A Loyalty Group Segmentation Model for Brand Purchasing Simulation

Author(s): Martin K. Starr and Joel R. Rubinson

Source: *Journal of Marketing Research*, Aug., 1978, Vol. 15, No. 3 (Aug., 1978), pp. 378-383

Published by: Sage Publications, Inc. on behalf of American Marketing Association

Stable URL: https://www.jstor.org/stable/3150586

REFERENCES
Linked references are available on JSTOR for this article:
https://www.jstor.org/stable/3150586?seq=1&cid=pdf-reference#references_tab_contents
You may need to log in to JSTOR to access the linked references.

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at https://about.jstor.org/terms

American Marketing Association and *Sage Publications, Inc.* are collaborating with JSTOR to digitize, preserve and extend access to *Journal of Marketing Research*

164.67.163.3 on Wed, 07 Jul 2021 14:32:18 UTC

MARTIN K. STARR and JOEL R. RUBINSON*

A model for consumer package goods is described by which consumers can be segmented into loyalty groups. A survey is used to obtain measures of consumer willingness to switch from a regular brand, if there is one. Each loyalty group is associated with a unique purchase probability vector. The probabilities are derived empirically from purchase behavior. By use of the purchase probability vectors, brand shares and repeat rates can be simulated by the loyalty group segmentation (LGS) model, which yields good fits. Empirical data were available which reflected the effect of price changes on brand switching behavior by loyalty groups. At first price elasticities based on deviations from average price were used with poor results. By a revised version of the model, average price was recomputed as the sum of the prices of competitive brands weighted by the percentage of the brand's total switching with each other brand. By use of such loyalty group cross-price elasticity measures, high correlations were obtained with the empirical observations of share, repeat rate, and switching behavior.

A Loyalty Group Segmentation Model for Brand Purchasing Simulation

The concept of segmentation generally is used in conjunction with the notion that particular brand attributes have the greatest appeal for specific demographic or psychographic segments [6,9]. This type of analysis is useful for determining optimal positioning in the development of a new brand or the repositioning of an existing one.

The concept of segmentation also has been applied by some researchers to the problem of allocation of resources. Assael [1] posits that sets of demographic attributes can be identified (through AID analysis) that will discriminate between elastic and inelastic consumers in relation to a particular brand's change in effective price. Therefore, resources can be allocated efficiently by offering a promotion to the more price elastic consumers rather than to those who are inelastic.

Though such a segmentation analysis may be useful in a specific instance, it does not have a theoretical underpinning. Thus, it is limited in terms of generalizing results and understanding consumer behavior. Further, in the past there has been no positive identification of unique price responses by loyalty groups. Frank et al. state [6, p. 71]:

> Concerning the marketing responses of various loyalty groups, there is little evidence to suggest that brand-loyal customers differ in terms of their response to different types of promotional activity. Massy and Frank (1965) found no statistically significant difference between the price dealing, and retail advertising elasticities for loyal and nonloyal families.

(The reference cited in the quotation is [8].) However, Wind [12] found loyalty segmentation useful as a means of discovering that a particular brand of beer had a loyal group which sought self-reward through drinking.

The authors, in analyzing loyalty groups of consumer package goods, propose a different approach. A model is described by which consumers can be segmented into loyalty groups. A loyalty group is identified as those consumers of a brand having the same vector of probabilities of purchasing any brand in the product class. Thus, all consumers are classified in terms of

---

*Martin K. Starr is Professor, Columbia University, Graduate School of Business. Joel R. Rubinson is Senior Marketing Research Analysis Manager—Marketing Operations Research Group, Lever Brothers Company, Market Research Department.

Journal of Marketing Research
Vol. XV (August 1978), 378–83

different multibrand loyalties. By use of the probability of purchase vectors, the shares, repeat rates, and switching data can be simulated.

The authors found a strong inverse relationship between degree of loyalty for a brand and elasticity to changes in effective price.[1] Because the model is both descriptive and predictive, relationships can be derived between price elasticity and diagnostic behavioral measures such as repeat rate and brand-to-brand switching patterns.

