Identifying Price Sensitive Consumers: The Relative Merits of Demographic vs. Purchase Pattern Information

BYUNG-DO KIM
Seoul National University

KANNAN SRINIVASAN
Carnegie Mellon University

RONALD T. WILCOX
Carnegie Mellon University

We have very limited knowledge of the antecedents of household-level price sensitivity. In this paper, we systematically examine the price sensitivities of a large number of households across multiple product categories to attempt to uncover the antecedents of price sensitivity. Using ERIM scanner panel data provided by A. C. Nielsen, we estimate the price sensitivity of each household in the panel for each of five product categories in two market areas. We test two competing structural models that link household price sensitivity to a series of demographic and shopping pattern variables. We find that the shopping pattern variables have substantially greater predictive validity in determining a household's price sensitivity. Thus, our model suggests that shopping pattern variables, commonly available to retailers through means such as scannable "loyal shopper" cards, provide retailers with better information about household-level price sensitivity than, typically much more difficult to procure, household-level demographic data.

INTRODUCTION

The most fundamental economic concept of pricing is the price elasticity of demand. The magnitudes of own- and cross-price elasticities provide a measure of the competitive market structure and yield critical information for designing optimal pricing strategies.

Byung-Do Kim, College of Business Administration, Seoul National University, 56–1 Shinlim-dong, Kwanak-ku, Seoul 151–742, Korea; E-mail: bxk@plaza.snu.ac.kr.

Journal of Retailing, Volume 75(2) pp. 173–193, ISSN: 0022-4359

Not surprisingly, price has been an important variable in virtually all of the scanner database studies. Almost without exception, these studies establish that price indeed affects brand choice in the category under investigation. While we know that consumers respond to price changes in a given category (Tellis, 1988), and we have some evidence that household price sensitivity is linked across categories (Ainslie and Rossi, 1998), we have very little understanding of the antecedents of household price sensitivity differences.

Understanding the antecedents of household-level price sensitivity is critical for retailers who increasingly look to targeted promotions instead of mass promotions to enhance profitability (Shaffer and Zhang, 1995). A growing literature has documented the usefulness of developing customer-level databases for effectively targeting price discounts (Chen, 1998; McCorkell, 1997; Petrison, Blattberg, and Whang, 1997; Shaffer and Zhang, 1997; *Supermarket Business,* 1996; *Progressive Grocer,* 1995; Deighton, Peppers, and Rogers, 1994). Within this growing sea of customer-level data it is clear that managers need some guidance in determining what subset of possible predictors are relevant for decision making purposes. Which pieces of information about consumers are truly necessary to predict household price sensitivity? Is household-level demographic information necessary, or are other more readily available types of information sufficient to make these decisions?

Many grocery retailers now offer customers "loyal customer cards" which provide discounts on various items in the store. These cards have also given retailers a wealth of new data which may be used to refine their merchandising tactics. While these cards contain information on which items a customer purchased, how often customers shopped at this store, a customer's overall shopping expenditure at this store, and other information as well, these cards generally do not contain detailed demographic information. While retailers would like very much to have demographic information they are hesitant to collect it because they believe that asking about things such as household income will deter customers from signing-up for their card.[1] Is this type of information really necessary? Would the retailers be better off by concentrating their resources, both human and capital, on collecting and interpreting purchase pattern data?

The goal of the paper is to determine what types of information are necessary for retailers to target individual consumers for price promotions. We begin this investigation by establishing that household-level price elasticities are linked across categories. Thus, while household-level price sensitivity may well vary across different categories, households can be thought of as being more or less price sensitive in grocery purchase decisions. From there, we build two competing structural models, similar to the ones suggested, but not tested, by Tellis (1988) to uncover the antecedents of household price sensitivity. From this investigation we are able to make inferences about what type of information is necessary for grocery retailers to make reasonable targeted promotional decisions.

There have been few attempts to generalize household-level price sensitivity across multiple categories. Telser (1962) studied four commodities (frozen orange juice concentrate, regular coffee, instant coffee, and margarine) and concluded that there were sizable price sensitivity differences across categories. Although it was conducted at the aggregate, and not household-level, Hoch, Kim, Montgomery, and Rossi (1995) examined the price elasticities for 18 categories across 83 stores. They applied a principal component analysis to assess commonality across categories in the store price elasticity estimates. Their results indicate a strong common component across categories.

Previous research, both in the marketing and economics literatures, has suggested that a consumer's demographic profile as well as shopping habits influence their overall price sensitivity. Early works in this area include Webster (1965) and Montgomery (1971). These early works found very weak association between a consumer's price sensitivity and their demographic profile. One major problem with these early studies, as noted by Blattberg et. al. (1978), is that since demographic variables commonly available (income, education, household size etc.) tend to be highly correlated it is difficult to isolate the relationships between individual demographic variables and the purchase behavior variables of interest. Even more recent studies that have included household demographic information, Blattberg et. al. (1978), Narasimhan (1984), Bucklin and Gupta (1992), Rossi and Allenby (1993), and Gupta and Chintagunta (1994) find disappointingly little evidence of the systematic impact of these variables on the variables of interest or their proposed model's ability to predict consumer choice.

One recent work that synthesizes these two areas of research, looking for similarities in cross-category price sensitivity and linking price sensitivity to observable variables, is Ainslie and Rossi (1998). This research documents significant correlation between the price elasticities of several categories. Further, Ainslie and Rossi (1998) link differences in household-level price elasticities to household demographic and shopping pattern variables. Our research extends this work by testing two competing structural models that incorporate both demographic and shopping pattern variables. Unlike Ainslie and Rossi, we differentiate between the proximate causes of price sensitivity, shopping patterns, and those causes which are more primitive, demographic profiles.

We allow these to impact price sensitivity both independently and through a hierarchical model, where the primitive demographic variables affect the proximate shopping pattern variables but not price sensitivities directly. We do this to examine whether shopping pattern variables are sufficient to make targeting decisions or whether the more primitive demographic information is necessary. We find that the shopping pattern variables have substantially greater predictive validity in determining a household's price sensitivity than a consumer's demographic profile. Thus, our model suggests that shopping pattern variables, which can be accessible to retailers through means such as scannable "loyal shopper" cards, provide retailers with better information about household-level price sensitivity than, typically much more difficult to procure, household-level demographic data.

