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A Model of Retail Outlet Selection for Beef☆

ABSTRACT: Multinomial logit models were used to explain consumer outlet selection when buying beef, specifically roasts, steaks, ground beef, and other types of beef. Outlets were grouped into supermarkets, butchers, warehouses, supercenters, and others, and the probability of selecting each outlet type over a range of demographic and other variables was tested. The models were estimated from household data, with 198,682 observations used in the estimation. Empirical results showed that the type of beef purchased and the size of the purchase played an important role in the choice of outlet. Furthermore, the increase in mobility seen when consumers buy larger unit cuts could not be fully explained by price discounting. Implications for the potential growth of each outlet type are discussed.

INTRODUCTION

The agro-food sector, particularly at the retail level in the food distribution chain, continues to show structural shifts, with some of the changes being reflected through consumers' choices for when and where food purchases are made. Supermarkets have grown and become more concentrated, while there has been entry of new outlet forms such as supercenters and large food distribution warehouses (Stevens, 1993; Marion and NC 177 Committee, 1986). Clearly, the different outlets provide consumers with alternatives that in turn may increase

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competition (Shughart, 1997; Pepall et al., 1999). Yet, if consumers show very little willingness to shift their purchasing patterns among outlets, the potential competition may be minimal. An important issue to competitiveness is the extent that consumers are willing to shift their purchasing patterns through different outlets. The degree of mobility in consumer outlet selection is likely tied to what is being purchased and to the characteristics of the consumers. This issue is of particular importance to various agribusiness sectors because consumer outlet mobility may ultimately impact the price linkage seen between the retail sector and food distributors and producers.

To empirically address outlet selection mobility, the following analysis was limited to the outlet selection for meat, specifically beef. Although beef is but one of thousands of food items, it can provide important insight into the role of different outlets for a highly perishable product that is a major component of most consumers' diets. In fact, Ward (1998) showed that more than 85% of all U.S. households purchase some beef within a 2-week period. Hence, in the following analysis, household buying patterns for beef across the major retail outlets was explored with the explicit purpose of measuring consumers' mobility.

With the use of individual consumer's household purchasing data, trends in the selection of outlet choices for beef consumption will be shown, with the outlets defined as supermarkets; warehouses; butchers; supercenters; and others, including convenience type outlets. Supermarkets are multiple department, self-service stores with annual sales exceeding millions of dollars. Warehouses provide food outlets with limited product variety and services, incorporating case lot stocking and shelving practices. Supercenters have an average size of about 14,000 $m.^2$, devoting about 40% of their space to groceries. Convenience stores are small outlets that are able to handle only a limited selection of food and nonfood products and are typically open extended hours (United States Department of Agriculture, 1994).

Consumer mobility can be illustrated by determining the propensity for selecting these outlets. Specifically, the probability of selecting each outlet type can be estimated, allowing the likelihood of using an outlet be related to what is being purchased and to the characteristics of the buyer. Outlet choices were expected to differ across demographics and seasons and according to the types and quantities of food purchased. Demographics were measured with income levels, household sizes, market sizes, women's employment levels, and ages of women. Women's demographics were expected to be important because food purchasing decisions are often made by women.

The outlet choices for beef as defined above simply represent alternatives; there was no implied order or ranking of the outlets. That is, supermarkets were not ranked above or below, say, butchers. For each time period, a household reported the beef purchasing events and identified the outlet selection for each purchase. Thus, over the full data set, the nonordered selections of each outlet type can be explained by using appropriate econometric models (National Panel Dairy [NPD], 1998). Specifically, the data structure suggested the use of a multinomial, unordered, logit model to explain the outlet selection mobility. Furthermore, because the type of purchase was expected to be relevant, beef purchases were grouped into four subcategories: roasts, steaks, ground beef, and other beef products. Price effects were considered when separate equations were estimated for each of the four meat cuts.

Outlet Selection Specification and Data

Given the discrete and unordered nature of the outlets defined above, an unordered, multinomial logit model was adopted and estimated (McFadden, 1973; Chow, 1983; Guadagni and Little, 1983; Long, 1997; Liao, 1994; Theil, 1969). With application of the multinomial logit model, the probabilities were estimated for choosing among supermarkets, warehouses, butchers, supercenters, and other retail outlets. This last category included neighborhood shops selling beef, convenience stores, and cooperative outlets.

In Eq. (1), the probability of choosing outlet j is defined where $j = 1, 2, \ldots, 5$. If $n = 2$, Eq. (1) is a binomial model that is typically estimated with logit and/or probit models. The βs carry the jk subscripts, with j denoting the outlet choice, and k distinguishing m independent (x) variables, with x_0 being a unitary vector. Standard maximum likelihood techniques were used to estimate the full model (Time Series Processor, 1997). The outlet choices were mutually exclusive, thus removing any potential problems with irrelevant alternatives, because on any reporting event you cannot be in more than one type of outlet at the same time. Note in Eq. (1) the exogenous variables are not related to specific outlets, hence x_k does not carrying the j subscript.

$$\text{Prob}(y = j|x) = \frac{\exp\left(\sum_{k=0}^{m} \beta_{jk} x_k\right)}{\left(\sum_{j=1}^{n} \exp\left(\sum_{k=0}^{m} \beta_{jk} x_k\right)\right)} \tag{1}$$

The variables x_k in Eq. (1) include a variety of demographic characteristics, seasonality, quantities, and types of beef purchased. The different explanatory variables were qualitative and thus required the use of dummy variables, as indicated with the definitions in Table 1. For most of the demographic variables, it was difficult to set forth theoretical arguments about the direction of mobility, if any. Yet differences were expected across the demographics, and the effects had

Table 1. Variable Definitions for NPD Household Meat Consumption Data

Type of variable	*Variable*	*Range*	*Frequency share (%)*
Demographics: income ($)	INC_1 (base)	0 to $24,999	34.95
	INC_2	$25,000 to $49,999	34.51
	INC_3	$50,000 to $74,999	20.18
	INC_4	over $75,000	10.36
Demographics: household size (number of people)	HSZ_1 (base)	1	6.53
	HSZ_2	2	31.30
	HSZ_3	3	22.69
	HSZ_4	4 plus	39.48
Demographics: market size (number of people)	MSA_1 (base)	0 to 49,999	22.74
	MSA_2	50,000 to 249,999	8.09
	MSA_3	over 250,000	69.17
Demographics: women's employment level (hours)	EMF_1 (base)	unemployed	49.05
	EMF_2	0 to 30	13.11
	EMF_3	over 30	37.84
Demographics: age of women (years)	AGF_1 (base)	0 to 29	8.72
	AGF_2	30 to 50	51.76
	AGF_3	over 50	39.52
Quantity of beef (pounds per buying occasion per household)	LBS_1 (base)	under 1 pound	14.46
	LBS_2	1 to under 2	40.38
	LBS_3	2 to under 5	35.66
	LBS_4	5 pounds or more	9.50
Type of beef (cuts)	$BFCUT_1$ (base)	other	11.44
	$BFCUT_2$	roasts	13.24
	$BFCUT_3$	steaks	28.73
	$BFCUT_4$	ground beef	46.59
Seasonality (quarters)	QTR_1	January–March	26.06
	QTR_2	April–June	26.72
	QTR_3	July–September	22.97
	QTR_4	October–December	24.25

to be empirically determined. Women's employment status was an exception, where the outlet selection should be closely tied to convenience and availability. Supermarkets were expected to be more convenient. Location of the household in terms of the market size should have also played a role. Rural residents may frequent the smaller local shops, whereas the major outlets may be of greater importance in the more populated regions. Also, market size may have had some implications for distance to the outlet, however, that could not be measured with the current database. Unfortunately, there was no distance-to-the-outlet measure within the data set, and this is a potential shortcoming of the study. Yet, given the use of the automobile within the U.S., the distance factor, although recognizing that it cannot be tested with the current panel data, was not expected to be of great importance.