LOOKING PAST MARKET SHARE

Analyses of brand switching patterns and tracking of diagnostic behavioral loyalty measures such as repeat rate reveal an inadequacy in assessing a brand's position on the basis of market share alone [10]. Unfortunately, brand tracking measures often lead to apparent anomalies; e.g., in many product classes small share brands are characterized by relatively high repeat rates [5]. For example, consider the data for selected brands of a price competitive and frequently purchased household cleaning product class (Table 1).

Brand C, although equal in share, apparently is in a "better position" than brand D. However, it would be difficult to make this information useful unless all brand share/repeat observations could be interpreted in terms of price elasticity.

RELATIONSHIP BETWEEN BRAND LOYALTY AND ELASTICITY

Consider a consumer who is strongly loyal toward a particular brand in a given product class. What behavior patterns would characterize this consumer? One would expect this person to have purchased the brand last time, probably the time before that, and to have purchased the brand almost exclusively on several purchase occasions. In other words, strong loyalty toward a brand should be defined as a high probability of purchasing it. Though several competitive brands may be available, a consumer who is a highly loyal customer of one particular brand will not purchase randomly. One can infer, then, that this person perceives product differentiation among brands, and prefers the one that he or she purchases most often. Consequently, in relation to someone less loyal, this consumer would be less sensitive to small (or even moderate) changes in brands' relative prices.

Table 1

SHARES AND REPEAT RATES FOR SELECTED BRANDS, SECOND HALF 1975

Brand	*Market share*	*Repeat rate*
A	19.5%	74.3%
B	12.0	63.0
C	6.0	73.1
D	6.0	59.5

Because of the high level of promotional activity in most product classes, it is reasonable to expect empirically that loyal consumers have low price elasticity.[2] One can infer that a consumer who has purchased the same brand, say, five times consecutively must have rejected some competitive brands' price promotions.

This line of reasoning can be extended to analyze the effects of market structure. For example, consider the following hypothetical purchase sequence.

Brand purchased:	A	A	A	C	A	A	C	A	A	A
Deal (D) or Nondeal (N-D) price:	D	N-D	N-D	D	N-D	D	D	N-D	D	N-D

This consumer primarily buys brand A whether or not it is on deal, but is willing to buy brand C occasionally only (as far as the data reveal) when it is on deal. Also, there is no indication that this consumer is willing to buy any other brand, even on deal. If many loyal users of A had similar preferences, switching between brands A and C would be high in relation to share and would imply a market structure in which brands A and C are perceived as highly substitutable. It is logical that more substitutable brands will have higher cross-elasticity and, as illustrated, a higher empirically derived probability of purchasing another brand when on deal often is observed which substantiates the higher cross-elasticity.

The similarities and differences between the authors' approach and those of Hendry [4,11], Bass [2], and Herniter [7] should be mentioned. The fundamental premises about preference that characterize the work of Hendry, Herniter, and Bass (HHB) are that (1) each consumer purchases brands in accord with a probabilistic preference vector and (2) these vectors are heterogeneous across the consumer population. Thus, the choice process is essentially zero-order and stochastic. The authors have made the same assumptions.

HHB derive a multinomial distribution of consumer brand preferences in terms of market brand shares alone by use of the criterion of entropy maximization. However, the distribution of preferences toward a brand can be misspecified if only its market share has been observed. In the case of two brands with equal shares, the one which is highly differentiated (or restricted in availability) will have fewer consumers willing (or able) ever to buy it but a higher average probability of purchase in relation to a brand with a more general appeal. Therefore, the authors take the reverse of the HHB approach and empirically estimate consumers' multibrand probabilities of purchase to simulate brand shares.

---

[1] Although there is also a systematic relationship between loyalty and advertising elasticity, it is not developed in this article.

[2] Conceivably a consumer can be loyal to a brand simply because it always has the lowest price. Such a consumer would be less sensitive to small or moderate price changes because an unusually large promotion would be needed to make another brand parity priced to the one normally bought.

Herniter and Bass assign a probability of 1.0 (completely loyal) to a fraction of each brand's customers. Hendry does not, allowing that each consumer has some probability of switching. Bass permits the percentage of completely loyal consumers to differ among product categories, assuming that some categories are nearly commodities whereas others have high degrees of brand differentiation. Herniter and Hendry assume that the degree of loyalty is independent of the product class and strictly a function of market shares. In the model the authors create three classes of loyalty wherein even the most loyal consumers have some probability of switching (based on empirical data). Also, because the authors' approach is more empirical it will reveal whether a category has unusually high or low consumer loyalty.