CONCEPTUAL MODEL

In an attempt to understand the managerially relevant predictors of household-level price sensitivity, our model departs from previous empirical research in this area in two important ways. First, before we attempt to relate these demographic and purchase pattern variables to overall price sensitivity, we use principal component analysis to transform these variables into a set of orthogonal demographic profile and shopping pattern meta-variables. By developing these uncorrelated meta-variables we are more easily able to disentangle the relationship between these variables and overall price sensitivity. Second, since it is reasonable to believe that shopping habits are influenced by a household's demographic profile, we explicitly model the demographic and purchase pattern variables as related. This particular structure, demographics affecting shopping patterns which in turn affect price sensitivity was suggested, but not tested, by Tellis (1988). Figure 1 provides a structural representation of the relationships we wish to test.

Before we set out hypotheses concerning the expected impact of each of the relevant variables, we must first operationalize these variables to see the demographic and purchase pattern meta-variables the data suggests. Only then can we interpret these variables and subsequently develop hypotheses. In the next section we detail the variables used in this study, provide a brief description of the markets from which they were obtained, and develop the constructs necessary to test the conceptual model.

ESTIMATION OF PRICE ELASTICITIES AND CONSTRUCTION OF DEMOGRAPHIC AND SHOPPING PATTERN META-VARIABLES

Description of the Market

We analyzed five product categories of ERIM scanner panel data provided by A. C. Nielsen Company. The data were collected from two separate market areas: Sioux Falls, South Dakota and Springfield, Missouri. The data used in our analysis cover a two-year period (85/2 through 87/5). We include only households who stayed in the panel for more than 100 weeks as evidenced by their shopping trips and have made at least one purchase in a given category during this period. The total number of remaining panelists range from 2,000 to 2,500 in Sioux Falls and from 900 to 1,100 in Springfield depending on the category.

For the simplicity of analysis, we restrict our analysis to major brands in each category. For ketchup, we select four brands of 32 ounce container (Hunt's, Heinz, Del Monte, and

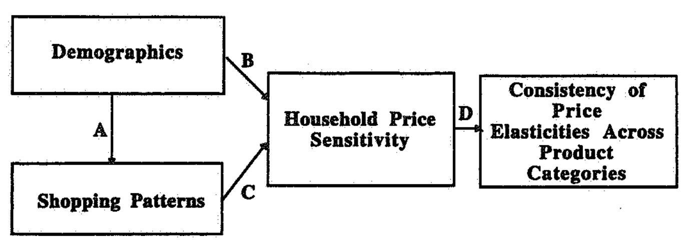

FIGURE 1

Conceptual Model of Household Price Sensitivity a store brand) which explain about 51% of total ketchup sold by all brands in Sioux Falls and 59% in Springfield. For margarine, limiting our attention to "4 sticks," we analyzed 5 major brands (Blue Bonnet, Parkay, Imperial, Fleischmann, and a store brand) which account for 68% of total "4 sticks" margarine sold by all brands in Sioux Falls and 72% in Springfield.

We perform similar data extraction for the categories peanut butter and toilet tissue. There are two forms of peanut butter (creamy and chunky) and most brands are available in both forms. For a given brand, the price correlation between two forms is about 0.9. Therefore, we aggregate over the two forms for each brand. We analyzed four brands of 18 ounce bottle (Peter Pan, Jif, Skippy, and a store brand) which account for 61% of total peanut butter sold by all brands in Sioux Falls and 63% in Springfield. We have included five brands (Star-Kist water and oil, Chicken-of-the-Sea water and oil, and a store brand) of 6.5 ounce "lite meat" can for tuna which account for 56 percent of total tuna sold in Sioux Falls and 61 percent in Springfield. For toilet tissue, we limit our analysis to one major size ("4 rolls") and create brand aggregates over different color and number of sheets per roll. Four brand aggregates (Northern, Charmin, SF Gentle and a store brand) are included in both market areas with Family Scott for Sioux Falls and Soft 'N' Pretty for Springfield selected as the fifth brand. These brands account for 39% of total toilet tissue sold in Sioux Falls and 53% in Springfield.[2]

From these panel data we calculated

1. Household-level price elasticities for each category
2. Two orthogonal demographic profile meta-variables
3. A shopping pattern meta-variable.

We proceed to describe the estimation procedure used to calculate the household-level price elasticities. Subsequently, we detail the construction of the demographic and purchase pattern meta-variables.

Household-Level Price Elasticities

Estimating brand price elasticities from scanner panel data, even at the aggregate-level, comes with some inherent pitfalls. First, brand choice is actually the final choice in significantly more complex decision process, several stages of which may well be affected by price. For example, the price of a particular brand may be a consideration in the store choice decision of some consumers. Further, after a store is selected, price may still affect category purchase incidence. Hence, brand price elasticities tend to understate the full impact of price on sales. The elasticities that can be estimated with scanner panel data are really *conditional* elasticities, conditioned on the previous stages of this hierarchical choice process.[3] Second, there may be several unobserved, or unobservable, variables which are correlated both with sales and price. For example, perceived quality may be both positively correlated with price as well as sales. Distribution intensity may be negatively correlated with price[4] and positively correlated with sales. Failing to control for these variables will undoubtedly bias price elasticity estimates.[5] While these limitations are of serious concern to marketing researchers, scanner panel data currently provides the richest commonly available data environment to study price sensitivity. Cognizant of these limitations, we move forward to estimation issues.

We estimate *individual (household) level* price elasticities for *each* category using a Bayesian fixed-effects method. We also control for variations across households in intrinsic preferences of brands within a category to minimize any bias in estimating the price elasticity. To facilitate direct interpretation and comparability, a multinomial logit of brand choice is proposed to estimate household level price elasticity. The probability of household i's purchasing brand j at occasion k can be written as

$$P_{ik}(j) = \frac{\exp(\alpha_{ij} + \beta_i x_{ijk})}{\sum_m \exp(\alpha_{im} + \beta_i x_{imx})} \tag{2.1}$$

where x_{ijk} is the logarithm of household i's observed price of brand j at occasion k and α_{ij}, β_i are household specific parameters. We apply the logit model to each household for a given product category to estimate household specific parameters and compute their price elasticities.

The Bayesian approach explicitly assumes a prior distribution of choice parameters across consumers. The major role of the prior is to ensure the existence of a posterior mode of the parameter so that we can avoid the problem of short purchase histories for each household. The prior distribution can be determined in various ways such as using researcher's prior knowledge about parameter estimates or adopting an empirical Bayes approach where the priors are estimated from the entire sample of households (Blattberg and George,1993). The need for prior information has often been forwarded as a criticism of Bayesian approaches to parameter estimation. The prior we specify for this application has two appealing features which taken jointly mitigate many of the concerns raised by critics of Bayesian estimation. First, as described below, the prior we specify arises from the data itself and not our subjective knowledge of the parameters. Second, the prior we impose is relatively diffuse, allowing the household-level purchase information to significantly impact the posterior parameter distributions. One result of this approach is that even when a given household's purchase history is relatively relatively short we will allow the observations that do exist to carry considerable weight in determining the posterior distributions. This implies that in presence of sparse data the posterior distributions themselves are likely to be quite diffuse.