$$y_j = \hat{\beta}_{j0} + \sum_{k=2}^{4} (\hat{\beta}_{j(k-1)}INC_{jk} + \hat{\beta}_{j(k+2)}HSZ_{jk} + \hat{\beta}_{j(k+5)}LBS_{jk} + \hat{\beta}_{j(k+8)}BFCUT_{jk} + \\ + \hat{\beta}_{j(k+11)}DQTR_{jk}) + \sum_{k=2}^{3} (\hat{\beta}_{j(k+14)}MSA_{jk} + \hat{\beta}_{j(k+16)}EMF_{jk} + \hat{\beta}_{j(k+18)}AGF_{jk}) + e_j \tag{2}$$

Seasonality was based on quarterly buying patterns and was captured with four dummy variables with the sum of the seasonal coefficients restricted to zero.[1] Size of the purchasing occasions was expected to have an influence. Consumers buying in larger volumes may shift to outlets generally considered to have fewer frills but larger unit sizes. Price was not included in the initial model because its effect on outlet choice could be redundant to the ones obtained by types of beef purchases already included in the model (e.g., steak prices should be higher than, say, ground beef prices). Later, price effects were considered when separate equations were estimated for each beef type. Also consumers may shop based on the product needed (e.g., roasts, steaks), hence, including the product category and not the corresponding price was justified with the model set forth in Eq. (2).

Household Purchasing Data

Data used in this analysis were based on household panel data collected by the NPD (1998). Individual households reported their eating occasions within the home, giving considerable detail on the types of meat products consumed. The NPD company concentrates on sampling and collection of panel data and spends considerable effort in making sure the panels are demographically representative of U.S. households. NPD maintains the household panel where participating households keep eating diaries that document their purchasing habits for a designated time (for more details about the database, see Ward, 1998). Using the definitions from Table 1 and the equation noted above, the estimable model is specified as set forth in Eq. (2), with each y_j taking either a zero or one value for the j^{th} outlet choice. Data on most demographics are readily available for the monthly database extending from the last quarter of 1992 through the first quarter of 1998. Although the full data set includes more than beef, this analysis was limited to purchases of beef for a total of 198,682 observations. A unique dimension to the data is that households report where they purchased their beef, thus providing the information for empirically estimating the outlet selection mobility. From the total quantity (pounds) of beef purchased by the households, 79.9% was purchased in supermarkets; 7.8% in butchers; 4.3% in warehouses; 0.6% in supercenters; and 7.4% in other outlets.

Table 2. Purchasing Frequency Distribution Across Beef Cuts and Purchase Sizes (obs = 198,682)

	Purchase Sizes (%)					
	Under 1 Pound	*1 to Under 2 Pounds*	*2 to Under 5 Pounds*	*5 Pounds and Over*	*Total*	*Beef Cut Share*
Other Beef	17.36	45.11	29.20	8.33	100.00	11.44
Roasts	.48	14.58	75.81	9.13	100.00	13.24
Steaks	27.65	41.11	25.51	5.73	100.00	28.73
Ground Beef	9.59	46.10	32.09	12.22	100.00	46.59
Size Shares	14.46	40.38	35.66	9.50	100.00	100.00

In Eq. (2), beef cuts (BFCUT) and the purchase sizes (LBS) were the only two variables that reflected characteristics of the product being purchased, whereas the other variables were related to the buyer or period of the purchase. Table 2 shows the distribution of the 198,682 purchasing frequencies across the beef types and sizes. Clearly, there could be some changes in the size distribution and possible correlation with the types of beef being purchased. The far right column shows the beef cuts purchasing distributions, and the bottom row corresponds to the four size categories. *Other beef and roasts* represented a small share of the beef purchases compared to the other two cuts. Each size unit was relatively important, with the large size unit showing the smallest share at 9.50%. The most pronounced share was roasts, where 76% of the purchases were in the *2 to under 5 pounds* range. In the subsequent logit model both sizes and beef cuts were included as independent variables. Given the information from Table 2, this is reasonable because there was no strong correlation across the sizes and cuts.

Table 3 shows the distributions across income groups for different outlets. Supermarkets accounted for the largest amount, with 91.14% of the household shopping frequencies, whereas the supercenters showed the smallest share, with less than 1%. Each income group was important, with the largest income category representing the smallest percentage (10.36%). It is clear, when comparing the percentages in this table, that one type of outlet is not concentrated in a particular

Table 3. Frequency Distribution Across Outlets and Incomes (obs = 198,682)

	Incomes (%)					
	Under $24,999	*$25,000 to $49,999*	*$50,000 to $74,999*	*Over $75,000*	*Total*	*Outlet Share*
Other outlets	32.90	35.23	19.66	12.21	100.00	2.26
Supermarket	34.40	34.42	20.03	10.15	100.00	91.14
Warehouse	20.96	37.72	24.73	16.59	100.00	2.83
Butcher	36.02	32.49	21.66	9.83	100.00	3.12
Supercenter	35.91	39.66	16.32	8.11	100.00	.64
Income Shares	34.95	34.51	20.18	10.36	100.00	100.00

Table 4. Frequency Distribution Across Outlets and Market Sizes (obs = 198,682)

	Market Sizes (population) (%)			
	Under 49,999	*50,000 to 249,999*	*Over 250,000*	*Outlet Share*
Other outlets	2.88	1.70	2.13	2.26
Supermarket	93.19	90.99	90.48	91.14
Warehouse	1.41	3.17	3.26	2.83
Butcher	1.68	3.11	3.59	3.12
Supercenter	.849	1.03	.534	.645
Total	100.00	100.00	100.00	100.00

income group. That is, the data include the full range of outlets within each income group.

Table 4 presents the distribution of the 198,682 frequencies across the different outlets and market sizes, with each column showing the outlet frequencies in percentage terms for each market size. Supermarkets accounted for 91% of the total number of purchasing occasions, and supercenters accounted for the smallest, with less than 1%. Again, market size may influence the outlet choice, but as seen in Table 4 all outlet choices were available in each market size.

Each household was classified according to five demographic groups, with each group taking a range of values. When all the actual combinations of demographics were tabulated, there were 352 different combinations of consumer profiles, for example, percentage of individual households with a certain range of demographic characteristics. Over the full data set, the consumer profile with the greatest probability of occurring was the household with two individuals having an income under $25,000 and living in an area with over 250,000 persons, unemployed, and over 50 years old. This profile group represented 4.28% of the households, thus implying that there really is no particularly dominant demographic group based on the five classifications. With the logit models, the effects on outlet mobility across specific demographics can be shown. Furthermore, and more important, consumer mobility can be measured across the demographics. That is, what happens to outlet selection mobility as one compares the consumer profiles from the most likely to the least likely to occur? The impact on mobility across consumer profiles will be addressed by using simulations after estimating the multinomial logit model.

