with lowest market share in this set was excluded.

These 15 alternatives were used for the rest of this study

and   account for about 53% of total sales. Appendix A lists

the final brand-size alternative set used.

B.   Analytic Approaches

Two approaches were considered in developing a model

which would utilize the coupon experiment. First, add a

coupon attribute to the model. For this purpose it would be

desirable to know which customers redeemed the coupon and

when they did so. Then, a binary indicator variable could be

created and set to 1 if the observation was purchased with a

coupon or 0 otherwise. Unfortunately, this information can

only be inferred through estimated average redemption rates.

Using   these   estimates presents a problem of possible

misredemption (i.e., coupons illegally redeemed but paid for

by the manufacturer). For example, an estimated redemption rate of 5% may be an overestimate if the estimated proportion of coupons misredeemed is 30%. The real redemption rate would be 3.5% (i.e., .05 - (.05 x .30) = .035).

Another problem with determining whether a coupon was used for a purchase comes from the time limit on probable usage which must be assumed. For instance, if a coupon drop was made on January 1, 1980, should redemption be assumed to occur by March 1, 1980? July 31, 1980? February 13, 1985? Not enough is known to estimate the proper time span.

In addition, if an assumption that a customer used a coupon is made, to which purchase should the coupon apply? Again, not enough is known to properly assign to the purchase an attribute indicating coupon usage.

To circumvent these uncertainties, a second approach utilizing the coupon experiment is to calibrate the model on the period prior to the coupon drop, then forecast over the period after the coupon drop for each group of consumers and compare:

1. actual versus predicted results, or

2. Group 1 versus Group 2 versus Group 3 results.

Assuming a model which performs reasonably well can be obtained, one should be able to spot the differential effects highlighted by the comparisons described above. Further, a general model will have been developed which can be used

across   time   and across various marketing control variables.
This thesis, therefore, uses this second approach.

CHAPTER 3: VARIABLES

The logit model requires a string of purchase
observations for calibration.   Associated with these
purchases are various attributes, such as price, promotion
loyalty, etc. A summary list of variables and their detailed
formulations is in Appendix B.

Depromoted Price (DPRICE)

The traditional external characteristic of a purchase
decision is price. In order to isolate changes in sales due
to normal shelf price from changes due to off-label discounts
or other promotions, price is defined here as the average
depromoted price per ounce. The depromoted price is defined
as the observed price plus any promotion price cut plus any
manufacturer's off-label promotion amount.

Promotion (PROMO)

Advertising and promotion are important stimuli in a
purchase decision.   Unfortunately, the UPC scanner data do
not include direct measures of advertising and promotion
activity. However, such activity can be inferred. If two of
the following three situations are observed, then a major
promotional activity is considered to have taken place and is
given the value 1:

1.   unusually heavy item movement

2.   downward price changes

3.   advertising

If two out of three are not observed, then the variable is given the value 0.

Promotional Price Cut (PCUT)

In addition to promotional activity, the retailer may choose to cut price. The UPC data also do not include direct measures of price cuts. Again, inferences are made to generate the variable. Price is tracked across weeks. Temporary downward price movements are marked. Presence and magnitude of price changes per ounce are put into the variable.

In order to avoid double counting, only price cuts coinciding with a promotion are kept. Thus, the final variable used in this study is promotional price cuts per ounce.

Off-label Promotions (OLPRO)

A marketing tool prevalent in the household cleaner category is off-label promotion by manufacturers. This promotion involves special labels on items which also requires a different UPC. For example, a label could say "20 cents off" on some Size 3 package of household cleaner.

Off-label packages of household cleaner are identical to their regular counterparts except for the off-label promotion which, in turn, leads to a different price. Since UPC's are different, when a consumer purchases an off-label promotion package, that fact is evident from their purchase record. The exact off-label discount amount is obtained from the UPC's description kept in the computer database. The label discount amount is entered into the off-label promotion variable.

Lag Promotion (LPRO)

Assuming prior purchase decisions of an individual consumer influence current decisions, a useful indicator variable could be lagged promotion. For our purposes, lag promotion equals 1 if the prior purchase of the customer was on promotion and the same brand as the current purchase observation. If not, LPRO is given a value of 0.

Loyalty

In addition to factors external to a purchase decision, the individual consumer has preferences. These preferences affect subsequent brand switching behavior and receptiveness to promotional activity. Loyalty is even more significant for marketing managers because:

1. a repeat purchaser is wanted,

2. increased consumption per purchase is helpful, and

3. switching from competing brands while not switching to competing brands is desirable.

A method for capturing these preferences quantitatively in a model is to define a loyalty variable for each customer and each brand-size alternative. For purposes of this study, carry over effects across one time period (i.e. week) are assumed.   Also, loyalty is assumed to be reinforced if the item is purchased and diminished if not.

Therefore, loyalty is calculated for the model along an individual's purchase sequence for each alternative using the formula,

$$Loyal(t) = .75*Loyal(t-1) + .25*B$$

where

Loyal (t) = loyalty in time period t

Loyal(t-1) = loyalty the prior time period

B =   1 if alternative purchased

0 if alternative not purchased

and loyalty for a consumer's first purchase is set equal to the alternative's average market share in the first 10 weeks of the sample period.   Further details can be found in Guadagni (1980) and Novich (1981).

Because of prior work indicating separate brand and size preferences, loyalty is divided into brand loyalty (BLOYAL) and size loyalty (SLOYAL).   The model is developed using

these two loyalty variables.

Dummy Variables

Dummy variables are used to account for inherent characteristics of each alternative not explained by other variables. There are 15 alternatives and dummy variables for 14 alternatives are defined in the model. Since the sum of the probabilities generated in the model must equal 1, one less dummy variable is necessary for model calibration. The variable equals 1 if the purchase observation is that alternative and 0 if not. The estimated model using only dummy variables then yields each alternative's market share.

In this thesis, dummies will be coded by two-character names. The first character of the name denotes the brand. The last character of the name denotes the size of the package. For example, a dummy variable name of "A2" means the dummy variable corresponds to Brand A, Size 2 package.

CHAPTER 4:   THE MODEL

Calibration

Purchases prior to May 6, 1980 of 300 randomly selected customers were used to calibrate the logit model. These customers had 1187 relevant purchase observations from July 25, 1979 to May 5, 1980. There were 1928 observations over the whole 65-week period.

In order to test the accuracy of the model's calculations, a simple market share model using only dummy variables as attributes was estimated initially. Market share was defined here as the proportion of observations found in the alternative. (i.e., number of observations for an alternative divided by total observations). Substituting the estimated coefficients into the choice probability equation defined in Chapter 2 then yielded predicted probabilities of choice for each alternative. Since no other attributes were in the model, the predicted probabilities were equivalent to predicting market share for each alternative. Exhibit 1 shows predicted and actual share for each alternative along with coefficients and t-values for each alternative. Predicted and actual shares are within .1 of each other. Model calculations appear to be working correctly.

However, although the predicted shares were close to

EXHIBIT 1

Initial Logit Calibration
with only
Dummy Variables as Attributes

Alternative	Actual Market Share (%)	Predicted Market Share (%)	Coefficient	t-value
A2	17.10	17.22	3.23	8.97
A3	8.80	8.90	2.57	7.02
A4	2.86	2.88	1.45	3.68
B1	7.16	7.21	2.36	6.39
B2	6.74	6.79	2.30	6.21
B3	6.82	6.87	2.32	6.25
B4	1.85	1.87	1.01	2.45
C1	5.73	5.77	2.14	5.72
C2	11.04	11.11	2.80	7.68
C3	6.32	6.36	2.24	6.02
C4	1.35	1.36	.69	1.60
D1	6.82	6.87	2.32	6.25
D2	12.55	12.64	2.92	8.06
D3	4.13	4.16	1.81	4.75

U-squared = .0788

actual, U-squared, which measures the model's goodness-of-fit to actual data, indicated that only 7.9% of uncertainty in the choice process was explained by the model over and above the null model which was defined earlier to be the equally-likely model. Clearly, other factors impact the choice decision of a consumer.

Other factors were included in a step-wise fashion in the model. Exhibit 2 contains results of each logit estimation. For each estimation, coefficients (b), t-values (t), and U-squared are shown. The exhibit is discussed below.

A.   Expectations Prior to Model Development

As a first approximation, disregarding dummy variables for the moment, all attributes except price should have a positive coefficient. A positive coefficient would indicate that as the variable increased, the probability of purchase would increase. On the other hand, one would expect price to have a negative coefficient which would indicate that as price increased, the probability of purchase would decrease. A priori, dummy coefficients could have either sign, depending on its market position relative to the excluded alternative.