Finally, Herniter's and Bass' models are descriptive but not decision-making; that is, given brand shares they can simulate a switching matrix, but the models do not forecast changes in shares as a function of, for example, price changes. The authors and Hendry have incorporated relationships between price elasticity and consumer preferences which permit simulation of the effect on shares and switching from price changes.

LOYALTY GROUP SEGMENTATION (LGS) MODEL, ORIGINAL DEVELOPMENT

Assume that consumers are heterogeneous in their probabilities of purchasing each brand [3, 13] and that these probabilities can be estimated. Essentially homogeneous loyalty groups can be constructed for each brand with respect to their probabilities of purchase for their own and other brands. The reason why each loyalty group can be considered homogeneous in its response to a change in any brand's price is explained in the preceding section.

By this approach, loyalty groups can be identified empirically. Therefore the number of groups and the degree of within-group homogeneity will be representative of the data source. Originally survey questions were devised to elicit consumers' (multibrand) primary and secondary brand loyalties.[3] All combinations of responses to the two-stage sequence of questions then were cross-tabulated against last time purchasing to determine the percentage in each group purchasing its primary brand. The observed results were remarkably consistent. Table 2 is a summary of the results of cross-tabulations from three years' semiannual data for the product category. The analysis was done for all brands and similar ranges[4] with nearly identical midpoints were found.

Table 2
SUMMARY OF RESULTS OF CROSS-TABULATIONS FOR BRAND PRODUCT CATEGORY, 1973–1975

	Over six observations range in percentage of group type purchasing brand of household cleaning product	
Loyalty group	*Lowest observed*	*Highest observed*
Primary brand (PB)		
Response group: 1	86.6%	88.8%
2	80.7	84.7
3	77.6	81.3
No primary brand	7.8	12.3
Some other primary brand:		
PB acceptable substitute	15.0	19.0
PB not acceptable substitute	0	2.0

This analysis led to a two-way classification of consumers. All consumers first were segmented by primary brand choice and then were assigned into one of three loyalty groups (corresponding to the three response groups shown in Table 2). Therefore, the number of loyalty groups equaled three times the number of brands, plus one group of consumers who had no primary brand.

Each loyalty group's probability of purchasing its respective primary brand was estimated through a series of cross-tabulations in the manner described. The probabilities of purchasing each less preferred brand, conditional on not purchasing the primary brand, were derived from a percentage breakout of those brands considered to be an acceptable substitute.

Therefore, if 25% of primary users of brand B found A to be the acceptable substitute, each of brand B's loyalty groups was estimated to have a probability of purchasing brand A *conditional on not purchasing B* of 25%. This conditional probability was multiplied by one minus the respective probability of purchasing brand B for each loyalty group to obtain its unconditional probability toward A.

This procedure allowed the construction of purchasing vectors such that:

$$\sum_{i=1}^{G} P(g)_{l,i} = 1 \qquad (1)$$

where $P(g)_{l,i}$ is probability of purchase of brand i

---

[3] It is essential to allow multibrand loyalty, identifying brand-to-brand degrees of substitutability through analysis of empirical purchase switching matrices.

[4] Except for small brands for which there were large sampling variations.

by primary users of brand g in loyalty group l, and G is number of brand alternatives. Also, on the basis of the empirical findings:

$$P(1)_{1,1} = P(2)_{1,2} = \text{------} = P(G)_{1,G} \quad (2a)$$

$$P(1)_{2,1} = P(2)_{2,2} = \text{------} = P(G)_{2,G} \quad (2b)$$

$$P(1)_{3,1} = P(2)_{3,2} = \text{------} = P(G)_{3,G} \quad (2c)$$

For example, a primary user of brand A in loyalty group 1 has the same probability of purchasing A as his or her counterpart for brand B has of purchasing B.