Multinomial Logit Outlet Estimates

Maximum likelihood procedures were used to estimate the multinomial logit model, and the resulting parameters and supporting statistics are reported in Table 5 with the estimates corresponding to the β_j coefficients from Eq. (2). Estimates

Table 5. Multinomial Logit Estimates for the Outlet Selection Models

	Supermarket		*Warehouses*	
	Coefficient Estimates (β_j)	*Coefficients t-values**	*Coefficient Estimates (β_j)*	*Coefficients t-values**
Intercept	4.2970	37.569	−2.3023	−12.680
INC2	−.07955	−2.0540	.47511	8.7748
INC3	−.05167	−1.1174	.65538	10.493
INC4	−.25518	−4.6515	.75732	10.487
HSZ2	−.59148	−7.3905	−.13709	−1.1460
HSZ3	−.35472	−4.2128	.08010	.64762
HSZ4	−.37584	−4.4693	−.11078	−.89613
LBS2	−.28945	−5.4472	.31146	2.7457
LBS3	−.40709	−7.3283	1.9782	18.123
LBS4	−1.4071	−23.504	2.4602	22.082
BFCUT2	.73548	11.782	−.04082	−.49852
BFCUT3	.32807	6.8302	.21028	3.1648
BFCUT4	.44884	10.025	.16929	2.7668
DQTR2	−.05819	−2.3059	−.02186	−.64902
DQTR3	−.01994	−.74135	−.04100	−1.1354
DQTR4	−.04289	−1.6350	−.07036	−1.9889
MSA2	.50814	.50814	1.3917	15.429
MSA3	.27044	.27044	1.1394	20.396
EMF2	−.14217	−.14217	−.01325	−.21106
EMF3	−.26993	−.26993	−.34671	−7.3831
AGF2	−.08352	−.08352	−.29460	−3.8918
AGF3	−.02589	−.25891	−.65608	−8.1273
	Butchers		Supercenters	
Intercept	.56290	3.8988	−.86807	−3.0134
INC2	−.09642	−1.9129	.13389	1.7316
INC3	.03974	.67311	−.05138	−.51559
INC4	−.26741	−3.6716	−.17670	−1.3880
HSZ2	−.81156	−8.5331	.56452	2.3517
HSZ3	−.65053	−6.4546	.93004	3.8227
HSZ4	−.63354	−6.2856	.49356	2.0163
LBS2	−.38462	−5.5106	−.19729	−1.8032
LBS3	.12673	1.7850	−.18434	−1.6199
LBS4	.19288	2.5443	−.43805	−3.5006
BFCUT2	−.15525	−1.9502	.96193	6.7161
BFCUT3	−.05993	−.97176	.66996	5.5182
BFCUT4	−.10591	−1.8498	.67399	5.8230
DQTR2	−.10685	−3.2189	.10304	1.9472
DQTR3	−.04362	−1.2432	−.20241	−3.3326
DQTR4	.00717	.21137	−.41086	−6.4925
MSA2	1.2086	13.657	.79289	6.8575
MSA3	1.1267	21.318	−.08583	−1.1563
EMF2	−.64193	−9.7863	−.86369	−7.5805
EMF3	−.64856	−14.114	−.74701	−10.077
AGF2	.08254	1.0540	−.96089	−10.399
AGF3	−.10690	−1.3014	−1.9072	−17.307

Notes: Number of observations = 198682; Log likelihood = −75391.0; Kullback-Leibler R^2 = .065484.
* Table t-value at 5% = 1.96.

are reported for supermarkets, warehouses, butchers, and supercenters, while the other outlet category is not shown because the probability for the j^{th} category is known once $j - 1$ of the outlets are estimated. For convenience, the t values instead of the standard errors are reported. The number of observations used in the final estimation is 198,682, and the likelihood value is shown at the bottom of the table. Because this analysis was based on cross-sectional and time series information and because the total number of observations was large, one would not expect to see the models explain a large amount of the variation in the outlet selection. The panel data set consisted of time series observations on each of several cross-sectional units. Cross-sectional and time series components in the model residuals should not present a problem given that household differences were captured with demographics and seasonality removes any lagged correlations in the residuals. Note also that the number of time units changes across households because every household did not consistently report each period. When practical, dummies for each household can be included to test whether the demographics are adequate for capturing household effects. In the current data set there are more than 6,000 households buying beef; hence it is impractical to include dummies in Eq. (2) to reflect household differences. Using the five demographics is a practical way to differentiate among the households, and the inclusion of additional demographics was limited by what was reported in the database. One quasi-measure of goodness-of-fit is the Kullback-Leibler R^2. This statistic shows that approximately 7% of the variation has been explained. Although a higher goodness-of-fit would be preferred, this low value is typical when using large pooled data sets. More interest is in the response of the variables and how they influence the probabilities and less with the use of the models for forecasting. Hence, the low Kullback-Leibler R^2 should not be of major concern.

Although in the following sections the probabilities over a range of variable values will be presented, it is also useful to draw some generalizations from the values in Table 5. As is apparent with the t values, most of the demographics and product characteristics were statistically significant. Because supermarkets are dominant among the outlets, their estimates were of particular interest. For example, movement to the largest income group leads to a decline in the use of supermarkets. Incomes negatively affect supermarkets while having a positive, significant impact on the use of warehouse outlets. As women spend more time at work, they are less likely to go to the supercenter and instead go to the supermarket or warehouse. Household size influences consumer mobility with negative coefficients in the case of supermarkets and butchers. Among the outlets, warehouses and supercenters showed the least significant responses in terms of the t values across the variables. This may, in part, be due to the small number of warehouses and supercenters in the data set relative to the other outlets. The size of meat purchases as measured with the pounds purchased per buying occasion and the types of beef being purchased were highly significant and numerically important as will be shown in the simulation section. Purchasing size was the most significant class of variables included in the models.

Overall, the coefficient signs were generally as expected, and the significance values of the variables were quite high. Given these values, then, the estimates can be incorporated into various simulation analyses to illustrate the outlet selection mobility as demographics, product characteristics, and seasonality are adjusted. Because the type of beef purchased was important across the outlets, the following simulations will always take into account the different types of beef. Furthermore, because the purchase size was so important, the simulation for this variable is first presented followed by the demographics and other variables. Table 5 gives the empirical counterpart to Eq. (2). Then for selected x_k values, the estimated y_js are inserted into Eq. (1) to simulate the different probabilities. That is, changes in the Prob (y) over values of the x_k variables provide the empirical mobility values.

Simulating the Outlet Selection Mobility

Eq. (2) can be expressed in matrix notation with $X\beta_{j,}$ where β_j corresponds to the coefficients in (2). Once the β_js are estimated, then three basic types of uses for the logit estimates are typically reported. First, as set forth in Eq. (1) the probabilities can be shown over a range of X values for each outlet. Second, standard odds ratios are easily shown where $\ln (P_j/P_l) = X(\beta_j - \beta_l)$. Given the dominance of the supermarkets, the odds ratio is not very interesting since the odds for supermarkets will always be large relative to the other outlets. Third, changes in the probabilities across the same outlet type are most revealing when considering different values for the X matrix. Again using $X\beta_j$, Eq. (3) shows changes where X_1 and X_2 represent two different sets of variable values defined in Table 1. Eq. (3) is particularly useful since one variable or a combination of several variables can be considered.

$$\Delta\ \mathrm{Pr}ob(y = j|\Delta X) = \left(\frac{\exp^{X_1\beta_j}}{\sum_{j=1}^{5} \exp^{X_1\beta_j}} - \frac{\exp^{X_2\beta_j}}{\sum_{j=1}^{5} \exp^{X_2\beta_j}} \right) \tag{3}$$