We adopted a prior suggested by Rossi and Allenby (1993). All households are pooled and the pooled parameter estimates ($\bar{\theta}$) and the corresponding variance covariance matrix (ψ) are computed. Their prior then becomes

$$\mathrm{MVN}\left(\bar{\theta}, \Sigma = \frac{N}{\nu}\psi\right) \tag{2.2}$$

where N is the total number of observations and ν is the scale term specified by the researcher.[6] We estimated the models for various values of ν. As the price elasticities remained relatively stable for different values of v, the point estimates of elasticity are computed with $v = 5$ which is the value suggested by Rossi and Allenby.

The posterior distribution of each consumer's parameters can be computed by multiplying the prior by their likelihoods. With the prior of equation (2.2), the posterior mode of the parameter vector for household i can be computed by maximizing the following log-likelihood:

$$\text{Post}(\theta_i) = \text{logl}(\theta_i) - (\theta_i - \bar{\theta}')' \Sigma^{-1}(\theta_i - \bar{\theta}') + \text{Constant} \tag{2.3}$$

Once the household-level parameter vector, θ_i, is estimated, the price elasticity of household i can be expressed as

$$\varepsilon_{is} = \beta_i \Sigma_k \Sigma_j Y_{ijk}(1 - P_{ik}(j))/K_i \tag{2.4}$$

where K_i is household i's number of purchase occasions for a given category and Y_{ijk} is a choice dummy which becomes 1 if household i purchases brand j on occasion k and 0 otherwise. Equation (2.4) can be interpreted as household i's price elasticity for a given category which is the choice share weighted average of the price elasticity for each brand.

A number of methods have been proposed by marketing researchers to estimate models with parameters that vary across households (Allenby and Lenk 1994; Rossi and Allenby 1993; Gonul and Srinivasan 1993; Kamakura and Russell 1989). In particular, the finite mixture model proposed by Kamakura and Russell (1989) and the Bayesian fixed effects model proposed by Rossi and Allenby (1993) are widely regarded as the standards for estimating household-level price elasticities. While we estimated household-level price elasticities using both the Bayesian fixed effects model as well as the finite mixture model, we report only the results of the Bayesian fixed effects estimation here. The Bayesian fixed effects method has the advantage of being able to better capture the price elasticity of households which are either very price sensitive or very insensitive.[7] Given the focus of this research, it is reasonable to select the estimation method which allows for the widest possible dispersion of the individual estimates. It is however notable that, while the results presented here do not fundamentally change if the finite mixture model is used, this model produced average category price elasticities that were uniformly greater in absolute value than the Bayesian fixed effects approach. Further, while the cross-category correlations between the household-level price elasticity estimates were positive and in general significant using the finite mixture model approach, this approach produced uniformly smaller correlations than the Bayesian fixed effects model. While an investigation into the exact reasons for these discrepancies is beyond the scope of this paper, it certainly seems worthwhile for future research to undertake a rigorous examination of this issue.

Table 1 provides a summary of the average household price elasticities for each category[8] and the cross-category correlations between the individual household-level estimates are given in Table 2.

A few things stand out from an initial examination of the data. First, the average category elasticities, while varying from category to category, are reasonably stable across the two markets. Second, the cross-category correlations in the household-level estimates,

Table 1

Household's Price Elasticities

	Sioux Falls, SD	*Springfield, MO*
Ketchup		
Number of observations	12,209	4,564
Number of households	2,079	931
Price elasticities	−1.78 (1.96)[1]	−1.42 (1.02)
Margarine		
Number of observations	34,166	14,882
Number of households	2,422	1,074
Price elasticities	−1.05 (0.88)	−0.85 (0.68)
Peanut Butter		
Number of observations	14,402	8,517
Number of households	2,215	1,043
Price elasticities	−1.29 (1.61)	−1.23 (0.91)
Toilet Tissue		
Number of observations	26,204	21,605
Number of households	2,569	1,146
Price elasticities	−1.86 (1.95)	−1.82 (1.11)
Tuna		
Number of observations	19,980	10,333
Number of households	2,110	1,109
Price elasticities	−1.61 (1.23)	−1.32 (0.71)

[1] The mean of price elasticities across households is −1.78 and its standard deviation is 1.96 for the panel.

while positive and significant in all cases, are surprisingly low. While the data suggests that household price sensitivity is linked across categories, and hence households may be able to be classified as more or less price sensitive, it also suggests that households may react to price very differently in different categories.

Finally, it is important to keep in mind that the overall effect of price on the probability of purchasing a given brand is almost certainly stronger than the results presented here. As noted earlier, brand choice is actually the final choice in significantly more complex decision process, several stages of which may well be affected by price. Offering a low price on a particular brand may positively impact the probability that probability that this store is chosen by consumers. It may also impact category purchase incidence, a lower price leading more purchases in that category. In this data, we observe brand choices *conditional* on these other choices. Because price cuts impact store choice and category purchase incidence positively (Walters, 1991), we are confident that our price elasticity estimates understate the total impact of price on the brand purchase decision.

Demographic Profile Variables

Several household-level demographic variables were available in the scanner panel datasets used for this study. In particular, the following variables were made operational using these data.

remained relatively stable for different values of v, the point estimates of elasticity are computed with $v = 5$ which is the value suggested by Rossi and Allenby.

The posterior distribution of each consumer's parameters can be computed by multiplying the prior by their likelihoods. With the prior of equation (2.2), the posterior mode of the parameter vector for household i can be computed by maximizing the following log-likelihood:

$$\text{Post}(\theta_i) = \log l(\theta_i) - (\theta_i - \bar{\theta}')' \, \Sigma^{-1}(\theta_i - \bar{\theta}') + \text{Constant} \tag{2.3}$$

Once the household-level parameter vector, θ_i, is estimated, the price elasticity of household i can be expressed as

$$\varepsilon_{is} = \beta_i \Sigma_k \Sigma_j Y_{ijk}(1 - P_{ik}(j))/K_i \tag{2.4}$$

where K_i is household i's number of purchase occasions for a given category and Y_{ijk} is a choice dummy which becomes 1 if household i purchases brand j on occasion k and 0 otherwise. Equation (2.4) can be interpreted as household i's price elasticity for a given category which is the choice share weighted average of the price elasticity for each brand.