In general, the absolute value of the t-statistics corresponding to the coefficients should be at least 2. A cutoff of 2 assures about a 95% significance level for the

EXHIBIT 2
Table of Results from Logit Estimations

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
U-SQRD	.079		.246		.303		.329		.331		.454	
	b	t	b	t	b	t	b	t	b	t	b	t
BLOYAL			5.39	24.29	5.26	23.64	5.38	23.76	5.40	23.80	5.22	18.76
SLOYAL					3.40	17.26	3.47	17.31	3.47	17.24	3.53	17.20
PROMO							1.55	13.68	1.05	5.95	1.11	5.62
OLPRO									48.48	2.99	37.50	2.22
PCUT									71.17	3.44	66.87	2.84
DPRICE									-3.00	-.49	.18	.03
LPRO											10.10	6.23
DUMMIES:												
A2	3.23	8.97	3.38	9.24	1.95	5.20	1.67	4.43	1.70	4.51	-.74	-1.75
A3	2.57	7.02	2.72	7.31	1.94	5.17	1.69	4.48	1.71	4.52	-.73	-1.71
A4	1.45	3.68	1.59	4.00	1.48	3.71	1.47	3.69	1.45	3.62	-1.02	-2.30
B1	2.36	6.39	2.98	7.92	2.41	6.31	2.41	6.30	2.39	6.25	2.35	6.10
B2	2.30	6.21	2.92	7.73	1.69	4.40	1.64	4.23	1.53	3.93	1.50	3.83
B3	2.32	6.25	2.94	7.77	1.94	5.02	1.92	4.95	1.79	4.59	1.75	4.46
B4	1.01	2.45	1.63	3.89	1.66	3.95	1.49	3.55	1.47	3.46	1.47	3.45
C1	2.14	5.73	2.53	6.68	1.98	5.16	1.95	5.09	1.96	5.10	1.95	5.06
C2	2.80	7.68	3.19	8.63	1.83	4.85	1.64	4.31	1.57	4.11	1.49	3.89
C3	2.24	6.02	2.63	6.97	1.79	4.69	1.55	4.03	1.41	3.63	1.43	3.66
C4	.69	1.60	1.08	2.48	1.09	2.50	1.09	2.48	.88	1.99	.92	2.06
D1	2.32	6.25	2.32	6.25	1.66	4.42	1.64	4.36	1.73	4.56	1.66	4.36
D2	2.92	8.06	2.92	8.06	1.57	4.20	1.37	3.67	1.31	3.49	1.23	3.27
D3	1.81	4.75	1.81	4.75	1.16	3.00	1.02	2.63	1.07	2.77	1.01	2.59

coefficient.   One   would   prefer   t-values   for   the   dummy variables to be insignificant while other variables remain significant.   Such   a   result   would indicate that the major factors explaining consumer response have been included. This would, in turn, imply to managers that a great deal of response could be obtained through activity such as promotion, price cuts, off-label discounts, etc. By using these attributes in the model, explanatory value of the attributes   (through   t-statistics)   along   with   total explanatory value of the model (through U-squared) can be estimated.   The   goal   is   to   obtain a U-squared as high as possible, with a small number of attributes.

B.   Results of the Model Calibrations

As seen in Exhibit 2, subsequent model development yielded   interesting   results.   The largest U-squared was .45, (Guadagni   obtained   a   U-squared   of   .55.)   the   biggest increment in U-squared occuring when loyalty attributes were included in the model. Like Guadagni's coffee study, LPRO was significant.

The signs of the coefficients, except price, agree with our priors.   However, when examining price across weeks, a steady upward inflationary trend is noticeable within each store, which could be causing problems. Also, when checking across stores, the overall general price level in some stores is up to 26% higher than in other stores.   A majority of

observations come from the higher priced stores, which adds another factor that could have an effect. But, the t-statistic for price is almost zero, which indicates that the price coefficient could actually be zero. In fact, the sign of the coefficient changes from negative to positive when LPRO is added to the model. In both Model 5 and Model 6, the t-statistic is insignificant. It is uncertain which coefficient is closer to the "true" underlying value. Almost all other coefficient t-values were significant, including t-values for the dummy variables.

With significant dummy variables, as this study found, the existence of a "core franchise" or some type of brand "image" built up over time could be inferred, even though significant dummies may mean there are more variables which should be included in the model. If a core franchise does exist, however, this tells managers that people do have substantial preferences for a particular alternative regardless of price, promotion, discounts, etc. Hence, these people could be less readily receptive to promotional activity. Following through then, one might also infer that the likelihood of switching and the probability of cannibalization would be less also. This result is heartening for each manufacturer's own brand, but bodes ill success for attracting customers away from competitors. The best strategy to follow may then be one which emphasizes innovation and total market expansion with new uses or users

rather   than   one   which tries to defend or expand share with promotional activity in mature brands.

In fact, the core-franchise concept is substantiated   by the   significance   of   brand   loyalty and size loyalty.   Even though promotion, off-labels and price cuts are   influential, the   preponderance   of   total effect, indicated by U-squared, goes to consumer loyalty.   One explanation for the lower, but still significant   t-values   for   promotion   attributes   like price   cut,   label   discounts,   and   promotion,   is   that promotional activity induces people to stock   up.   That   is, the promotional activity has induced the consumer to not only purchase   sooner,   but purchase   more than normally.   So while probability of purchase increases, probability of   subsequent purchase   decreases.   This may mean that the effect of these attributes is short run while loyalty has   long-term   impact. In   fact,   Guadagni   found   promotion insignificant if lagged more than one purchase.

Further evidence for the core-franchise hypothesis   lies in   the   insignificant t-statistic for the price coefficient, given the other attributes in the   model.   One   might   infer that   if   a   coupon   effect   did exist, informational effects would   dominate.   That   would   imply   that   perhaps   coupons actually   inform customers and change preferences rather than convey a good buy.   As noted in   Guadagni   (1980),   a   useful calculation is simulating price elasticity of consumers.   The calculation   is   straightforward,   but   is   not shown in this

thesis, since the main focus is on couponing.

Thus far, developing the logit has provided many tantalizing insights to pursue; the next steps are to choose a final model and see how well that model performs. The Chi-squared test is the traditional measure of a model's statistical significance compared to a null model. In addition, two "non-null" models can be compared using the Chi-squared test by simply taking the difference between the Chi-squares obtained from the two models. (See also Hauser (1976).) As Exhibit 3 shows, the model with the largest U-squared and significant Chi-squared statistic is Model 6. Thus, Model 6 is chosen to be used in the remainder of this study. This model has a U-squared of .45.

Validation

Because logit is a choice model which produces probabilities of choice, not choices, actual versus predicted results on an observation by observation basis is not instructive. In order to compare the model to actual events, actual and predicted aggregate shares must be calculated and a number of preliminary steps taken:

1. Some time period (e.g., week or month) must be defined.

2. Observations must be collected for each time period.

Predicted probabilities can then be converted to an average predicted market share per time period and compared to actual

EXHIBIT 3

FROM Model	TO Model	Degrees of Freedom	Chi-Squared (FROM)	Chi-Squared (TO)	Chi-Squared (CHANGE)
1	2	1	507.87	1581.48	1073.61
2	3	1	1581.48	1947.92	366.44
3	4	1	1947.92	2115.07	167.15
4	5	3	2115.07	2127.93	12.86
5	6	1	2127.93	2917.74	789.82

Chi-Squared = 2 * n * H(A) * U-Squared

where n = number of observations

H(A) = natural logarithm of the number of alternatives

= ln 15 = 2.708

Degrees of Freedom = number of parameters in "TO" model -
number of parameters in "FROM" model

(For further reference, see also Hauser (1976))

---

market shares during the defined time period. This study uses 4-week time periods beginning with August 1, 1979, which makes 16 periods available to evaluate the model. Periods 1 to 10 correspond to the calibration period. Periods 11 to 16 correspond to the post coupon drop period; the model was not calibrated using observations from this period.

To validate the model, predicted market share is compared to actual market share:

1. using observations from the calibration group,

2. using observations from some sample group of
    customers different from the calibration group
    (a holdout group), and

3. using observations from the calibration group and
    holdout group, but restricting to a specific store.

If the model tracks well over the calibration observations,
then one can be fairly confident that the model is accurate.
If the model also tracks well for a holdout group, then one
can be fairly confident that the model holds in general,
across the population sampled for this study. If the model
tracks well for specific stores, then one can be fairly
confident that the model is useful both for overall strategy
(e.g., corporate planning) and individual store strategies
(e.g., mix of marketing control variables). If the model
tracks well in all three conditions, then a   powerful
managerial tool will have been developed. The remainder of
this chapter examines the three validation situations.

A. Calibration Group Tracking

Exhibit 4 shows plots of actual market share and
predicted market share by brand across the calibration time
periods for the 1187 observations obtained   from   the
calibration group of customers mentioned above.