Using the above estimates and Eqs. (1) and (3), the probabilities and the changes in the probabilities are shown over a range of exogenous variable values. In each simulation the probabilities for the four outlets (supermarkets, warehouses, butchers, and supercenters) are shown for each type of beef cuts and under the various categories of demographics. The results are compared based on the change of probability of outlet choice with a shift in the value of each binary (x^{th}) explanatory variable. In most cases a comparison is made between the low and

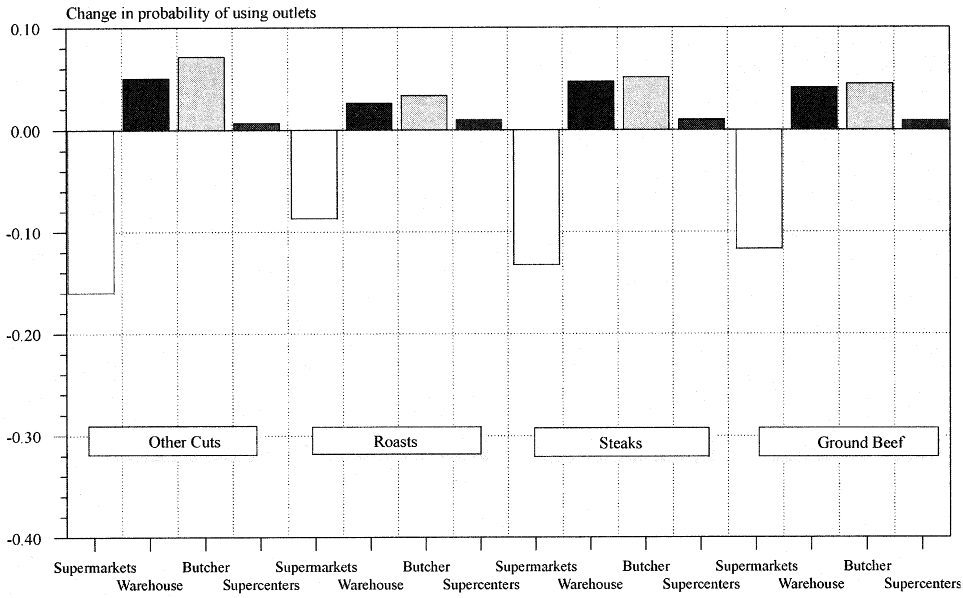

Figure 1. Change in probability of using retail outlets when comparing size of beef purchases (i.e., comparing purchase size of beef cuts from under 1 pound to 5 pounds and over).

high values of each demographic variable (e.g., X_1 could be the high value and X_2 the low value.) For example, look at the smallest to largest purchase size in Fig. 1.

Purchasing Size and Outlet Probabilities

Beef purchases ranged in size from under 1 pound to over 5 pounds (see Table 1). For this range, the simulated effects on the outlet choice for the four types of beef cuts are presented in Fig. 1. The bottom axis shows the four outlets for each meat cut, while the left axis gives the corresponding change in probability of using that outlet when comparing purchases from under one pound to 5 pounds and over (see Table 2 of the distribution of unit sizes). In each case the probability changes are predicted, while holding the demographic variables to the base level. For each meat cut, the likelihood of using supermarkets declines as the per unit purchase size increases, as seen with the negative bars in Fig. 1 for each beef cut. Likewise, the adjacent positive bars show how the other outlets gain from the supermarkets' loss. Other cuts present the greatest variation with a decrease of 16.0 percentage points in the probability of using supermarkets (i.e., the probability declined from 95.7% to 79.7%). Butchers picked up most of the supermarket loss with an increase of 7.15 percentage points from 2.29% to 9.44%. The probability of using warehouses increases by 5.06 percentage points, from 0.13% to 5.19%. For

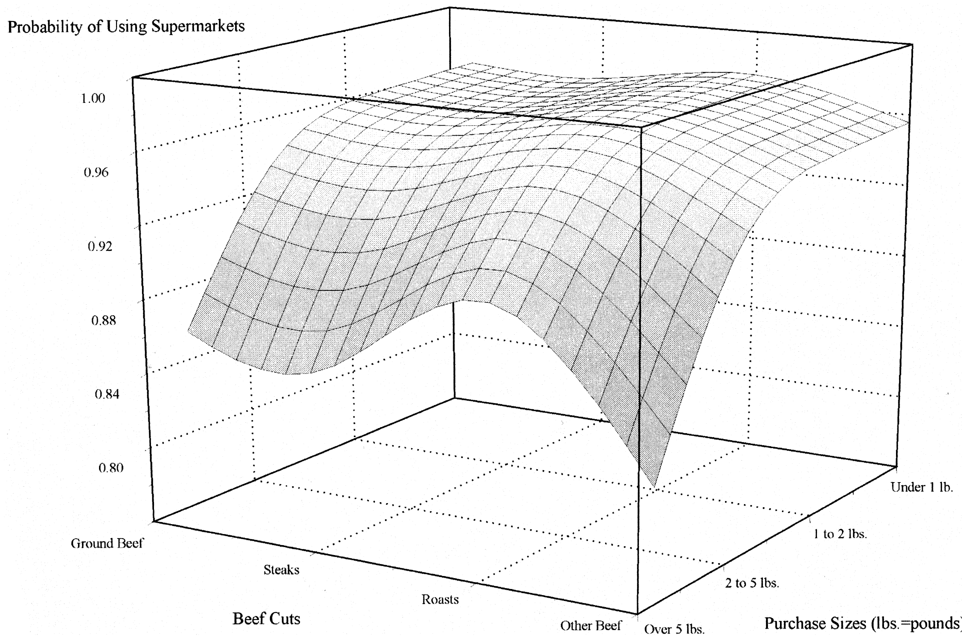

Figure 2. Change in supermarket probability for size of purchases across different types of beef.

ground beef purchases across the size range of under 1 pound to over 5 pounds, the probability of going to the supermarket declines by 11.67 percentage points from 97.03% to 85.36%. Warehouses and butchers captured most of the loss in the likelihood of using supermarkets with a gain of 4.10 and 4.47 percentage points, respectively. Because supermarkets reflect the most frequently used outlet for beef purchases, it is useful to further expand on Fig. 1 by illustrating the actual purchasing mobility for this outlet. Fig. 2 shows changes in the supermarket outlet choice for different purchase sizes and beef cuts. Clearly, as the size of the purchase increases from less than 1 pound to 5 pounds or more, the probabilities of shopping in the supermarkets decline. The greatest impact occurs with other cuts where the probability drops by 16.0 percentage points. For steak purchases, there is a decrease in the probability of going to the supermarkets of 13.2 percentage points. Combined, Figs. 1 and 2 establish that consumers do shift among outlets, with some of the decision being tied to the purchase size.

Supercenters show extremely small gains while butchers and warehouses are the primary benefactors from the supermarket loss. Further, the mobility away from supermarkets is clearly tied to the meat cut as seen when viewing the response to other cuts in comparison with roasts. Household outlet mobility is considerably less when buying roasts.