A number of methods have been proposed by marketing researchers to estimate models with parameters that vary across households (Allenby and Lenk 1994; Rossi and Allenby 1993; Gonul and Srinivasan 1993; Kamakura and Russell 1989). In particular, the finite mixture model proposed by Kamakura and Russell (1989) and the Bayesian fixed effects model proposed by Rossi and Allenby (1993) are widely regarded as the standards for estimating household-level price elasticities. While we estimated household-level price elasticities using both the Bayesian fixed effects model as well as the finite mixture model, we report only the results of the Bayesian fixed effects estimation here. The Bayesian fixed effects method has the advantage of being able to better capture the price elasticity of households which are either very price sensitive or very insensitive.[7] Given the focus of this research, it is reasonable to select the estimation method which allows for the widest possible dispersion of the individual estimates. It is however notable that, while the results presented here do not fundamentally change if the finite mixture model is used, this model produced average category price elasticities that were uniformly greater in absolute value than the Bayesian fixed effects approach. Further, while the cross-category correlations between the household-level price elasticity estimates were positive and in general significant using the finite mixture model approach, this approach produced uniformly smaller correlations than the Bayesian fixed effects model. While an investigation into the exact reasons for these discrepancies is beyond the scope of this paper, it certainly seems worthwhile for future research to undertake a rigorous examination of this issue.

Table 1 provides a summary of the average household price elasticities for each category[8] and the cross-category correlations between the individual household-level estimates are given in Table 2.

A few things stand out from an initial examination of the data. First, the average category elasticities, while varying from category to category, are reasonably stable across the two markets. Second, the cross-category correlations in the household-level estimates,

TABLE 1

Household's Price Elasticities

	Sioux Falls, SD	*Springfield, MO*
Ketchup		
Number of observations	12,209	4,564
Number of households	2,079	931
Price elasticities	−1.78 (1.96)[1]	−1.42 (1.02)
Margarine		
Number of observations	34,166	14,882
Number of households	2,422	1,074
Price elasticities	−1.05 (0.88)	−0.85 (0.68)
Peanut Butter		
Number of observations	14,402	8,517
Number of households	2,215	1,043
Price elasticities	−1.29 (1.61)	−1.23 (0.91)
Toilet Tissue		
Number of observations	26,204	21,605
Number of households	2,569	1,146
Price elasticities	−1.86 (1.95)	−1.82 (1.11)
Tuna		
Number of observations	19,980	10,333
Number of households	2,110	1,109
Price elasticities	−1.61 (1.23)	−1.32 (0.71)

[1] The mean of price elasticities across households is −1.78 and its standard deviation is 1.96 for the panel.

while positive and significant in all cases, are surprisingly low. While the data suggests that household price sensitivity is linked across categories, and hence households may be able to be classified as more or less price sensitive, it also suggests that households may react to price very differently in different categories.

Finally, it is important to keep in mind that the overall effect of price on the probability of purchasing a given brand is almost certainly stronger than the results presented here. As noted earlier, brand choice is actually the final choice in significantly more complex decision process, several stages of which may well be affected by price. Offering a low price on a particular brand may positively impact the probability that probability that this store is chosen by consumers. It may also impact category purchase incidence, a lower price leading more purchases in that category. In this data, we observe brand choices *conditional* on these other choices. Because price cuts impact store choice and category purchase incidence positively (Walters, 1991), we are confident that our price elasticity estimates understate the total impact of price on the brand purchase decision.

Demographic Profile Variables

Several household-level demographic variables were available in the scanner panel datasets used for this study. In particular, the following variables were made operational using these data.

TABLE 2

Correlations of Household Price Elasticities Across Categories

	Ketchup	*Margarine*	*Peanut Butter*	*Toilet Tissue*	*Tuna*
Sioux Falls Market					
Ketchup	1.00				
Margarine	0.11*	1.00			
Peanut Butter	0.15*	0.18*	1.00		
Toilet Tissue	0.14*	0.16*	0.18*	1.00	
Tuna	0.08*	0.11*	0.14*	0.15*	1.00
Springfield Market					
Ketchup	1.00				
Margarine	0.05*	1.00			
Peanut Butter	0.09*	0.11*	1.00		
Toilet Tissue	0.12*	0.14*	0.13*	1.00	
Tuna	0.08*	0.11*	0.09*	0.16*	1.00

1. Income: Measured as the natural log of self reported annual household income.
2. Education: A dummy variable taking the value 1 if the male head-of-household has earned a bachelors or higher level degree and taking the value 0 otherwise.
3. Household Size: The number of people who permanently reside in a given household.
4. Home Ownership: A dummy variable taking the value 1 if the household owns a home, and that home is their primary place of residence. The variable takes the value 0 otherwise.
5. Retire: A dummy variable taking the value 1 if the household's primary shopper is retired and 0 otherwise.

Since these demographic constructs are not independent, a fact which has caused considerable problems in earlier research, we performed a principal component analysis to construct orthogonal demographic profile meta-variables. We also explored other possibilities for summarizing the demographic information, most notably multiple correspondence analysis. Multiple correspondence analysis is a mathematically better procedure for summarizing variables which are not intervally scaled, such as our education and retirement dummies (Hair, Anderson, Tatham, and Black, 1992). However, particularly in cases where some of the variables are not dichotomous, multiple correspondence analysis will lead to a large number of possible dimensions and subsequently obscure the interpretation of any given single dimension. This is the case here, where household size can take on seven different values and even relatively coarsely defined income groups will have several categories. Thus, recognizing the deficiencies of principal component analysis on nonintervally scaled variables, we nevertheless use this approach to preserve the interpretability of the resulting dimensions.

The rotated factor pattern of these variables is given in Tables 3A and 3B.[9] For both datasets, the principal component analysis produced two unique dimensions. The first factor is defined largely by household size, education level and income. These three

TABLE 3A

Principal Component Analysis of Demographic Variables for Sioux Falls Market

	Factor 1	Factor 2
Income	.796	−.009
Education	.592	−.160
H.H. Size	.598	−.315
Home Ownership	.655	.468
Retire	−.163	.866
% Variance Explained	35.9	21.8
Eigenvalues	1.80	1.17

variables load positively onto this dimension. Retirement status defines the second dimension, loading positively onto factor two. We will call our first demographic meta-variable "Young Suburbia" (YS), since a high factor score on this dimension indicates relative wealth and education as well as the probable presence of children.[10] We term the second meta-variable "Retirement." Given the agreement of both markets on these dimensions we are confident in their descriptive ability.

Household Shopping Patterns

The datasets also contain information on the shopping patterns of each household. These include information on the household's average shopping expenditure, shopping frequency, propensity to purchase store brands, and store loyalty. From this data we operationalize the following shopping pattern variables.