As shown by the plots, the model tracks quite well.   In
general, peaks and valleys are matched; even trends are
followed. Individual differences by period are probably due

EXHIBIT 4
Actual Market Share vs. Predicted Market Share
by Brand for Calibration Observations
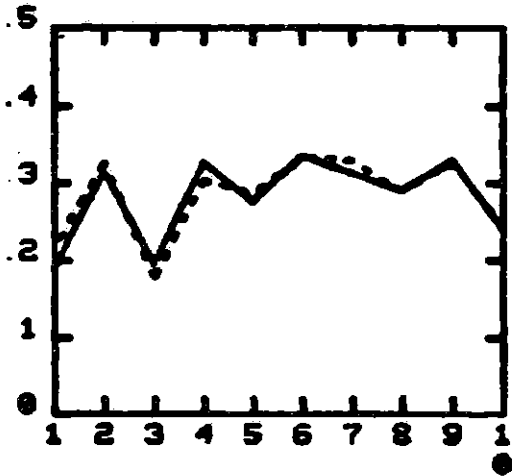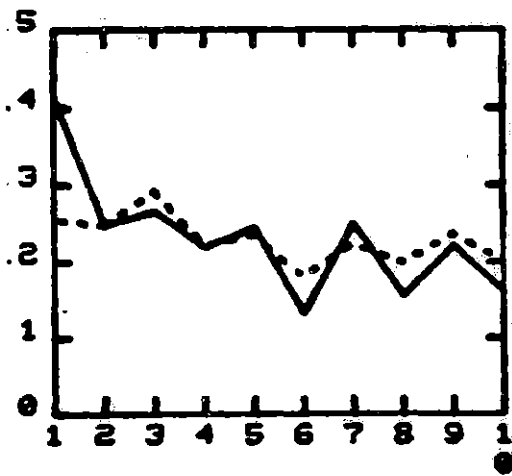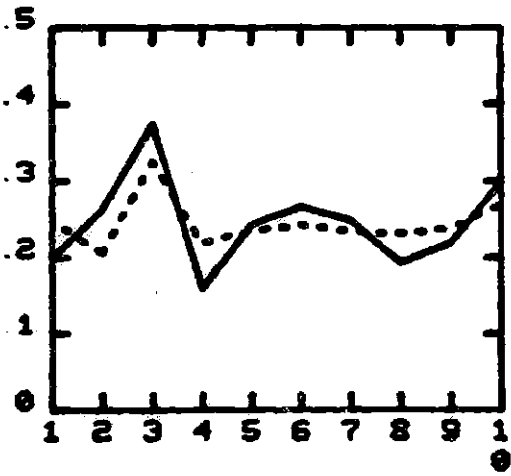
BRAND A

BRAND B

BRAND C

BRAND D
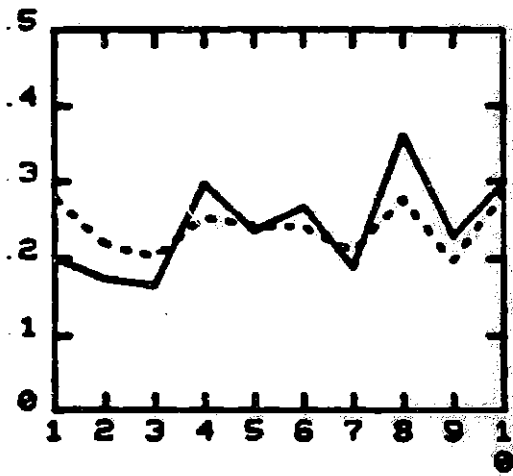
——— Actual Market Share
..... Predicted Market Share

not only to random error and missing explanatory variables,
but also to actual promotional activity which has gone
undetected in the model. (Of course, differences could also
be due to using an incorrect model.)

A more basic problem is obtaining a large enough number
of observations to properly estimate share. As a rule of
thumb, about 150 observations per time period or 2400 total
observations are needed. Only 1928 total observations were
available over all brands. Since Brand A is the dominant
brand, more observations are available and as Exhibit 4
shows, the fit of predicted to actual shares is best for this
brand.

Another explanation for this divergence between
predicted and actual share could be found in the loyalty
variables. As defined before, the variables are started
using the alternative's average market share during the first
10 weeks of the sample period across all stores. Trying to
apply this very broad measure as a good estimate of the value
of an individuals basic loyalty is questionable. This
start-up problem may be alleviated by omitting the first
observation for each customer in the model. Further study
needs to be done to develop a more accurate loyalty
attribute.

In any case, Exhibit 5 shows actual market share across
time in relation to a 1.6 standard error band about predicted
share by brand. Assuming a hetergeneous binomial

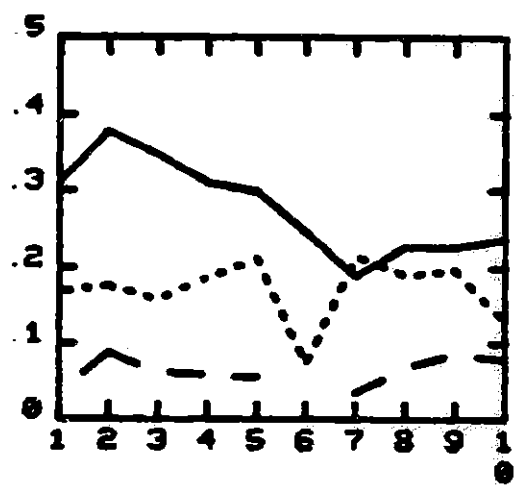EXHIBIT 5
Actual Market Share vs. a 1.6 Standard Error Band
around Predicted Market Share by Brand
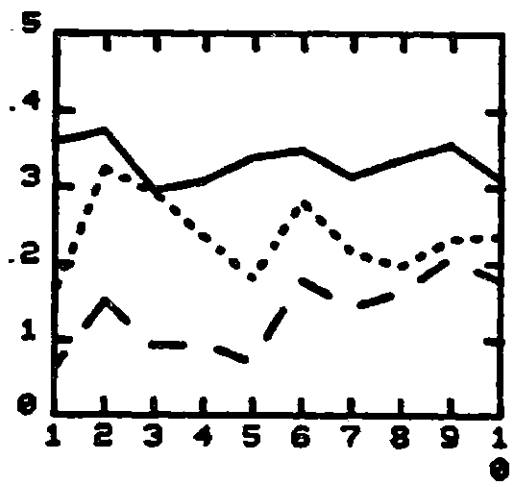Calibration Observations
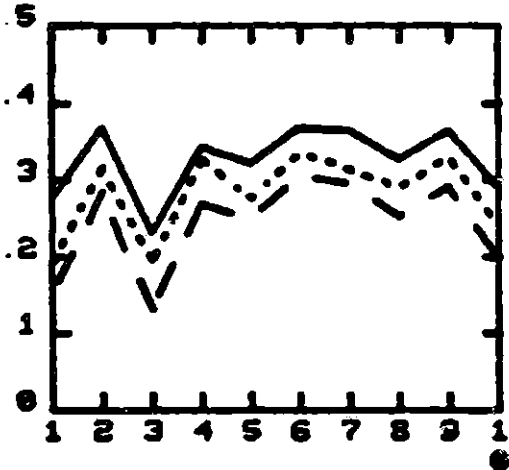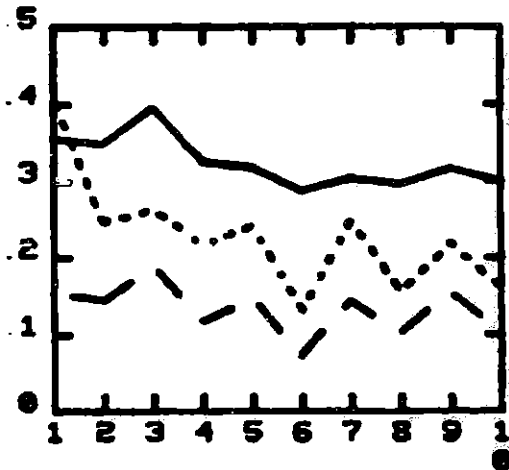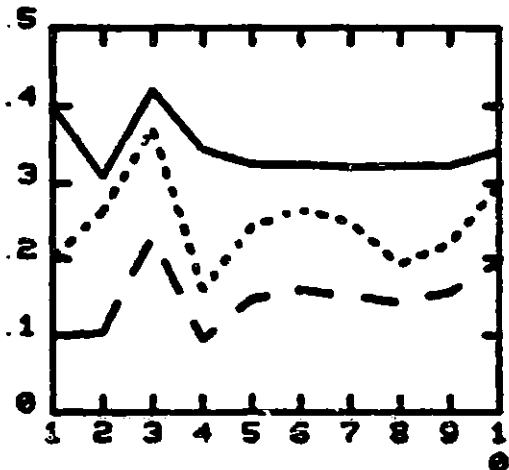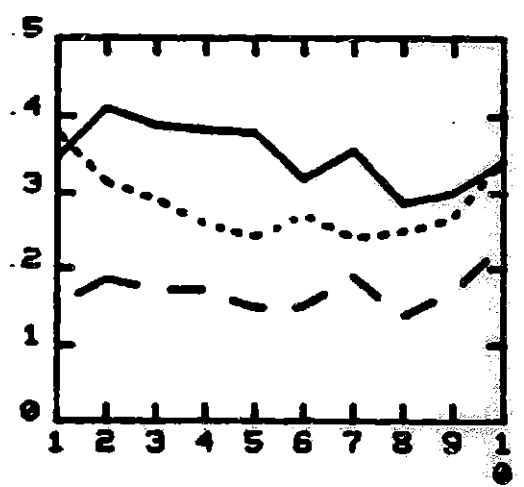
BRAND A