By use of this LGS model, market shares can be simulated. Brand i's share is the sum of each group's probability of purchasing i multiplied by the number of consumers in each respective group, divided by the sample size.

$$(3)\quad E(S_i) = \frac{\left\{\left[\sum_{g=1}^{G}\sum_{l=1}^{L}[P(g)_{l,i} \times N(g)_l]\right] + P(NP)_i \times N(NP)\right\}}{\left[\sum_{g}^{G}\sum_{l}^{L} N(g)_l + N(NP)\right]}$$

where $E(S_i)$ is the expected share of brand i, L is number of loyalty groups, $N(g)_l$ is number of consumers in loyalty group l with primary brand g, $P(NP)_i$ is the probability of purchasing i given no primary brand, and $N(NP)$ is number of consumers with no primary brand.

If one assumes a zero-order process [2,3,7,11] and lets the denominator of equation 3 be represented by N^* (which is the total number of consumers in the sample), the repeat rate for brand i is:

$$(4)\ R_i = \frac{\left\{\left[\sum_{g=1}^{G}\sum_{l=1}^{L}[P(g)_{l,i}]^2 \times N(g)_l\right] + [P(NP)_i]^2 \times \mathrm{N}(NP)\right\}}{S_i \times N^*}.$$

The number of buyers switching from brand i to brand j is:

$$Sw_{j/i} = \left[\sum_{g=1}^{G}\sum_{l=1}^{L} P(g)_{l,i}P(g)_{l,j\neq i} \times N(g)_l\right] + P(NP)_i \times P(NP)_{j\neq i} \times N(NP).$$

Note that the switching is exactly the same from j to i. This is another explanation of equilibrium switching in the marketplace, which does not seem to have been discussed elsewhere.

Applying the LGS model to the selected brands listed in Table 1 yielded the results shown in Table 3. The fact that the simulated results fit closely with the actual indicates that the purchase probability vectors properly represent consumer behavior.

Table 3
COMPARISON OF ACTUAL TO SIMULATED VALUES, SECOND HALF 1975

	Market share		*Repeat rate*	
Brand	*Actual*	*Simulated*	*Actual*	*Simulated*
A	19.5%	22.0%	74.3%	74.3%
B	12.0	11.8	63.0	61.9
C	6.0	7.2	73.1	72.0
D	6.0	6.3	59.5	61.1

Brands A and C had higher repeat rates than B and D because a greater percentage of each brand's share comes from consumers who are loyal to those brands. This observation can be understood from equation 4. Using the notation N_i^* for total number of buyers of brand i, where $N_i^* = S_i \times N^*$, equation 4 denominator, one observes that the ratios

$$\sum_l N(A)_l/N_A^* \text{ and } \sum_l N(C)_l/N_C^*$$

are larger than the ratios

$$\sum_l N(B)_l/N_B^* \text{ and } \sum_l N(D)_l/N_D^*.$$

It directly follows that if there is a strong inverse relationship between a group's degree of loyalty and degree of price elasticity, brands with higher repeat rates must have lower price elasticity.

To test for this relationship, regression analysis was used to estimate the price elasticity of each loyalty group of brand C.[5] Each analysis had 13 semiannual observations, through 1975.

Equations were of the form[6]:

$$Y_{l,t} = \alpha + \beta_1 X_{1,t} + \beta_2 X_{2,t} + E \quad (5)$$

where:

$Y_{l,t}$ = number in loyalty group l and buying brand C at time t,
$X_{1,t}$ = "relative" price of C at time t, and
$X_{2,t}$ = share of advertising spending of C at time t.

Initially, average price was calculated in a typical way as the sum of the price for each brand weighted by its share. Relative price then was computed as brand C's price divided by the average price.

The first results were not encouraging, as the partial correlations with price were on the order of 0.1. In examining the prices of each brand, the authors observed an interesting pattern. Brands that were highly substitutable for C (identified through an analysis of switching data) were increasing in price over time, whereas brands that were less substitutable for C were not. Therefore brand C's price was increasing in relation to that of less (not more) substitutable brands.

---

[5] The LGS model originally was developed to provide an estimate of brand C's price elasticity. A more complete analysis is underway.

[6] A constant price elasticity (multiplicative) model was used originally but it provided a poorer fit than the linear model. A trend term also was included originally but it was deleted because it was highly intercorrelated with price over time.

Because brands that are more substitutable were hypothesized to have higher cross-price elasticity, average price was recomputed as the sum of the prices of competitive brands weighted not by their shares but by the percentage of brand C's total switching with each brand respectively. A significant change in the level and trend of C's relative price was observed after this adjustment (Table 4).