1. Average Shopping Expense: The average amount, measured in dollars, spent on a shopping trip. To ease interpretation, the natural log of this amount is used.
2. Average Shopping Frequency: The average number of trips per week this household makes to the grocery store.

TABLE 3b

Principal Component Analysis of Demographic Variables for Springfield Market

	Factor 1	Factor 2
Income	.827	.050
Education	.644	.014
H.H. Size	.581	−.363
Home Ownership	.496	.638
Retire	−.201	.815
% Variance Explain	34.5	24.1
Eigenvalues	1.72	1.21

3. Store Brand Propensity: A measure of the willingness of a given household to purchase store brands.[11]
4. Store Loyalty: We use the entropy index to capture this variable. The entropy index of household i is computed by $\Sigma_i F_{ij} \ln F_{ij}$ where F_{ij} the fraction of the visits by household i to store j during the observation period.[12] A higher number reflects a greater degree of store loyalty.

Just as in the case of the demographic variables, we perform a principal component analysis on the shopping pattern variables to uncover unique dimensions of household shopping patterns. Somewhat surprisingly, the data suggests that there is only one unique dimension (Tables 4A and 4B).

Again data from both the Sioux Falls and Springfield markets suggest this single, very similar, dimension. Given this one unique dimension, the factor loadings are consistent with what one would intuitively expect. Households that spend more money on grocery items tend to be the same households that shop more frequently, are less store loyal and more willing to try a store brand. Since returns to price search will be higher for these households it is not surprising that they are more willing to shop around for good price and be willing to try store brands. We term this meta-variable "Shopping Intensity" since a high factor score indicates a household which spends a good deal of money and energy grocery shopping.

HYPOTHESES AND TWO STRUCTURAL MODELS

We have reduced nine variables, five demographic variables and four shopping pattern variables, to three meta-variables. These meta-variables will be used in conjunction with the price elasticities to test the conceptual model. For two of the three meta-variables we can develop hypotheses, based on previous literature, concerning their effect on overall household price sensitivity. For one of the meta-variables, Young Suburbia, no such formal hypothesis will be possible. We set out formal hypotheses for Retirement and Shopping Intensity and then discuss why an *a priori* hypothesis for Young Suburbia is not possible.

TABLE 4A

Principal Component Analysis of Shopping Pattern Variables, Sioux Falls Market

	Factor 1
Shopping Expense	.720
Shopping Frequency	.823
Store Loyalty	−.564
Private Label	.389
% Variance	41.6
Eigenvalue	1.67

Table 4B

Principal Component Analysis of Shopping Pattern Variables, Springfield Market

	Factor 1
Shopping Expense	.622
Shopping Frequency	.867
Store Loyalty	−.538
Private Label	.119
% Variance	38.1
Eigenvalue	1.44

Our entire conceptual model of consumer shopping behavior, and indeed the hypotheses that follow, rest squarely on the notion that household price sensitivity is linked across product categories. Stigler (1961) and Becker (1964) suggested that just this type of pattern might arise. In his seminal work on the economics of information Stigler points out that, owing to heterogeneity in demographic variables such as income, different consumers have different search costs and hence rationally choose to engage in price search to a greater or lesser extent based on these costs. Consumers choose to search price until the marginal benefit of search, the expected savings from finding a lower price, equals its marginal cost. Stigler maintains that "the chief cost [of search] is time," and that different consumers will have different time costs. Hence, we would expect search, and thus observed price sensitivity, to vary monotonically with time costs. We will use Stigler's framework to derive testable hypotheses on the effects of demographic and shopping pattern variables on overall price sensitivity. Formally then

H1: *Household price sensitivity will be positively linked across product categories.*

By definition, households in which the primary shopper is retired do not have many of the time constraints associated with work that other households have. Since Stigler (1961) suggested that the main impediment to price search for most consumers is the cost of time, we would expect these households to search more for a deal price. Hence, owing to this reduced time constraint, these households will exhibit a greater overall sensitivity to price.

H2: *Overall household price sensitivity will be positively related to its Retirement score.*

In order to develop a formal hypothesis for the effect of Shopping Intensity on household price sensitivity we must understand how each of the variables that are linked to Shopping Intensity should affect this factor. Shopping expense, shopping frequency and store brand propensity all load positively onto Shopping Intensity. Drawing on previous arguments from search theory (Becker, 1965; Stigler, 1961) shopping expense and frequency, two related constructs, should be positively related to household price sensitivity since households which spend more money at the grocery store and visit the grocery store more frequently have greater expected returns to price search. Since store brands are generally viewed as low cost alternatives to national brands, we would expect that a household's propensity to purchase store brands indicates a certain amount of price sensitivity. We would expect households that purchase an above average proportion of store brands to be more price sensitive.[13] Store Loyalty loads negatively on shopping intensity. Consumers who are more store loyal are less likely to search other stores for better prices. Hence, the expected relationship between store loyalty and household price sensitivity is negative. Since the factor loadings for Shopping Intensity are exactly consistent with the expected impact of each of its component variables on price sensitivity it is clear that we should expect a household's score on Shopping Intensity to be positively related to its overall price sensitivity. Formally then

> **H3:** *Overall household price sensitivity will be positively related to its Shopping Intensity score.*

The chief defining variables of Young Suburbia (YS) are income, education and household size. All three load positively onto this factor. The usual economic argument is that income and education should be negatively related to price search since households with higher income and education have a greater opportunity cost of time (Narasimhan, 1984; Blattberg et. al. 1978). Thus, we would expect income and education to be negatively related to overall price sensitivity. The problem is that these variables are often correlated with other variables that tend to increase price sensitivity. This is the case here as well. YS is also defined by larger households, a demographic characteristic that we would expect in increase price sensitivity because of its impact on the grocery budget and hence shopping patterns. Thus, the factor score of YS increases both in variables that we expect to have a positive impact on price sensitivity as well as one which we expect to have a negative impact. It is therefore impossible to make *a priori* predictions about the overall effect of YS on household price sensitivity.

In order to test the validity of the proposed conceptual model, we estimate two structural models that link the demographic and shopping pattern variables to overall price sensitivity. We estimate two models to see if demographic meta-variables affect price sensitivity directly or indirectly through the shopping pattern meta-variable (see Figure 1). Through examining the predictive validity of these two models we can uncover the relative merits of demographic vs. purchase pattern information in indicating household price sensitivity.