BRAND B

4-WEEK PERIOD

4-WEEK PERIOD

BRAND C

BRAND D
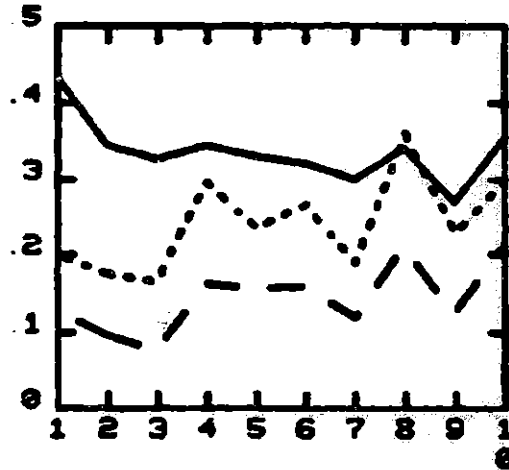
4-WEEK PERIOD

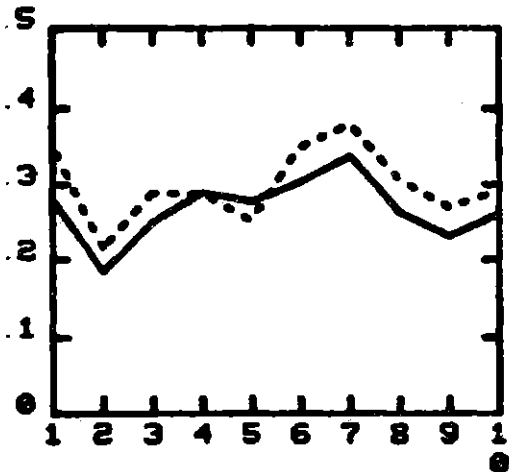4-WEEK PERIOD

———— Predicted Share + 1.6 Standard Errors
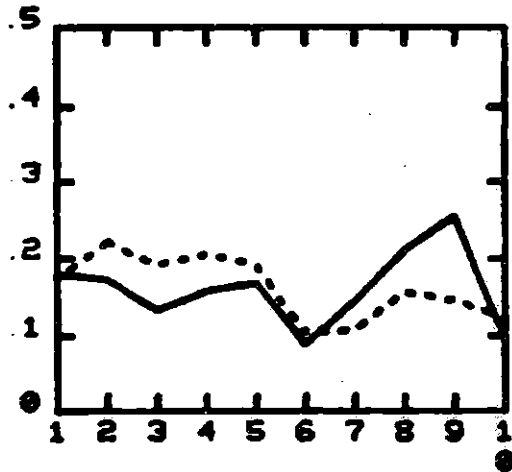••••• Actual Market Share
----- Predicted Share - 1.6 Standard Errors

distribution underlies market share, a standard error for each predicted market share point can be calculated using the formula,

$$SE(p) = \sqrt{(average(p(i)) - average(p(i)^2))/n}$$

where

SE(p) = standard error of predicted market share

p(i) = predicted probability of observation i

p = predicted market share

= average predicted probabilities of observations in the time period

n = number of observations during the time period

Using a 1.6 standard error band, one can expect 9 out of 10 points to fall within the band. If actual market share falls within the standard band around the predicted value, then we can say the model is tracking very well. In every case but two, actual shares lie inside the band. And even those two cases are within two standard errors (95% interval). The model appears to track well over time.

It should be noted that the band range of roughly .10 to .40 can be narrowed with more observations. The standard errors here are due, in part, to the low number of observations per time period available for estimation.

B. Holdout Group Tracking

As mentioned before, a model should be validated cross-sectionally. In order to validate the model across the

population,   456 random customers different from the original
calibration set of 300 customers were used. These   customers
generated   2683 observations which are used to generate
predicted market shares based on the logit coefficients
estimated from the calibration group.   Again assuming a
binomial distribution underlies market share, a standard
error for each predicted market share point can be calculated
as   before.   Exhibit 6 shows actual market share and the
standard error band around predicted share across time
periods for the 4 brands as before. In fact, actual share
occurs inside the band 90% of the time. Again, even points
outside the band are well within two standard errors. Again,
the model tracks well.

C. Store Tracking

     In   a   prior   study   (Novich   (1981)),   significant
differences were found among stores. Each store was found to
have an individual "personality". This study, however, is
attempting to derive a model useful across all stores.
Exhibits 7a and 7b are plots of predicted and actual shares
by brand for two sample stores. Shares were calculated using
observations from both the calibration and holdout groups to
obtain a reasonable number of observations. Unfortunately,
the average number of observations per period by store was
still roughly 78.   The small number of observations may
account for a majority of the deviations between predicted

EXHIBIT 6
Actual Market Share vs. a 1.6 Standard Error Band
around Predicted Share by brand for
Holdout Observations

BRAND A
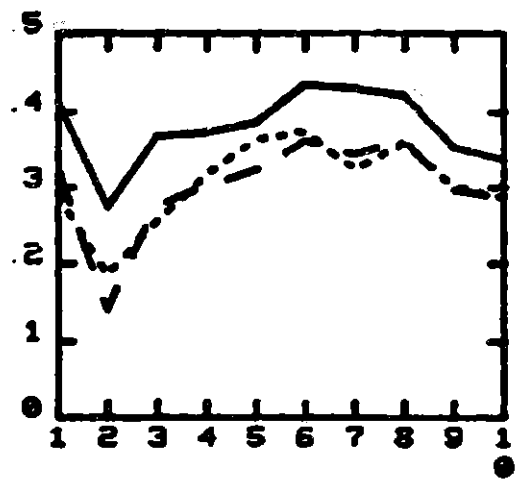
BRAND B

4-WEEK PERIOD

4-WEEK PERIOD

BRAND C

BRAND D

4-WEEK PERIOD

4-WEEK PERIOD

```
———————   Predicted Share + 1.6 Standard Errors
.....     Actual Market Share
—————     Predicted Share - 1.6 Standard Errors
```

EXHIBIT 7a
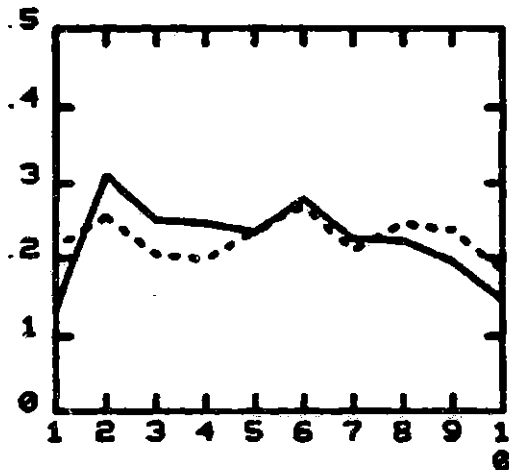### Actual Market Share vs. Predicted Market Share
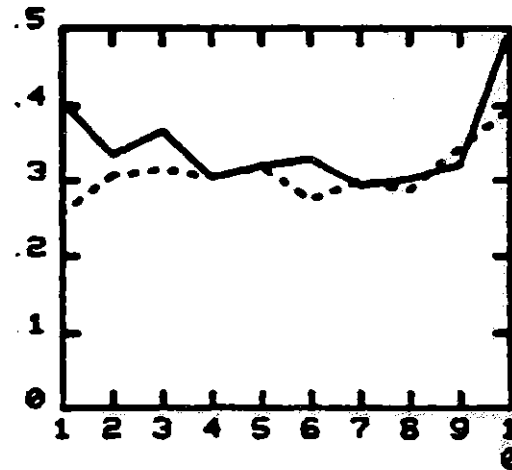### by Brand for Store X

BRAND A

BRAND B

BRAND C

BRAND D

4 WEEK PERIOD

4 WEEK PERIOD

4 WEEK PERIOD

4 WEEK PERIOD

——— Actual Market Share
..... Predicted Market Share

EXHIBIT 7b
Actual Market Share vs. Predicted Market Share
by Brand for Store Y
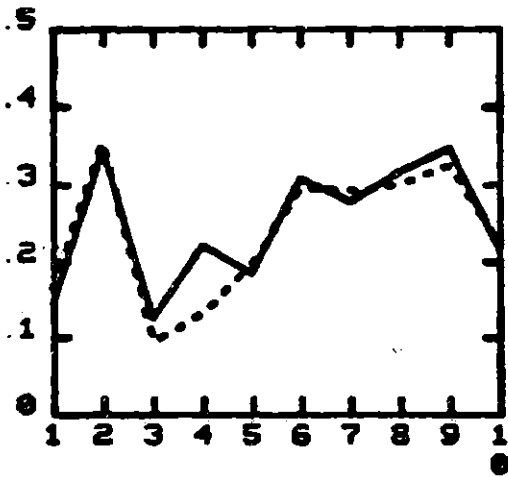
BRAND A