Adjusted relative price then was used in the regression, with important results: the partial correlation went from the order of 0.1 with unadjusted relative price to 0.7–0.8 with the adjusted variable.

The estimated β_1 coefficients gave the following results for a 10% increase in adjusted relative price (starting value = 1):

Price Elasticity by Loyalty Group

Loyalty group	*% change in number of buyers*
1	− 8
2	−12
3	−22
No primary brand	−28

The R^2s for all regressions ranged from .79 to .98. Also, the standard errors represented considerable reductions in the dependent variables' variations; Y_1 (observed) ranged from 63 to 99 with $\sigma_{E_1} = 6.3$, Y_2 ranged from 71 to 126 with $\sigma_{E_2} = 4.1$, and Y_3 ranged from 160 to 364 with $\sigma_{E_3} = 10.9$.

Comparing these coefficients with the probabilities of purchase by loyalty group from Table 2, one can see that an empirical basis now has been established on which to posit an inverse relationship between degree of loyalty, and consequently repeat rate, and degree of price elasticity. Furthermore, the improved fit obtained by adjusting relative price by the degree of brand-to-brand substitutability provides an empirical basis for asserting that brands which are more substitutable have higher cross-price elasticity.

Table 4
RELATIVE PRICE OF BRAND C

		After adjustment	*Before adjustment*
1969	2nd half	101.0%	104.4%
1970	1	100.8	104.2
	2	100.8	104.8
1971	1	101.0	105.5
	2	100.8	105.5
1972	1	99.4	103.2
	2	99.8	105.6
1973	1	99.6	106.0
	2	99.4	105.8
1974	1	98.5	106.2
	2	98.3	105.9
1975	1	98.2	105.9
	2	98.0	106.5

Refinements in LGS Model

After the foregoing analysis was completed, the elasticity mechanism in the LGS model was refined. Market shares, repeat rates, and switching patterns all are determined simultaneously from probability of purchase vectors. Accordingly, it follows that changes in market shares, switching, and repeat rates must also be determined simultaneously.

In the case of a two-brand market, brands' price elasticities must be determined simultaneously. The number of share points lost by one brand in response to a marketing action must be equal to the gain of the other brand, because a closed set always is assumed. As market shares are the result of consumers' brand preferences, changes in shares must be the result of changes in these preferences. Therefore, simultaneous determination of brands' price elasticities is accomplished by estimating parameters separately for each loyalty group.

It is postulated for the revised model that in relation to each other two brands do not change in desirability if a third brand changes price. Switching between the two brands should be affected only minimally (as only the third brand becomes more desirable) through the constraint that an individual's probabilities of purchase must sum to one. Computing price elasticity to changes in *average* price will partially obscure the share-to-price relationship for a brand (because of misspecification). The result will be to overstate the effect on switching between two brands that do not change price and to understate the effect when at least one of the brands does change price. Therefore, in computing brands' price elasticities the probability of a primary user of g choosing brand i is conditional upon (1) the price of $g \div$ the price of i and (2) the constraint that probabilities of purchase for each loyalty group must sum to one. The response parameters to changes in price ratios must be estimated separately for each loyalty group, and are used as follows:

$$(6) \quad d(P(g)_{l,i}) = \left[\eta_l\, d\left(\frac{Pr_g}{Pr_i}\right)\right] \times P(g)_{l,i} \quad \text{if } d\left(\frac{Pr_g}{Pr_i}\right) \text{ is positive}$$

$$= \left\{1 - \left[\eta_l\, d\left(\frac{Pr_g}{Pr_i}\right)\right]\right\} \times P(g)_{l,i}; \quad \text{if } d\left(\frac{Pr_g}{Pr_i}\right) \text{ is negative}$$

where:

$d(Pr_g/Pr_i)$ = change in the brand g's price minus the change in brand i's price, divided by brand i's initial price, and

η_l = the price elasticity parameter of loyalty group l.

As is consistent with equations 2a, b, and c, η_l is independent of the primary brand. After $P(g)_{l,i}$ is adjusted, the probabilities of purchase of this loyalty group for all other brands must be adjusted proportionately so that equation 1 will hold.

Also, because $|\eta_1| < |\eta_2| < |\eta_3|$, a brand with a higher percentage of its share coming from more loyal customers will have a lower price elasticity and, from equation 4, it will also have a higher repeat rate.