Demographics and Outlet Mobility

Demographics were shown to have a statistically significant impact on each outlet type, as presented in Table 5 with the logit estimates. Although these demographics are of interest, most of the individual effects considered in isolation of the other demographics are quite small. Women's employment status and women's ages are the two variables that were expected to be closely aligned with the need for convenience during the buying occasion. Women's employment status ranged from unemployed to working over 30 hours per week. Ages ranged from less than 30 years to over 50 years old. The simulated effects on the outlet choices for the four types of beef cuts for these ranges are presented in Table 6. Both aging and time constraints associated with employment increased the probability of buying beef through supermarkets. For each case, the probabilities were calculated for the largest purchase sizes and are shown comparing the upper and lower values to each demographic. Each probability declines when considering the smaller purchase sizes, hence the values in Table 6 represent the upper limits of the change attributed to each demographic variable. Household incomes ranging from under $25,000 to over $75,000 are also simulated in Table 6. In contrast to the previous demographics, rising incomes have a negative impact on the use of supermarkets, indicating greater outlet mobility among the higher income groups. For outlets such as warehouses, a fee is sometimes required to buy, and the higher income groups would be more capable of paying the fees. Higher incomes may indicate the ability to pay any transaction costs associated with movements among the outlets. Finally, higher incomes likely reflect the wider range of buying habits that such income groups have relative to the lower income households. This wider range of buying options may carry over to food purchases.

A similar decrease in the likelihood of using supermarkets was seen as the size of the household increases from a single person to four or more household members. Warehouses and supercenters pick up most of the loss in the probability of using supermarkets. A measure of the willingness to change outlets showed some differences according to the community size, with supermarkets showing negative gains between the rural and urban markets. This response was somewhat surprising.

Seasonality was also representative of household behavior where purchasing patterns differed cyclically and were closely tied to customs of different consumers and to special occasions. Seasonal differences, with quarterly variations in the outlets, showed mixed levels of significance. The quarterly changes were particularly significant for supermarkets, warehouses, and supercenters. Although showing some impact, the magnitude of the seasonal response was quite small relative to the other outlet mobility factors.

Whereas the above discussion dealt with separate demographics, a more

Table 6. Changes in Probabilities Attributed to Variables Associated with Convenience (Age of Women and Women's Employment Levels), Incomes, Market Sizes, and Household Sizes

Beef Cuts	*Supermarkets*	*Warehouses*	*Butchers*	*Supercenters*
Response to age of women	Percentage point changes from the base associated with women under 30 years of age to women over 50 years			
Other cuts	−.150	−1.71	1.53	−.970
Roasts	.736	−.859	.751	−1.35
Steaks	.777	−1.55	1.17	−1.42
Ground Beef	.715	−1.35	1.01	−1.30
Women's employment	Percentage point changes from the base associated with women unemployed to women working over 30 hours per week.			
Other cuts	1.99	−.263	−2.81	−.437
Roasts	1.32	−.160	−1.32	−.622
Steaks	1.79	−.261	−2.01	−.647
Ground Beef	1.58	−.239	−1.76	−.592
Response to income levels	Percentage point changes from the base associated with income levels under $25,000 compared to $75,000 and over.			
Other cuts	−7.49	7.75	−.990	−.0239
Roasts	−4.59	4.29	−.273	.0434
Steaks	−7.22	7.30	−.654	−.0214
Ground Beef	−6.54	6.48	−.510	−.0021
Market size responses	Percentage point changes from the base associated with market size under 50,000 households compared to over 250,000.			
Other cuts	−12.48	5.25	9.30	−.491
Roasts	−6.95	3.19	5.06	−.595
Steaks	−10.51	5.23	7.08	−.686
Ground Beef	−9.47	4.71	6.34	−.608
Household size responses	Percentage point changes from the base associated with household size with single person to four or more household members.			
Other cuts	−2.41	1.37	−2.36	1.58
Roasts	−2.79	.70	−1.09	2.20
Steaks	−3.14	1.23	−1.72	2.29
Ground Beef	−2.94	1.09	−1.47	2.10

informative approach to the demographics and mobility is to determine whether variations in all of the household characteristics really make a difference. Each household is characterized by a combination of the five demographics, and each combination represents one household profile (see Table 1). Three hundred fifty-two profiles were identified, with the largest group representing 4.3% of the sample. By the 23rd largest group, the percentage of the population in that particular profile is under 1% of the households. What is apparent is that no one combination of demographics dominates.

Do the demographics really make a difference? Using the multinomial logit model and simulating the probabilities of selecting each outlet for each profile, one can clearly see the impact of variations in the groups of demographics. Fig. 3a shows the percentage of individual households across different profile groups going to supermarkets to buy ground beef. Given the importance of purchase size initially shown in Figs. 1 and 2, the profiles were simulated according to beef unit size (e.g., for cuts under 1 pound and for cuts 5 pounds or more.) For purchases under 1 pound, the probability of going to supermarkets was in the range 92–98% for all household profiles. For purchases of 5 pounds or more, the probability of going to the supermarket declined to between 57% and 88%. The obvious difference in mobility is again due to the purchase size. Yet within each purchase size, variations in the probabilities are attributed to demographic differences. Demographics make a difference, but the extent of that difference depends on the units being purchased. Similar patterns were seen for households buying steaks, where for purchases under 1 pound the probability of going to the supermarket fell between 90% and 98%. For purchases of 5 pounds or more the probability ranged between 53% and 87% (Fig. 3b). The degree of difference that profiles make can be shown with the coefficients of variation of each series (e.g., CV $= \sigma/\mu$). Relative variations in the probability of using supermarkets when buying large cuts was over four times that for cuts under 1 pound for both ground beef and steak purchases. For both ground beef and steak purchases, the relative variation across the 352 different consumer profiles was clearly tied to the purchase sizes. Demographics mostly made a difference after differentiating by what is being purchased and the per unit size.

Figs. 3a and b can be particularly important to management policies when developing consumer targeting programs. For example, using supermarkets selling large steak cuts as shown in Fig. 3b, it is easy to identify the profiles of households where the probability of using the outlet falls below, say, 65% or 70%. Those profiles in this lower range indicate a group that supermarkets may need to target to lower exit. Similarly, other outlets may want to target profiles above, for example, 75% to entice greater mobility. What is clear in this kind of comparisons is that very little mobility associated with demographic groups can be expected among those households buying the small unit sizes.

PRICE IMPACT ON OUTLET SELECTION

The logit models in Table 5 included variables identifying the beef cuts, showing that the type of beef purchased influences the outlet selection (again, see Fig. 1). Meat prices obviously differ across these meat cuts and among outlets. Given that