The model in which the demographic meta-variables influence household price sensitivity independently of the shopping patterns is termed the "Independent Model," while the structural model indicating that demographics affect price sensitivity through purchase patterns is termed the "Hierarchical Model."[14] These models are constructed to be as close to the conceptual model as possible, while maintaining the ability the estimate the individual linkages. In particular, the Independent Model is equivalent to setting $A = 0$ in the conceptual model, that is, disallowing the link between demographics and shopping patterns. The Hierarchical Model sets $B = 0$, restricting demographics to affect price sensitivity through shopping patterns but not directly. The models are estimated for both markets to see if both panels suggest the same conceptual structure.[15]

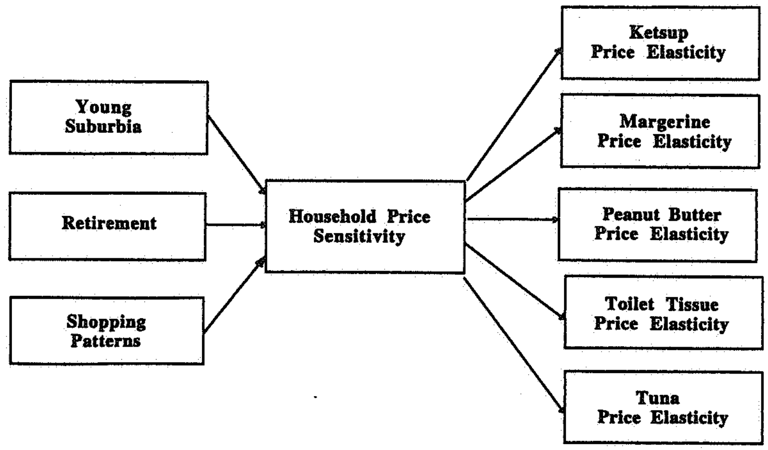

FIGURE 2

Independent Model

One estimation issue is worth noting. The estimation of the price elasticities and parameters of the structural model are done sequentially. We first estimate the price elasticities as described in (3.2) and then use these elasticity estimates as inputs in the structural model. Clearly, joint estimation of the elasticities and structural parameters would be preferred. Given the sparseness of the data and the lack of outside survey information to help identify household price sensitivity, joint estimation was not possible. The variances of the parameter estimates of the structural model incorporate the variances of the elasticity estimates.

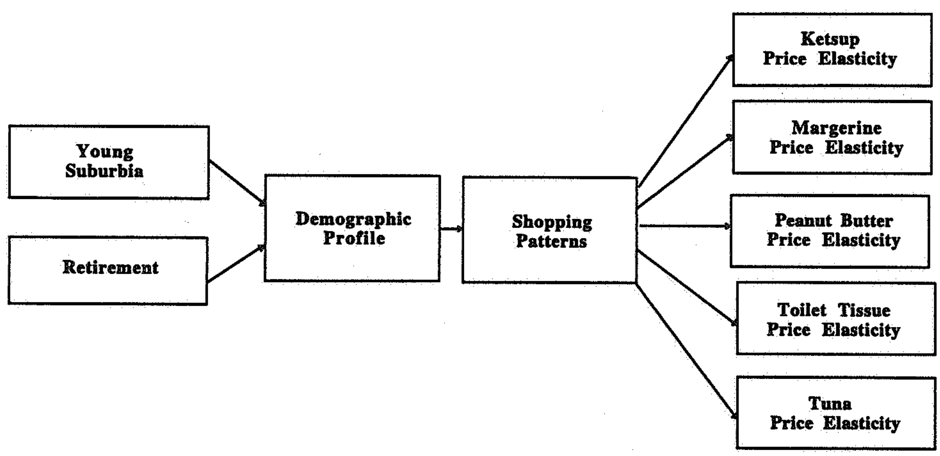

FIGURE 3

Hierarchical Model

TABLE 5

Impact of Demographic and Shopping Pattern Variables on Household Price Sensitivity: Independent Model

	Sioux Falls, SD	*Springfield, MO*
Demographic and Shopping Pattern Links		
Shopping Intensity → Price Sensitivity	1.031 (.039)*	.972 (.086)*
Young Suburbia → Price Sensitivity	.138 (.097)	.273 (.238)
Retired → Price Sensitivity	.111 (.092)	−.188 (.242)
Category Elasticity Links		
Price Sensitivity → Ketchup Elasticity	−.103 (.051)*	−.036 (.052)
Price Sensitivity → Margarine Elasticity	−.066 (.022)*	−.099 (.033)*
Price Sensitivity → Peanut Butter Elasticity	−.325 (.042)*	−.051 (.045)
Price Sensitivity → Toilet Tissue Elasticity	−.292 (.049)*	.053 (.054)
Price Sensitivity → Tuna Elasticity	−.098 (.032)*	−.088 (.035)*
Chi-Square	183.04 (18 df)	46.34
p-value	.00000	.00026
Joreskog Adjusted GFI	.927	.937
AIC	.160	.210

* represents that the given estimate is significant at p = 0.05.

RESULTS

The main results of the estimation are given in Tables 5 & 6. These results, in conjunction with some of the data analysis presented earlier, point to several interesting conclusions.

Household Price Sensitivity is Related Across Product Categories

Consistent with the implications of search theory, the data suggests that a household's price sensitivity or insensitivity is related across product categories. The results are most striking for the Sioux Falls market where all five elasticity loadings are negative and significant.[16] The results from the Springfield market are less impressive. While four of the five loadings have the correct sign, only two, margarine and tuna, are significant. The point estimate for toilet tissue has the wrong sign but is insignificant. Two factors influence this difference between the markets. First, the Springfield market is consistently less price sensitive than the Sioux Falls market (see Table 1). This, in and of itself, will make these linkages more difficult to capture. Second, the number of observations from the Springfield market is roughly 1/2 of that captured in the Sioux Falls market. Overall, seven out of ten of the price elasticity loadings were in the correct direction and significant for each of the two models estimated. This provides a reasonable level of support for the hypothesis that a household's price sensitivity is systematically linked across categories. Hypotheses 1 is supported by the data.

TABLE 6

Impact of Demographic and Shopping Pattern Variables on Household Price Sensitivity: Hierarchical Model

	Sioux Falls, SD	*Springfield, MO*
Demographic Links		
Young Suburbia → Demographic Profile	1.025 (.035)*	.827 (.093)*
Retired → Demographic Profile	.265 (.123)*	.578 (.151)*
Shopping Pattern Link		
Demographic Profile → Shopping Intensity	.197 (.025)*	.275 (.050)*
Category Elasticity Links		
Shopping Intensity → Ketchup Elasticity	−.116 (.054)*	−.023 (.052)
Shopping Intensity → Margarine Elasticity	−.080 (.024)*	−.089 (.033)*
Shopping Intensity → Peanut Butter Elasticity	−.342 (.044)*	−.020 (.045)
Shopping Intensity → Toilet Tissue Elasticity	−.295 (.052)*	.069 (.053)
Shopping Intensity → Tuna Elasticity	−.105 (.034)*	−.093 (.035)*
Chi-Square	186.40 (20 df)	47.71
p-value	.00000	.00047
Joreskog Adjusted GFI	.934	.940
AIC	.159	.203

* represents that the given estimate is significant at $p = 0.05$.