Thus, the LGS model completely factors brands' loyalty profiles and competitive environments into the simultaneous simulation of price elasticities. The model can simulate the effects on shares, repeat rates, and switching of simultaneous or sequential price changes by any number of brands, as well as a single change in price.

CONCLUSIONS

The LGS model segments heterogeneous consumers into essentially homogeneous loyalty groups. Because all consumers are classified, and each loyalty group's probabilities of purchasing brands 1, ..., G sum to one, shares, repeat rates, and switching data can be simulated. However, even if the simulated values were close to those observed on all measures for all brands, as they were for the product class analyzed, the simulation would not be particularly useful unless different values for brand measures could be shown to imply different marketing strategies.

Toward this goal, a systematic inverse relationship between degree of loyalty and degree of price elasticity was developed intuitively and then was supported empirically. As it was shown that brands with higher repeat rates must have a greater percentage of share coming from consumers who are loyal to those brands, a brand with a higher repeat rate must have a lower price elasticity. This conclusion provides a new view with respect to the 1972 conclusions of Frank et al. [6].

Additionally, brands that are more substitutable, as measured by higher switching in relation to share, were shown to have greater cross-price elasticity than less substitutable brands.

This relationship can be shown to be consistent with that between repeat rate and price elasticity by considering a highly differentiated brand. If a brand is less substitutable for all other brands, its total switching will be restricted and therefore its repeat rate will be higher. Clearly, if a brand has a low cross-price elasticity with all other brands, its total price elasticity also will be low.

The LGS model has been useful in developing principles with which brand tracking data can be interpreted more meaningfully. The authors plan to estimate more accurately the price elasticity parameters for each loyalty group. The price gaming simulations can be validated against marketing case histories. The model eventually will be used as a planning tool for pricing decisions. It can be valuable in assessing a brand's vulnerability to price reductions by each competitor alternatively or collectively. A brand's opportunity for share growth (i.e., competitors' vulnerability) through a price reduction also can be simulated.

REFERENCES

1. Assael, Henry. "Segmenting Markets by Response Elasticity," *Journal of Advertising Research*, 16 (April 1976), 27–35.
2. Bass, F. M. "The Theory of Stochastic Preference and Brand Switching," *Journal of Marketing Research*, 11 (February 1974), 1.
3. ———, A. Jeuland, and G. P. Wright. "Equilibrium Stochastic Choice and Market Penetration Theories: Derivations and Comparisons," *Management Science*, 22 (June 1976), 1051–63.
4. Butler, D. H. and B. F. Butler. "HendroDynamics—Fundamental Laws of Consumer Dynamics," Chapter I, 1970 and "HendroDynamics—Fundamental Laws of Consumer Dynamics," Chapter II. New York: The Hendry Corporation, 1971.
5. Frank, R. E. "Is Brand Loyalty a Useful Basis for Segmentation?" *Journal of Advertising Research*, 7 (June 1967), 27–33.
6. ———, W. F. Massy, and Y. Wind. *Market Segmentation*. Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1972.
7. Herniter, J. "An Entropy Model of Brand Purchasing Behavior," *Journal of Marketing Research*, 10 (November 1973), 361.
8. Massy, W. F. and R. E. Frank. "Short-Term Price and Dealing Effects in Selected Market Segments," *Journal of Marketing Research*, 2 (May 1965), 171–85.
9. McCann, J. M. "Marketing Segment Response to the Marketing Decision Variables," *Journal of Marketing Research*, 11 (November 1974), 399–412.
10. Shoemaker, R. W. and F. Robert Shoaf. "Repeat Rates of Deal Purchases," *Journal of Advertising Research*, 17 (April 1977), 47–53.
11. Starr, M. K. "The Hendry System," *Speaking of Hendry*. New York: The Hendry Corporation, 1976, 107–22.
12. Wind, Y. "Enduring vs. Situation-Dependent Customer Characteristics as Bases for Market Segmentation: An Evaluation," presented at the American Marketing Association Educators' Conference, August 1970.
13. Zufryden, F. S. "A Composite Heterogeneous Model of Brand Choice and Purchase Timing Behavior," *Management Science*, 24 (October 1977), 121–36.