4 WEEK PERIOD
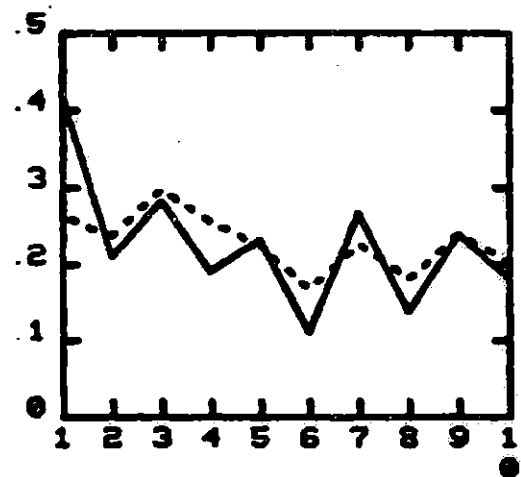
BRAND B

4 WEEK PERIOD
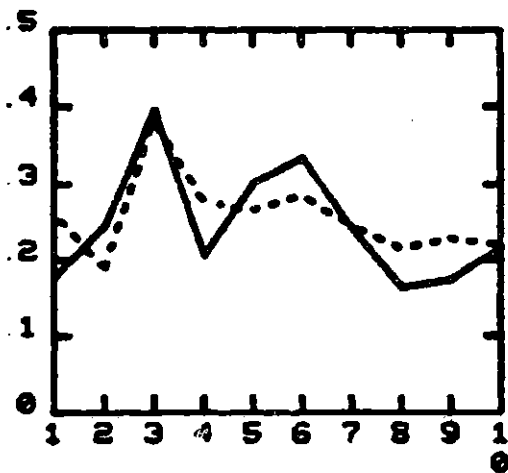
BRAND C

4 WEEK PERIOD

BRAND D
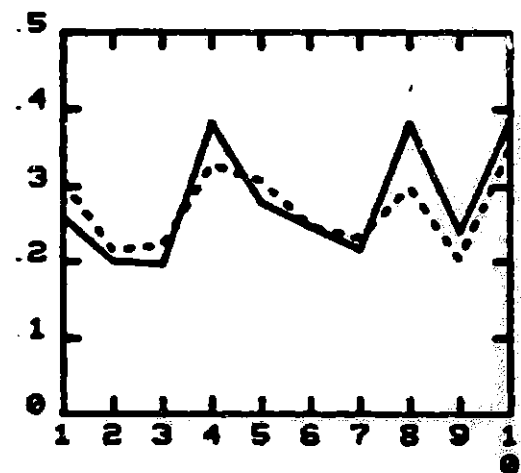
4 WEEK PERIOD

—————— Actual Market Share
••••• Predicted Market Share

and   actual,   as seen on the graphs.   Appendix C shows actual
share versus a 1.6 standard error band for the   two   stores.
Actual share falls within the band over 91% of the time.

The most   interesting   phenomenon   occurring   in   these
graphs,   however,   is   the   fact   that the model still tracks
trends reasonably well.   Only   the   most   extreme   peaks   and
valleys   are   missed.   It   is very rare that any model would
track such extreme points well.   Overall, the   general   model
developed in this study tracks behavior not only across time
and across the sample population, but also across stores.

CHAPTER 5:   CONSIDERING COUPONS

Since the model which was calibrated in the first part
of the preceeding chapter performs remarkably well, we can
now turn to evaluating couponing as a promotional tool for
manufacturers.   If, indeed, coupons have an effect, then
significant differences among the three coupon groups should
be found.

As mentioned earlier, customers in Group 1 received a
coupon for Brand B. Customers in Group 2 received a coupon
for Brand C. Group 3 did not receive a coupon for household
cleaners.   It should be noted that customers in each group
come from both the calibration and validation groups because
of the need for as many observations as possible, but each of
the coupon groups is mutually exclusive.

Since Group 3 serves as a control group in the coupon
experiment, we will study their behavior first. This group
has a two-fold purpose:

1. to check the model's forecasting ability, and

2. to compare with Group 1 and Group 2 (i.e., to null
   out other environmental factors which affect
   all the groups).

Exhibit 8 shows plots of predicted and actual share for
the control group for the four brands. The model tracks
actual share very closely, both during and after   the
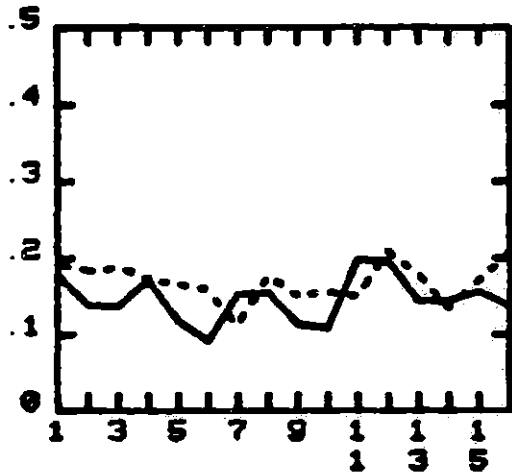calibration period.   There were 1455 observations, with an

EXHIBIT 8
Actual Market Share vs. Predicted Market Share
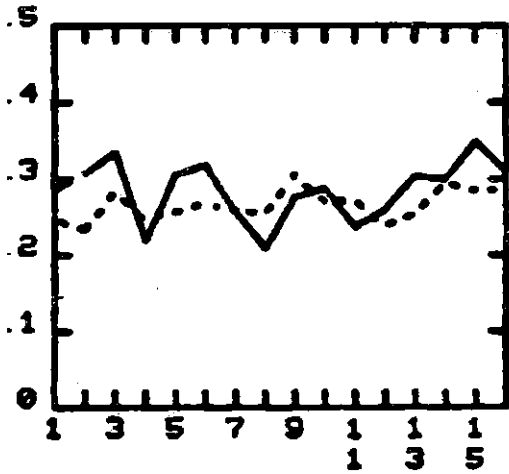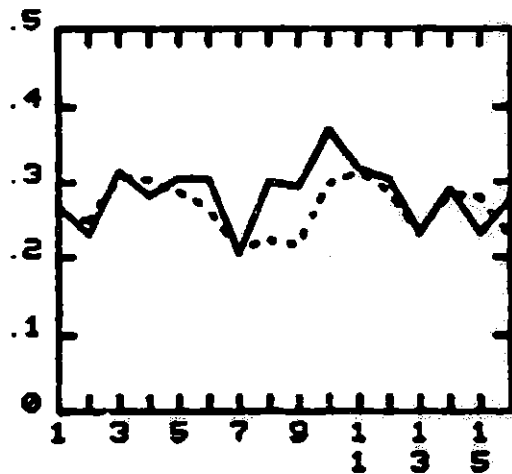### by Brand for Control Group
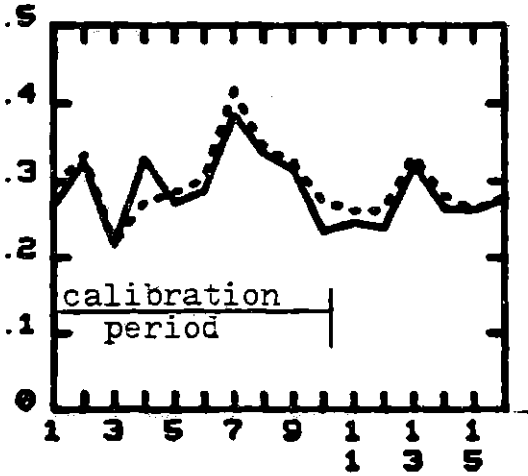
BRAND A

BRAND B

BRAND C

BRAND D

——— Actual Market Share
..... Predicted Market Share

average of 90 observations per   period.   Appendix D shows

plots of actual share versus a 1.6 standard error band around

predicted share for the 4 brands. Actual share falls within

the band 100% of the time. Several additional salient points

must be noted, however.

Point 1

The model (reflected by predicted shares) is still able

to   track trends even with yet another combination of

customers and purchases past the calibration period, thus

showing its adaptability and forecasting ability.

Point 2

The predicted shares appear to fluctuate less wildly

than the actual, indicating that

1. mean aggregate responses are reflected in
   the model, and

2. the model does well given the lean number of
   attributes and observations in the model.

Point 3

Most important, the possibility of using the model

instead of the control group to evaluate the coupon

experiment arises. If this is the case, then the model may

make conducting coupon tests unnecessary. Manufacturers will

not have to wait for results from the experiment before

acting. Managers will be able to react to the market

environment in a more timely manner in addition to being in a better position to begin proactive marketing tactics.

So the coupon experiment will first be evaluated using the model.   Then   results will be compared to a prior study done by MDS which uses the control group.   Possible econonmic considerations will be addressed.

Evaluating the Coupon Group Using the Model

A.   Group 1

Customers in Group 1 generated 1263 observations, or about 79 observations per period. Exhibit 9 shows actual share versus predicted share for each brand. It appears that the coupon brand, Brand B, benefited from the coupon during the first four periods after the drop (i.e., periods 11 to 14). Predicted share is below actual share for four periods then begins to track close to actual again. Correspondingly, predicted share for other brands is generally above actual. If one assumes the model is a good estimate of normal expected share, it could be inferred that the gain in Brand B is mostly from Brand C.   Interestingly, Brand C is manufactured by the same company as Brand B. Thus, possible cannibalization effects can be seen.