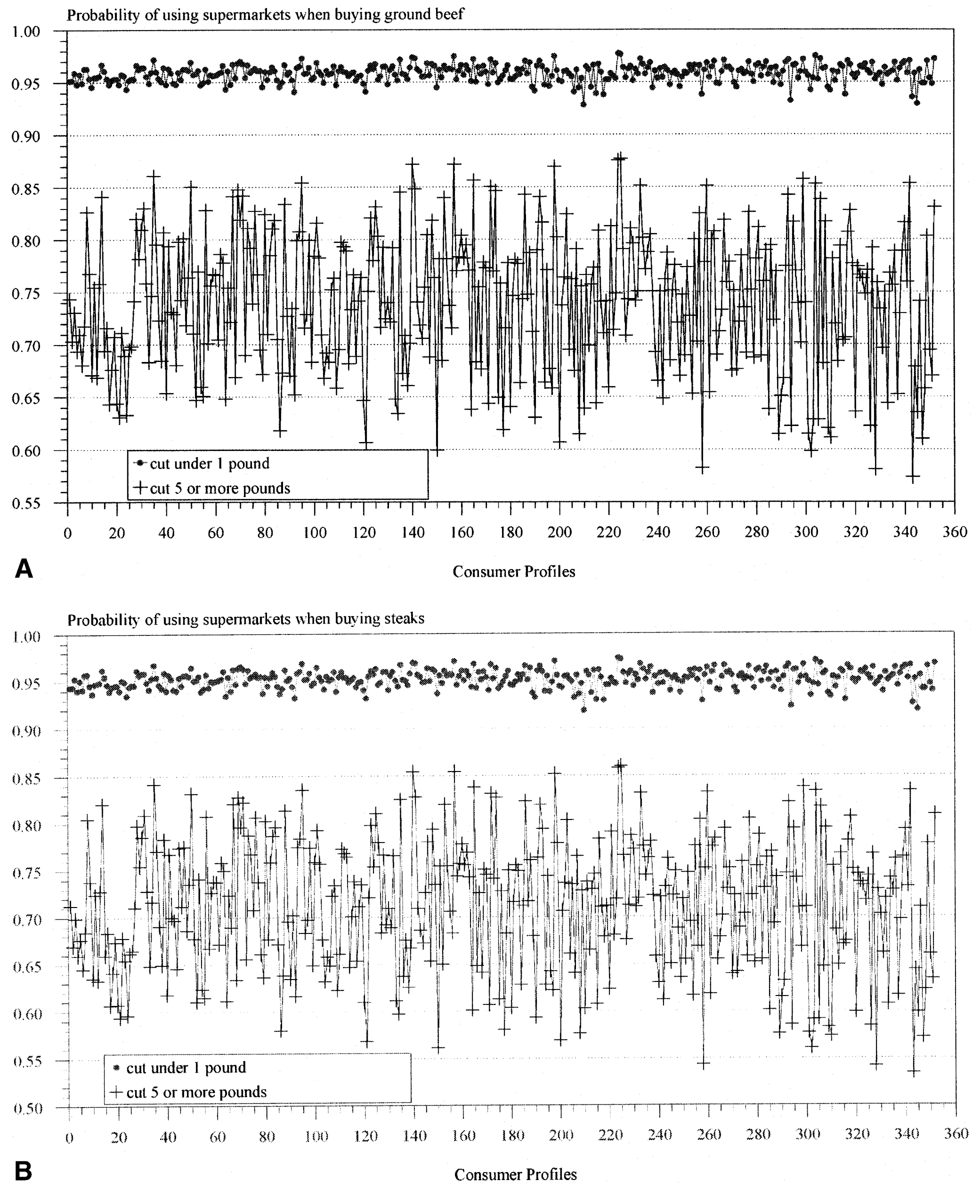

Figure 3. Probability of using supermarkets across demographic groups when buying (a) ground beef and (b) steak.

the values of the meat types differ, it was not possible to include both meat types and the corresponding prices in the same equation because the two variables are expected to be highly correlated. As estimated with the logit models in Table 5, the meat type is most likely picking up demand differences associated with the

Table 7. Coefficients for the Price Effects in the Multinomial Logit Models Estimated by Beef Cuts for Each Market Outlet

	Ground Beef	*Steaks*	*Roasts*	*Other Beef*
Supermarket	−.18030	−.14268	−0.08730	−0.14478
(*t* value)	(−4.17022)	(−4.69925)	(−1.19276)	(−2.90919)
Warehouse	0.36468	0.38868	0.71423	0.36111
(*t* value)	(6.22056)	(9.53081)	(8.28679)	(5.60958)
Butchers	0.92463	0.35726	0.82320	0.28932
(*t* value)	(17.41232)	(9.03999)	(9.57845)	(4.78733)
Supercenters	−1.04001	−0.40395	−0.21772	−0.33487
(*t* value)	(−10.07149)	(−5.95407)	(−1.40791)	(−2.36892)

type as well as price differences. The importance of price on the outlet selection needs to be considered (Pashigian and Bowen, 1991). One approach for measuring the potential effects of prices is to estimate separate equations for each meat cut, replacing the price variable for the meat cut in each equation. This gives four equations, one for each beef cut, while still accounting for demographics included in the aggregate model of Table 5.

Four separate equations, assuming independence in the residuals across equations, were estimated. The estimation could be considerably more complicated if the residuals across the equations were correlated. Given that the same right-hand-side variables enter all equations, multivariate issues are not expected to be important compared to when there are considerable differences in the exogenous variables among the equations (Verbeke, Ward, Viaene, 2000).

In general the estimates for the four separate equations show that prices do have significant impacts on the outlet shares. Yet the impacts are still small in magnitude. Table 7 includes the price coefficients along with the *t* statistics, and the complete estimates are available from the authors. In Table 7, each column corresponds to a separate, multinomial logit equation estimated by beef cuts, while each row gives the price coefficients for the outlet used when purchasing that particular beef type. The resulting price coefficients reveal the effects of price changes on the probability of using the different outlets when buying specific beef cuts. Overall, the price effects were statistically significant, with the most pronounced effect being the negative impact on supermarkets. Although these price coefficients represent the underlying importance of pricing, the actual impact on outlet mobility from price differences is best shown by using the predicted probabilities for each outlet. These changes in probabilities are illustrated in Fig. 4. Starting with the average price for each beef type over all the outlets, increases and decreases in beef prices were simulated with the prices being changed by $\pm$ 1 standard deviation to the mean (maximum range of $\pm$ standard deviation to the average price). The numerical shifts in probabilities associated with this price range were quite small for all beef types. There was a

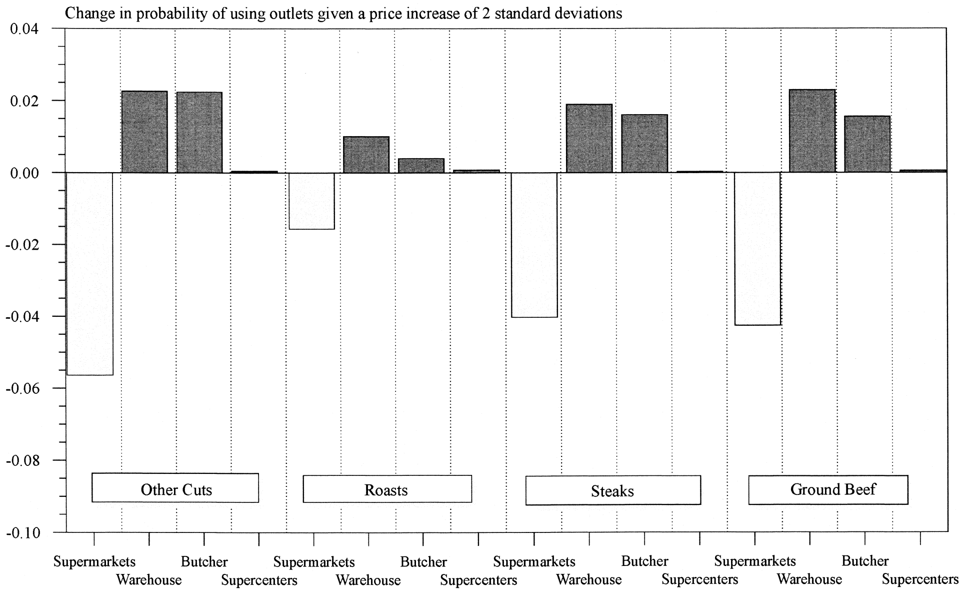

Figure 4. Change in probability of using retail outlet as supermarket prices are ranged from ± SD to the mean price for each type of beef using the largest cuts.

5.63 percentage point decrease in the probability of the household going to the supermarkets to buy other cuts over this price range. Warehouses and butchers picked up part of this decline, with an increase of 2.27 and 2.24 percentage points, respectively. For steaks, roasts, and ground beef, the likelihood of going to supermarkets declined by less than 5 percentage points over this price range. Warehouses and butchers picked up most of this decline. In each of these simulations, only the supermarket prices were changed. Hence, the simulations show the market adjustments when supermarkets become more or less competitive, while other outlets' prices remain fixed. Because supermarkets were dominant, adjustments in the supermarket price seemed reasonable to show how consumer mobility was adjusted.