Household Demographic Variables Affect Overall Price Sensitivity Only to the Extent that they Affect Shopping Patterns

This is both an unexpected and very important result. The data clearly suggests that knowledge of shopping patterns is sufficient for making predictions about overall household price sensitivity. The demographics of a household, while certainly influencing shopping patterns, add nothing to the predictive validity of the model beyond their influence on shopping patterns. To see this, note the differences in the estimated linkages between the independent and hierarchical models for both markets. While the links between the demographic meta-variables and household price sensitivity are not significant in the independent models, these links are significant and of the expected sign in the hierarchical model. In the hierarchical model both demographic meta-variables load positively onto the latent demographic profile construct which in turn links positively to shopping intensity. Also, the fit statistics favor the hierarchical structure.[17] Since both markets suggest the same structure in this regard, the data strongly suggests that linkages indicated by the hierarchical model are a more accurate representation of the dynamics of the marketplace.

The Meta-Variable Shopping Intensity is a Significant Indicator of Overall Price Sensitivity.

By examining the linkages estimated from both the hierarchical and independent models it is evident that the meta-variable Shopping Intensity plays a significant role in determining overall price sensitivity. In the independent model, the link between Shopping Intensity and Price Sensitivity is positive and significant in both markets. In the hierarchical model, seven of the ten linkages between Shopping Intensity and the category price elasticities are significant and directionally as expected. Overall then, the data strongly supports Hypotheses 3.

Households in which the Primary Shopper is Retired are More Price Sensitive than Households in which the Primary Shopper is not Retired.

The hierarchical model suggests the following. Retirement is positively linked (.265) to the latent demographic profile variable. The demographic profile variable is positively linked (.197) to shopping intensity. Shopping intensity is linked to price elasticities as previously discussed in Result 3. Hence, while the models suggest that retirement has no direct impact on household price sensitivity, it does impact household shopping patterns which in turn affects price sensitivity. The data does support Hypothesis 2.

LIMITATIONS OF THIS RESEARCH

This research is restricted to the relatively few household descriptive variables that are commonly available in scanner datasets as well as the limited number of product categories on which the data is available. A larger number of product categories, as well as a broader assortment, would allow researchers to begin to characterize the underlying psychological constructs which may well account for the cross-category differences we see in household price sensitivity. Indeed, the relatively weak cross-category correlations we find suggest that there are fundamental differences in the importance of price in different categories. Exploring the antecedents of these category-level differences would add substantially to knowledge. This research would also benefit from a richer description of the demographic and shopping pattern profile of households. As marketing information systems develop and these datasets become more accessible to academic researchers we expect that more relationships between demographic, purchase pattern and overall price sensitivity variables will emerge.

SUMMARY AND FUTURE RESEARCH DIRECTIONS

While there are numerous scanner data based studies in marketing, most of them focus on analysis on a single product category. In this paper, in a large-scale data analysis, we examine price sensitivity across a number of product categories We find strong evidence to support the notion that shopping patterns are more useful for predicting household-level price sensitivity than demographic variables. This particular finding is very useful to managers since, as noted previously, household-level demographic information about their customers is both costly and difficult to obtain. Our results suggest that the shopping pattern information many retailers already have at their disposal is enough to make some inferences about household-level price sensitivity.

While we do find evidence that household-level price sensitivity is linked across product categories, and that purchase pattern information is useful in describing some of the cross-household heterogeneity in this sensitivity, we want to be careful not to overstate the managerial significance of our findings. Indeed, while many of the elasticity correlations are statistically significant, it is clear that a great deal of the cross-category variance in price sensitivity remains unexplained. While retailers and manufacturers may well desire the ability to use their available data to develop very precise predictions about household-level price sensitivity the current state-of-the-art does not allow for that often desired level of precision. This points to the need for managers not to abandon their product-focused marketing efforts. While the information we uncover here can complement these existing efforts, the results are in no way strong enough to advocate a radical shift in strategy away from a product orientation towards a household-level orientation.

Our results also suggest that demographic information as well as shopping pattern information may be more parsimoniously summarized by fewer unique meta-variables. As richer sets of demographic and shopping pattern information becomes available it would be advisable for researchers to check whether a reduction in the number of meaningful dimensions is still possible and if the structure of the model presented here is robust.

As mentioned previously, our household-level price elasticity estimates are really conditional estimates, conditioned on both store and category choice. Since we would expect that a low price in a given category may affect the store choice probability positively and likewise the category purchase probability positively it is reasonable to suspect that our conditional price elasticities are biased downward relative to the total impact of price on brand choice. We suspect that in some categories this bias will be severe, while in others it will make little difference. Research which provides and understanding of exactly where in this hierarchical choice process price has its greatest impact for different types of products would be useful to marketing practitioners and academics alike.

Finally, although we did not present the results of the finite mixture model estimation, it is clear that household-level price elasticity estimates are sensitive to the estimation technique chosen. The parametric empirical Bayes approach we utilize here is one of a number of competing techniques for developing individual-level estimates when individual-level choice data is sparse. Since this is such a fundamental measure in marketing it is important that future research resolve this issue, laying out guidelines for selecting the best estimation technique in different situations.

Acknowledgement: This research was partially supported by the Faculty Development Fund from the Graduate School of Industrial Administration, Carnegie Mellon University. We would like to thank Bob Blattberg and Peter Boatwright for valuable comments. We also thank A. C. Nielsen for providing the data.

NOTES

1. Conversations we had with several grocery industry executives indicated that this was the conventional industry wisdom.

2. The UPC's used in this study represent a substantial proportion of the total volume for the popular sizes in these categories. In particular, for ketchup, these UPC's have 96.1% of all 32 oz. purchases. Similarly, for peanut butter our UPC's represent 88.7% of sales for the given size, stick margarine 71.3%, and tissue 72.5%.

3. We thank an anonymous reviewer for pointing this out to us.

4. High priced brands may be more selectively distributed.

5. To determine the direction of the bias created from the omitted variable take the product of the signs of the correlations between the omitted variable and price, and the omitted variable and sales. The sign of this product will be the direction of the bias.

6. A justification for using the normal distribution for the prior can be found in Zellner and Rossi (1984).

7. Essentially, the finite mixture model of Kamakura and Russell (1989) constrains all individual estimates to lie within the convex hull of the estimated point masses and hence reduces the dispersion of the individual household estimates.