Exhibit 10 shows cumulative actual minus predicted shares starting from period 10, for Brand B. The cumulative
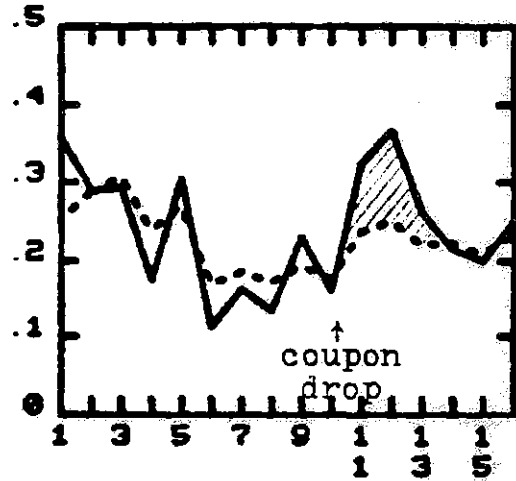
EXHIBIT 9
Actual Market Share vs. Predicted Market Share
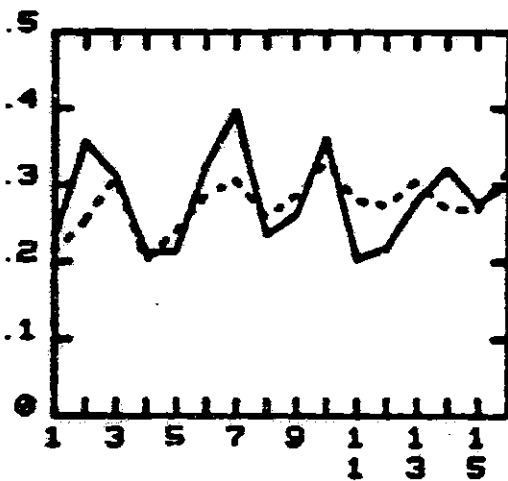### by Brand for Brand B Coupon Group (Group 1)

BRAND A
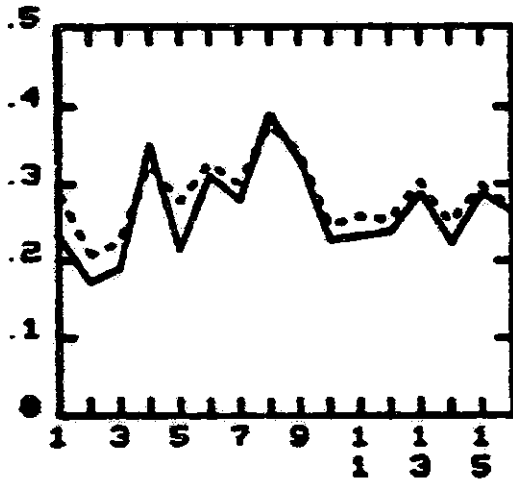
4 WEEK PERIOD
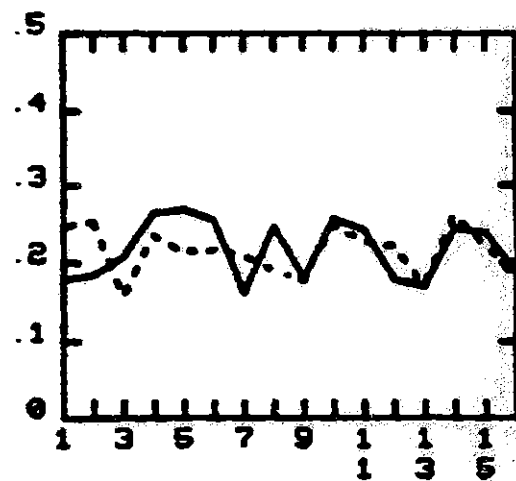
BRAND B

coupon
drop

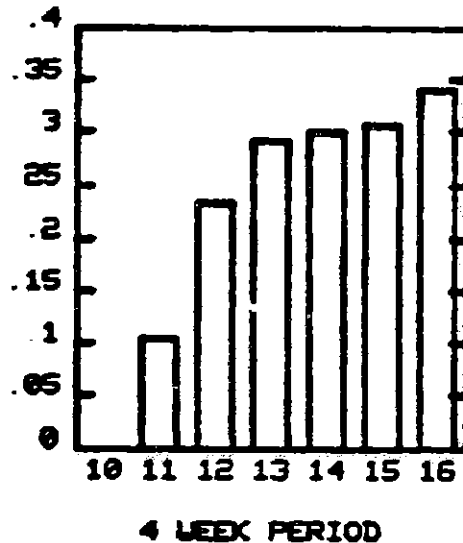4 WEEK PERIOD

BRAND C

4 WEEK PERIOD

BRAND D

4 WEEK PERIOD

——— Actual Market Share
..... Predicted Market Share

EXHIBIT 10
Cumulative Actual minus Predicted Market Share
Post Coupon Drop Date for Couponed Brand B

4 WEEK PERIOD

effect increases at a marginally decreasing rate which also
lends credence to the hypothesis that as elapsed time since
the drop increases, the effect of the coupon decreases. If,
at the end of five 4-week periods the cumulative share gain
in Brand B is about 34 points, and each share point contains
about 13 purchases per 4-weeks, and each purchase averages
about $1.18 per package, then Brand B has gained
approximately $521.56 over 5 periods (i.e., 34 share points x
13 purchases per share point x $1.18 price per purchase).
Extrapolation can yield rough figures for possible

incremental revenues due to the coupon drop.

B.   Group 2

Group 2 can be evaluated similarly. Customers in Group
2 had 1292 observations averaging 81 observations per period.
Exhibit 11 shows actual versus predicted share for each
brand.   In Group 2's case, differences between actual and
predicted are even more striking than in Group 1. The coupon
brand, Brand C, shows a large jump immediately after the drop
in period 11 and remains above predicted. Again assuming the
model is the norm, the gain probably came from the other
brands rather than from a specific brand as seen with Group
1.   The coupon for Group 2 appears to have had a greater
effect overall than the coupon for Group 1.

Exhibit 12 shows Brand C's cumulative actual minus
predicted shares post coupon drop date, similar to Exhibit
10. Again, marginally increasing gains at a marginally
decreasing rate are observed.   However, in this case, it
appears that the rate decreases at a slower pace than in
Group 1's case, implying that the coupon for this Brand may
have had a longer term effect in addition to taking longer to
start. Unlike Group 1, whose cumulative difference began
decreasing after 5 periods, Group 2's cumulative difference
still shows a steady upward trend.   Even though still
increasing, incremental revenues will be calculated at the
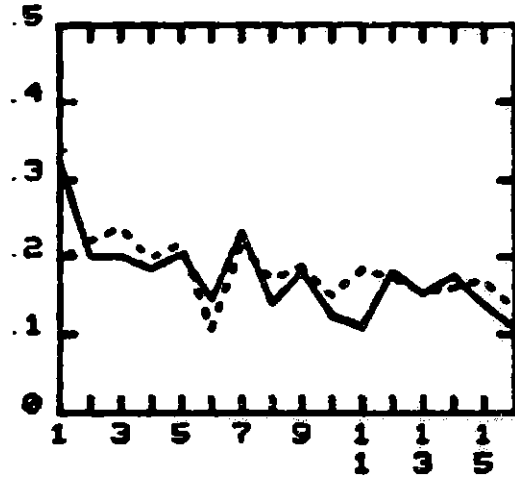last time period available in this study: Brand C gained 35

EXHIBIT 11
Actual Market Share vs. Predicted Market Share
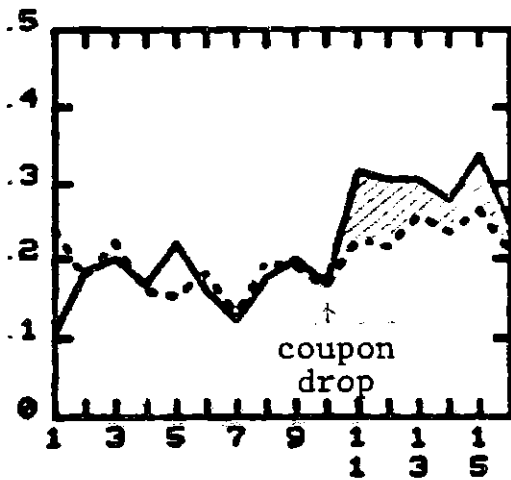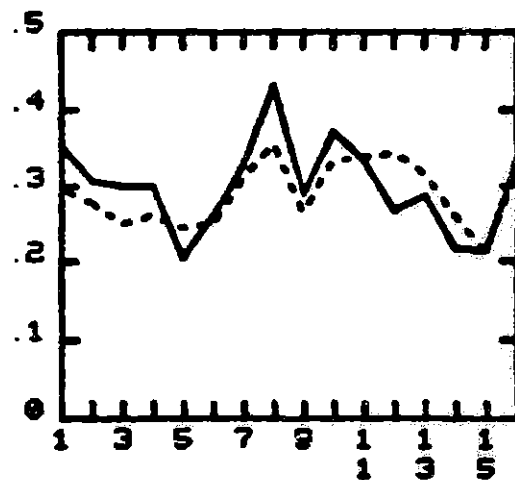### by Brand for Brand C Coupon Group (Group 2)
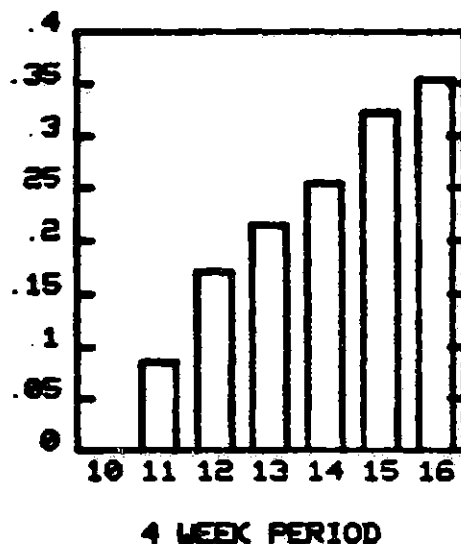
BRAND A
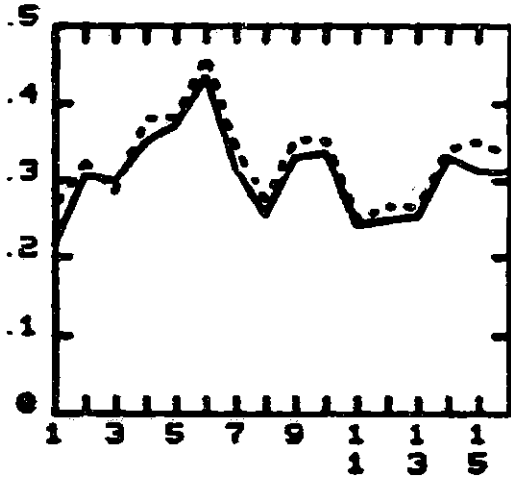
BRAND B