Overall, prices did have a relatively small impact on the outlet mobility. This is especially interesting when compared to the previous charts where larger probability shifts were seen when considering cut sizes. Among the different types of beef cuts purchased by the households, ground beef, steaks, and roasts accounted for 88% of the total purchases. Although a 5 percentage point drop on the probability of going to supermarkets might appear relatively small, the offsetting gains to the other outlets represent substantial increases in the probabilities. Also, given the small price effects, one would expect the meat type estimates in the original logit model to be primarily reflecting different meat types and less so the impact of price differences.

Volume Discounting and Outlet Mobility

In Table 7 multinomial logit models were estimated for each meat cut but replacing the beef cuts with actual prices. Because price and cut size are included in these new logit estimates, questions about potential endogenous problems with these two variables become an issue. Specifically a portion of the size effect may be due to volume discounting, that is, the size effect is reflecting per unit price discounts. If the estimated shifts in probabilities associated with cut size were totally caused by volume discounting, the equivalent change in probabilities should be seen by increasing or decreasing the price variable. Yet consumers may change their purchasing outlets when buying large cuts for reasons extending beyond the volume discounts. Knowing the relative importance of the cut size beyond the price effects has important management implications.

Given the *j* outlets and *i* beef cuts, if the price in the logit model is related to the purchase size, LBS, then for each beef cut the $\triangle \mathrm{Price_i}$ [Eq. (4)] represents the change in price with increases in the cut size as defined in Table 1. Because the cut sizes are binary, the price changes will be discrete values measured with the λs.

Eq. (2) can be respecified where the price replaces the beef cuts, and four equations are estimated, one for each beef cut. Let the respecified equations be written as in Eq. (5a) with the αs replacing the βs from the original Eq. (1). In Eq. (5a − 5b), h_{ij0} represents the effects with the smallest cut size, and h_{ij1} is the addition effect as different cut sizes are considered. Once the coefficients for h_{ij0}, h_{ij1}, and the λs are known, then it is possible to separate out the price discounting component of the purchase size effects on outlet mobility. Given the volume discounting suggested with Eq. (4), then h_{ij2} [Eq. (5c)] provides the resulting price discount effect on the probabilities, where for the three size changes, $h_{ij2} = \delta_{ij1}\lambda_{i1}$, $\delta_{ij1}\lambda_{i2}$, or $\delta_{ij1}\lambda_{i3}$.

$$
\begin{aligned}
\mathrm{Price_i} &= \lambda_{i0} + \sum_{k=2}^{4} \lambda_{i(k-1)}\mathrm{LBS_k} + \varepsilon_i \\
\hat{\Delta}\ \mathrm{Price_i} &= \sum_{k=2}^{4} \lambda_{i(k-1)}\mathrm{LBS_k}
\end{aligned}
\tag{4}
$$

As already established with Figs. 3a and b, the probabilities of using different outlets change with the cut size. First the change in the probability of using different outlets will depend on the cut size by using h_{ij0} and h_{ij1}, as illustrated with Eq. (6a) where $\triangle_1$ compares the probabilities to the smallest cut size (i.e.,

h_{ij0}). In Eq. (6a) the size effect h_{ij1} represents the combined effects of size, including any price benefits associated with the larger volumes. If prices drop, there may be less reason to shift outlets, hence the price discounting captured with h_{ij1} may be somewhat smaller than would be seen without the price effect. If the discount exists, then a second comparison would show what the size effect would have been after compensating for the price discount (i.e., adding h_{ij2} back to the equation.) In Eq. (6b) $\triangle_2$ shows the resulting change in probability of using outlet j after compensating for the price discount associated with the larger cut sizes. Let $h_{ij1} = h_i^* - h_{ij2}$, where both h_{ij1} and h_{ij2} are now known and h_i^* is the effect of size cut without the price discounts or $h_i^* = h_{ij1} + h_{ij2}$. If the λ_{ik-1} in Eq. (4) were zero, then $h_{ij1} = h_i^*$, and any impact from the size cuts is not from price discounting. Whereas, if $h_i^* = 0$ then $h_{ij1} = h_{ij2}$, any change is strictly associated with pricing. Comparing the probability changes between $\triangle_1$ and $\triangle_2$ provides a direct way to separate the price discounting effect (if any) from other effects associated with larger cut sizes.

$$h_{ij0} = \hat{\alpha}_{ij0} + \sum_{k=2}^{4} (\hat{\alpha}_{ij(k-1)}INC_{ijk} + \hat{\alpha}_{ij(k+2)}HSZ_{ijk} + \hat{\alpha}_{ij(k+5)}DQTR_{ijk})$$

$$+ \sum_{k=2}^{3} (\hat{\alpha}_{ij(k+8)}MSA_{ijk} + \hat{\alpha}_{ij(k+10)}EMF_{ijk} + \alpha_{ij(k+12)}AGF_{ijk}) + \delta_{ijl}PRICE_{ij} \tag{5a}$$

$$h_{ijl} = \sum_{k=2}^{4} \delta_{ijk}LBS_{ijk} \tag{5b}$$

$$h_{ij2} = \delta_{ij1}(\hat{\Delta}\ Price_i) = \delta_{ij1}\left(\sum_{k=2}^{4} \lambda_{i(k-1)}LBS_{ik}\right) \tag{5c}$$

Eq. (4) for each beef cut and the multinomial logit models represent a classic recursive system where the price/volume equation is to obtain the λs and then the logit models are estimated

$$\Delta_1\ Prob(y = j|\Delta LBS,i) = \left(\frac{\exp^{h_{ij0}}}{\sum_{j=1}^{5} \exp^{h_{ij0}}} - \frac{\exp^{h_{ij0}+h_{ij1}}}{\sum_{j=1}^{5} \exp^{h_{ij0}+h_{ij1}}}\right) \tag{6a}$$

Table 8. Volume Discounting Estimates Across Meat Cuts (See Equation (5))

	Volume Discounting Coefficients				
	λ_{0i}	λ_{i1}	λ_{i2}	λ_{i3}	R^2
Ground Beef	2.0631	−0.2378	−0.5484	−0.6820	0.1298
	360.84660	−37.85041	−84.1630	−89.2828	
Steaks	3.1315	−0.42747	−0.6988	−0.6886	0.07551
	418.8129	−44.2073	−64.7400	−38.1632	
Roasts	2.5970	−0.5079	−0.6870	−0.7804	0.01648
	44.3003	−8.5245	−11.6826	−12.9735	
Other	2.7982	−0.3793	−0.7020	−0.8866	0.0990
	217.4065	−25.0398	−43.1930	−39.2255	
	Percent Discount from Smallest Unit size				
	Under 1 Pound	1 to Under 2 Pounds	2 to Under 5 Pounds	5 Pounds and Over	
Ground Beef	0.00%	11.53%	26.58%	33.06%	
Steaks	0.00%	13.65%	22.31%	21.99%	
Roasts	0.00%	19.56%	26.46%	30.05%	
Other	0.00%	13.55%	25.09%	31.68%	

$$\Delta_2 \, \mathrm{Prob}(y = j|\Delta \mathrm{LBS}, i) = \left(\frac{\exp^{h_{ij0}}}{\sum_{j=1}^{5} \exp^{h_{ij0}}} - \frac{\exp^{(h_{ij0}+h_{ij1}+h_{ij2})}}{\sum_{j=1}^{5} \exp^{(h_{ij0}+h_{ij1}+h_{ij2})}} \right) \tag{6b}$$

the traditional way (Davidson and MacKinnon, 1993, p. 643; Green, 1997). Price and cut size are independent of the residuals because the equations are recursive (i.e., there is not feedback as occurs in a simultaneous system). Hence, the coefficients for the price discounting equations (λs) can be used along with the logit estimates to derive the relative size discounting effects in $\triangle_1$ and $\triangle_2$.