8. The average price elasticities are within the range of those found by Gonul and Srinivasan (1993).

9. We use varimax rotation and a minimum eigenvalue = 1 as our factor extraction criterion.

10. The name for this dimension was inspired by the population segment description of Young Suburbia in Michael J. Weiss's *The Clustering of America.*

11. This measure is obtained from performing a principal components analysis on variables which measure the proportion of a household's store brand purchases in each of the five categories. The details of this analysis are available from the author's upon request.

12. The entropy index is frequently used to measure the distribution of market shares among firms in antitrust analysis (Encaoua and Jacquemin, 1980; Tirole, 1988).

13. For research on the types of households which are more likely to purchase store brands see Bettman (1974).

14. Notice that the hierarchical model does not contain a latent variable for overall household price sensitivity. Since only one manifest meta-variable, Shopping Intensity, directly affects the price elasticities, the overall price sensitivity latent variable is not identifiable in this structure.

15. We used maximum likelihood estimation for both models. In addition to the links between the variables, we estimated an error term for each manifested endogenous variable. The variances of the latent variables are normalized to one so that the subsequent parameter estimates may be directly interpreted as regression weights.

16. Note that elasticities here are negative numbers so a negative loading can be interpreted as an increase in the absolute value of the price elasticity.

17. We reported these fit statistics because both the Joreskog Adjusted GFI and AIC adjust for the differences in the number of parameters between the two models. For a good exposition of the relative merits of the different fit statistics that have been developed for these models see Rick R. Hoyle, *Structural Equation Modeling.*

REFERENCES

Allenby, G. and P. Lenk. (1994). "Modeling Household Purchase Behavior With Logistic Normal Regression," *Journal of American Statistical Association*, **89**(December): 1218–1231.

Ainslie A. and P. Rossi. (1998). "Similarities in Choice Behavior Across Multiple Categories," *Marketing Science*, **17**(2): 91–106.

Becker, G. (1965). "A Theory of the Allocation of Time," *Economic Journal*, **75**(September): 493–517

Bettman, J. R. (1974). "Relationship of Information-Processing Attitude Structures to Private Brand Purchasing Behavior," *Journal of Applied Psychology*, **59**(1): 79–83.

Blattberg, R. and E. George. (1993). "Shrinkage Estimation of Price and Promotional Elasticities: Seemingly Unrelated Equations," *Journal of American Statistical Association*, **86**(2): 304–315

Blattberg, R. and S. Neslin. (1990). *Sales Promotion: Concepts, Methods, and Strategies*. Englewood Cliffs, NJ: Prentice Hall, Inc.

Blattberg, R., T. Buesing, P. Peacock, and S. Sen. (1978). "Identifying the Deal Prone Segment," *Journal of Marketing Research*, **15**(3), 369—377.

Bucklin, Randolph E. and Sunil Gupta. (1992). "Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach," *Journal of Marketing Research*, **29**(2), 201–215.

Chamberlain, Gary. (1980). "Analysis of Covariance with Qualitative Data," *Review of Economic Studies*, **47**, 225–238.

Chen, Yuxin. (1998). "Competitive Individual-Marketing Strategies Under Imperfect Knowledge about Customers," *working paper*, Washington University, St. Louis.

Deighton, John, Don Peppers, and Martha Rogers. (1994). "Consumer Transaction Databases: Present Status and Prospects." in Blattberg, Glazer, and Little, (Ed.), *The Marketing Information Revolution*. Boston, MA: Harvard Business School Press.

Encaoua, D. and A. Jacquemin. (1980). "Degree of Monopoly, Indices of Concentration and Threat of Entry," *International Economic Review*, **21**(1): 87–105.

Gonul, F. and K. Srinivasan. (1993). "Modeling Multiple Sources of Heterogeneity in Multinomial Logit Models: Methodological and Managerial Issues," *Marketing Science*, **12**(3): 213–229.

Gupta, Sachin and Pradeep K. Chintagunta. (1994). "On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models", *Journal of Marketing Research*, **31**(1): 128–136.

Hair, Joseph F., Rolph E. Andersen, Ronald L. Tatham, and William C. Black. (1992). *Multivariate Data Analysis*, New York: Macmillan.

Hu, Li-Tze and Peter M. Bentler. (1995) "Evaluating Model Fit." Pp. 76–99 in Rick H. Hoyle (Ed.), *Structural Equation Modeling:* Sage Publications.

Kamakura, W. and G. Russell. (1989). "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, **26**(4): 379–390.

McCorkell, Graeme. (1997). *Direct and Database Marketing*. London: Kogan Page Limited.

Montgomery, David B. (1971). "Consumer Characteristics Associated with Dealing: An Empirical Example," *Journal of Marketing Research*, **8**(February): 118–20.

Narasimhan, Chakravarthi. (1984). "A Price Discrimination Theory of Coupons," *Marketing Science*, **3**(2): 128–147.

Petrison, Lisa, A., Robert. C. Blattberg, and Paul Whang. (1997). "Database Marketing: Past, Present, and Future," *Journal of Direct Marketing*, **11**(4): 109–125.

Progressive Grocer. (1995). "Using Databases to Seek out the Brand Loyal Shoppers: **74**(2): 10.

Rossi, P. and G. Allenby. (1993). "A Bayesian Approach to Estimating Household Parameters," *Journal of Marketing Research*, **30**(2): 171–82.

Shaffer, Greg and Z. John Zhang. (1995). "Competitive Coupon Targeting," *Marketing Science*, **14**(4): 395–416.

Stigler, George. (1961). "The Economics of Information," *Journal of Political Economy*, **69**(3): 213–225.

(1996). *Supermarket Business*. "Data Base Dividends," **51**(3): 109–115.

Tellis, G. (1988). "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales," *Journal of Marketing Research*, **25**(4): 331–341.

Telser, L. G. (1962). "The Demand for Branded Goods as Estimated from Consumer Panel Data," *The Review of Economics and Statistics*, **4**(3): 300–324.

Tirole, J. (1988). *The Theory of Industrial Organization*, Cambridge, Massachusette: The MIT Press.

Walters, Rockney G. (1991). "Assessing the Impact of Retail Price Promotions on Product Substitution, Complementary Purchase, and Interstore Sales Displacement," *Journal of Marketing*, **55**(2): 17–28.

Webster, Frederick E. (1965). "The Deal Prone Consumer," *Journal of Marketing Research*, **2**(2): 186–189.

Weiss, Michael J. (1988). *The Clustering of America*. New York: Harper & Row.

Zellner, Arnold and Peter E. Rossi. (1984). "A Bayesian Analysis of Dichotomous Quantal Response Models," *Journal of Econometrics*, **25**(3): 365–393.