BRAND C

BRAND D

coupon
drop

——— Actual Market Share
..... Predicted Market Share

4 WEEK PERIOD

EXHIBIT 12
Cumulative Actual minus Predicted Market Share
Post Coupon Drop Date for Couponed Brand C

4 WEEK PERIOD

cumulative   share   points   by the end of 6 periods, giving an
estimated increment of $536.90 (i.e., 35 share   points   x 13
purchases   per   share   point x $1.18 price per package) or 3%
higher than Group 1.

An extension to these calculations   is   to   multiply   by
gross   margin   and   subtract   out distribution and redemption
costs to yield profitability estimates.   Differences   between
coupons could then be estimated.

One explanation for the difference   between   the   coupon
effects   on   the two groups is dissimilar consumer perception

of various brands. Brand B may be perceived as competing close to generic-type brands, whereas Brand C may have a higher price/quality image. If this is the case, promotions for Brand B may substantiate the lower price/quality image. Consumers who buy this brand may be more receptive to promotional activity and hence be more likely to switch brands, thus, the shorter-term coupon effect seen in Group 1. Brand C, on the other hand, may attract more loyal shoppers who respond less quickly to promotions, but want to take advantage of the "good buy" and, in effect, increase their loyalty.

Overall, Brand C seems to respond better to the coupon effort than Brand B. It should be noted that estimates of incremental sales in this study are conservative (i.e., underestimated) because if a coupon was used by a customer for a purchase, the purchase would have been included in the customer's purchase string when estimating share. Including the coupon purchase increases loyalty. Increased loyalty increases probability of purchase. Thus, predicted shares are overestimated and actual minus predicted shares are underestimated.

Comparison with Prior Study

At this point, one might say that the coupons were effective and that the coupon for Brand C was more effective than the coupon for Brand B. In fact, a prior study done by

Robert L. Klein of MDS also shows significant effects of the coupons when testing each coupon group against the control group. Brand B was found to be affected very quickly, whereas Brand C was affected more slowly. The same situation is found here. Magnitude of the effects were somewhat different due to the different evaluation technique used.

Future work should be done to evaluate the effectiveness of couponing relative to other marketing tools such as advertising and price. More intensive work could be done on consumer perceptions and promotional activity. If definite "clean" inferences are desired, controlled experimentation is a useful tool. However, the results in this study show that analysis of historical data is a powerful evaluative technique. Many more cases need to be studied, especially with respect to effects on loyalty.

CHAPTER 6: CONCLUSION

In summary, UPC scanners have provided data required for modeling the complexities of sales response in specific market environments. The model developed in this thesis uses scanner data to calibrate individual purchase probabilities. These probabilities translated into predicted market shares track actual shares very well given the number of observations available. The model was validated across time, across population, and across store.

In addition, interesting observations could be made from the model's results. Loyalty had significant positive effects on purchase probability. Price cuts and off-label promotions had similar significant effects. Lag promotion was very significant. Depromoted price had insignificant effects. These results coincide with the "core franchise" hypothesis which says that inherent consumer preferences independent of marketing variables exist. Most important, marketing variables cannot be analyzed in a vacuum. The model allows adaptation to individual changing, dynamic environments.

In the future, to make the model even more powerful, work can be done to define the variables more accurately. For instance, the loyalty variable has a start-up problem. To obtain a reasonable estimate, a long string of purchases are required. Since the household cleaner category studied

here is a relatively low involvement, low purchase frequency group (average interpurchase time in this category is 6 weeks), longer time periods of purchases are needed.

Another intriguing result is the similarity of results between this study and Guadagni's study in the coffee category. Further testing to see if the logit model applies across categories will provide more insights into modeling the marketplace and sales performance.

In turn, the model developed in this thesis gives managers a good method of evaluating marketing variables, such as price, store promotion, couponing, etc.   Areas for further study such as impacts on sales forecasts, purchase frequency, consumer loyalty and overall profitability can be done.   Relative effectiveness of different marketing variables can be evaluated.   The different coupon effects seen in this study have different strategy implications. In one case, cannibalization has to be considered. In the other case, general market share increases gained from competitors must be considered.   These will impact brand image and supporting marketing strategy.

In the final analysis, managerial effectiveness and productivity can be enhanced through the development of frameworks and methodologies such as those discussed here. Objective and timely support of strategy formulation through the use of modeling techniques can indeed be a key to insight for today's knowledge worker.

APPENDIX A

Brand — Size Alternative Set

|	Size			
	1	2	3	4
Brand				
A		x	x	x
B	x	x	x	x
C	x	x	x	x
D	x	x	x	x

APPENDIX B

Variables Used in the Logit Model

Depromoted = Observed Price + Promotion * Price Cut +
Price   Off-Label Discount Amount

Promotion =   1 if Advertising + Unusual Movement + Price
                     Cuts is greater than 1
                   0 otherwise

Promotion =   ` amount of price cut during promotion
Price Cut   0 if no price cut or promotion

Off-Label =   amount of off-label discount
Promotion   0 if no discount

Lag   =   1 if customer's prior purchase observa-
Promotion   tion was on promotion and the same brand
                     as the current observation
                   0 otherwise

Loyalty   = .75 * Loyalty in prior period + .25 * B

   where B =   1 if brand or size purchased
                   0 if brand or size not purchased

Dummy *   =   1 if purchase observation is the
Variables   alternative
                   0 otherwise

* Dummy variables for each alternative but 1

APPENDIX C
Actual Market Share vs. a 1.6 Standard Error Band
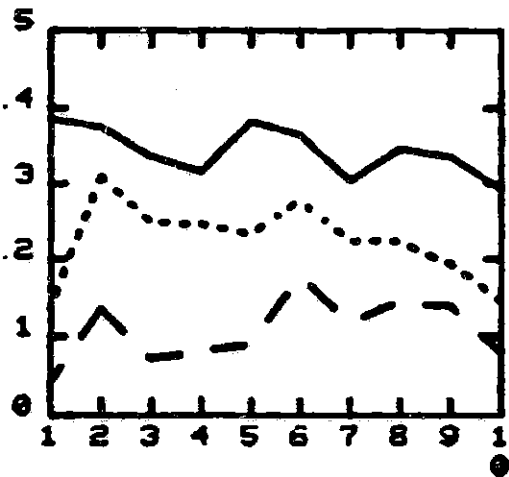### around Predicted Share by Brand for Store X
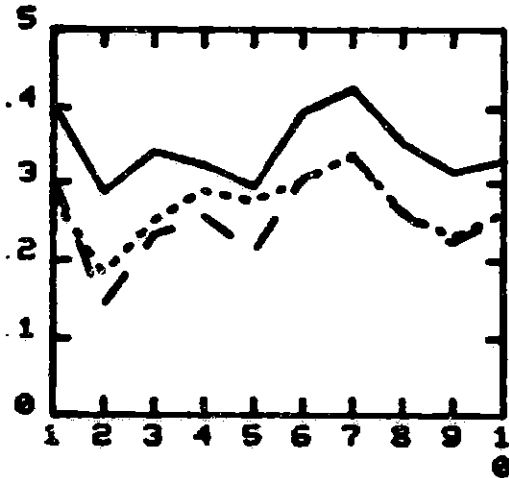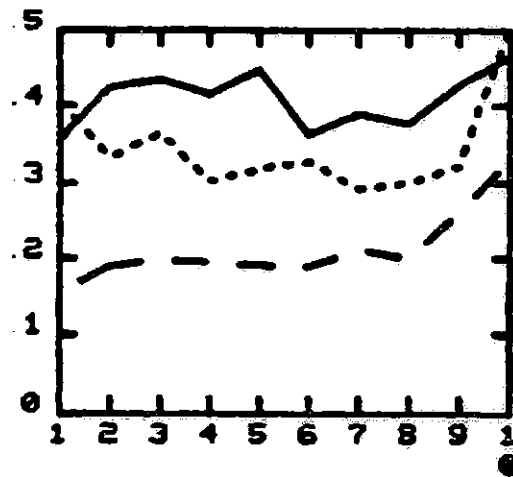
BRAND A

4—WEEK PERIOD
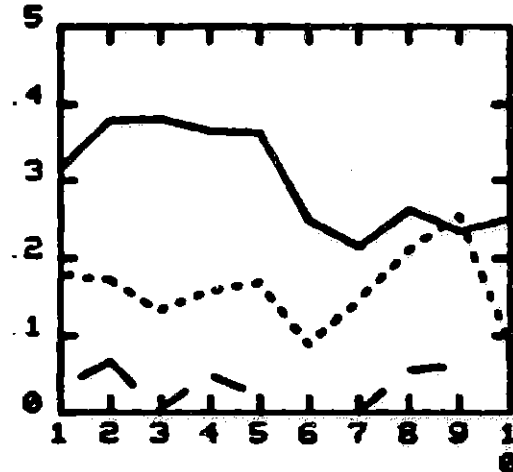
BRAND B

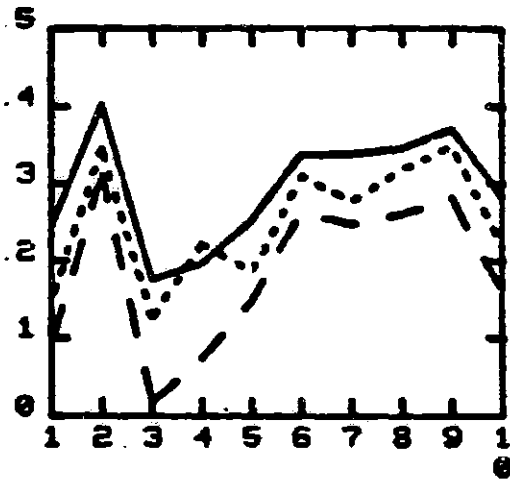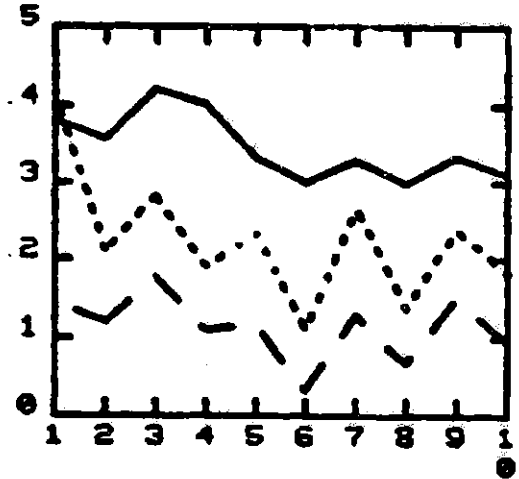4—WEEK PERIOD

BRAND C

4—WEEK PERIOD

BRAND D

4—WEEK PERIOD

—————— Predicted Share + 1.6 Standard Errors
• • • • • Actual Market Share
— — — — Predicted Share - 1.6 Standard Errors

APPENDIX C (continued)
Actual Market Share vs. a 1.6 Standard Error Band
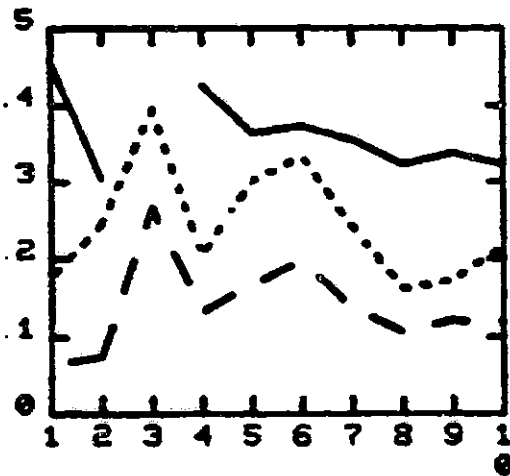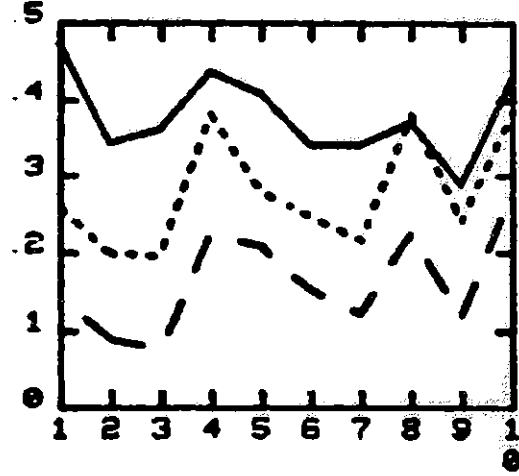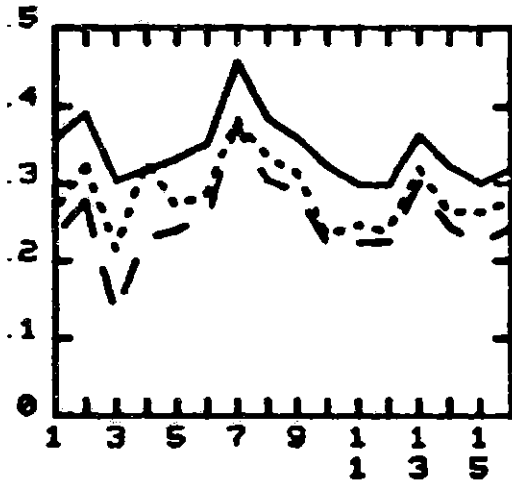### around Predicted Share by Brand for Store Y

BRAND A

BRAND B

4-WEEK PERIOD

4-WEEK PERIOD

BRAND C

BRAND D

4-WEEK PERIOD

4-WEEK PERIOD

——— Predicted Share + 1.6 Standard Errors
..... Actual Market Share
----- Predicted Share - 1.6 Standard Errors
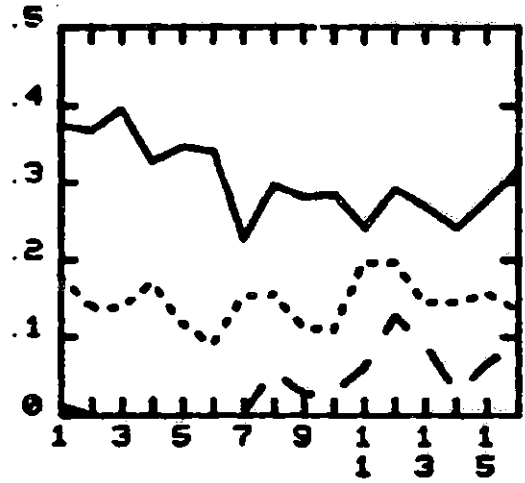
APPENDIX D
Actual Market Share vs. a 1.6 Standard Error Band
around Predicted Share by Brand for Control Group
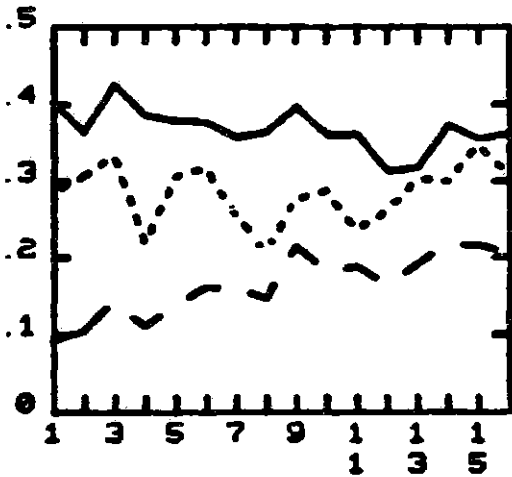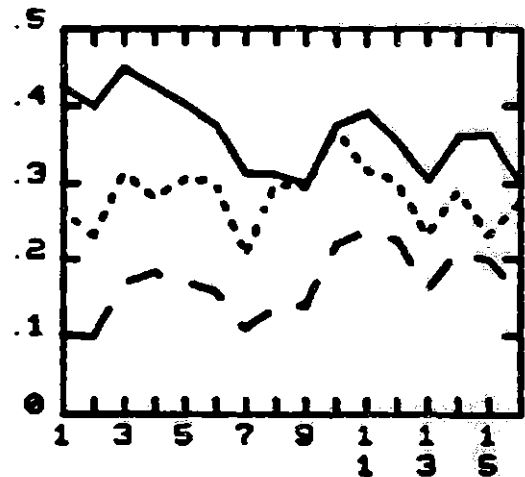
BRAND A

BRAND B

4-WEEK PERIOD

4-WEEK PERIOD

BRAND C

BRAND D

4-WEEK PERIOD

4-WEEK PERIOD

—————— Predicted Share + 1.6 Standard Errors
•••••   Actual Market Share
—————— Predicted Share - 1.6 Standard Errors

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