Table 8 provides the resulting Ordinary Least Squares estimates for Eq. (4) for each beef type. For each equation, the impacts from the unit sizes (LBS) were statistically significant and had the expected negative signs. Yet for each beef cut, the amount of price variation accounted for any unit size was small as seen with the low R^2. That is, while there are volume discounts, prices show major variation independently of the unit size. The bottom portion of Table 8 expresses the price discounts in percentages with the maximum usually in the range of 30%. Considering steaks as one example, prices are discounted 14% between the smallest cut and from 1 to 2 pounds. Beyond 2 to 5 pounds, there is little additional discounting (i.e., the percentage discounts from 2–5 pounds and 5+ pounds are very close).

Table 8 shows that the discounting is present. Then using Eqs. (6a and b), the relative importance of these results can be shown. Figs. 5a-d show the changes in the

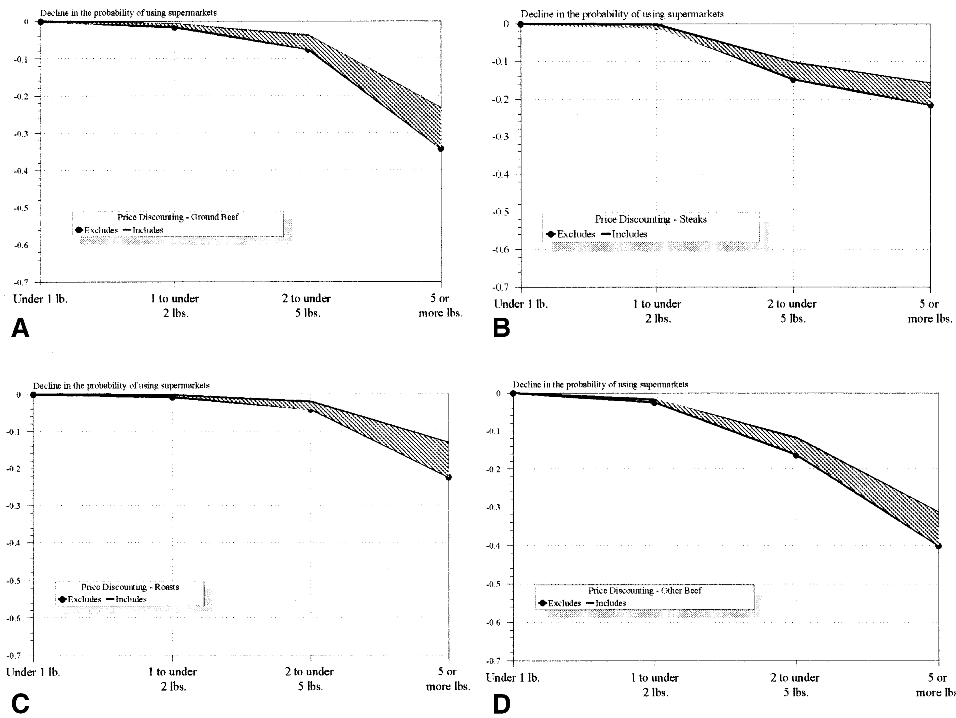

Figure 5. Changes in supermarket probabilities with and without price discounts with 5a representing ground beef; 5b, steaks; 5c, roasts, and 5d all other beef.

probabilities ($\triangle_1$ and $\triangle_2$) of using supermarkets. In each figure, the bottom axis is the change in cut size, while the left axis is the change in probability of buying through supermarkets. The scales are kept the same across the four graphs so they can be easily compared. The upper line is the $\triangle_1$, or the change in probability with the price discounts included, while the lower line is $\triangle_2$, or the change in probability after compensating for the price discount or holding the effective purchasing price fixed. The shaded area in each plot is the change in probability after removing the price discounting effects from the unit size impact. The fact that these shaded areas are generally quite small indicates that a large portion of the effect of unit size is not related to the impact of volume discounts. Clearly, the probability of using supermarkets declines as larger unit sizes are purchased. Yet even after compensating for the price discount effects, the importance of unit size is still apparent. That is, the probability of using supermarkets when buying larger cuts will occur even if prices are not discounted. Something else associated with buying larger sizes is attracting buyers away from supermarkets. To illustrate, in Fig. 5b the probability of using supermarkets for buying steaks declines by 10 and 16 percentage points for the larger two cuts (i.e., 2–5 pounds and 5 pounds and over). Holding the equivalent price fixed ($\triangle_2$) the probability changes are 15 and 21 percentage points. Clearly, for the larger cuts consumers are more mobile, and the probability of using supermarkets goes down, yet most of the decline is not attributed to price discounting. Although price discounting is important, consumers shift outlets as they purchase larger beef sizes for reasons beyond the unit price benefits (Wavner and Barsky, 1995).

Implications and Conclusions

Consumers' willingness to switch outlets when buying food can be a major element contributing to the relative competitiveness of retail outlets. If consumption decisions are rigid and persistent purchasing habits prevail, then consumer mobility or willingness to switch sources can be quite limited. Are consumers likely to switch outlets when shopping for basic food items such as beef? If they are, what factors influence these decisions? Answers to both of these questions are important to retail managers to deal with consumers and to food industries such as beef producers. Outlet marketing behavior and management strategies are directly tied to the degree of consumer outlet mobility. If there is very little chance of consumers reducing their use of supermarkets, then pricing, marketing, and services strategies should be considerably different. Thus consumer mobility, much like the theory of barriers to entry and exit, can have profound influences on the dynamics of the outlets and how they need to behave to encourage entry or discourage exit. In general, analyses shows both the importance of the consumers characteristics (demographics) and the attributes of the product being purchased.

An unordered, multinomial logit model of outlet choices was used to evaluate the impact of demographics, seasonality, types of purchases, price, and quantities on consumers' selection of outlets for beef. Empirical results indicated that the type and size of beef purchased are major factors influencing the outlet choice. Income levels, household sizes, women's employment levels, and prices also have an effect on the outlet choice. Supermarkets continue to maintain a high probability of being used as the primary meat outlet. Yet consumers do shift outlets when buying large beef cuts. The probabilities of using supermarkets decline as large unit sizes are purchased, and the loss by supermarkets is captured by warehouses and butchers. Supercenters, although growing in total dollar volume, show little gain when supermarkets are less likely to be chosen. Demographics are mostly important when considering large unit sizes. Household buying habits differ across demographic characteristics, but the total impact is quite small for those households buying the small cuts. In contrast, the variation in outlet selection is more than four times as great when considering those buying the largest cut sizes. That is, household entry and exit among the outlets is far greater over the demographics as the purchasing sizes increase. Clearly from a marketing standpoint, to either encourage or discourage outlet mobility, any outlets targeting consumers who are buying the larger units have the greatest potential for impacting consumer mobility. This can be particularly important to management policies when developing consumer-targeting programs. Profiles of households where the probability of using, for example, supermarkets is below a certain level can be identified. This way, supermarkets are able to target this group of consumers to try to increase the likelihood of shopping in their outlets. If the outlet is primarily catering to households making small purchase sizes, then there is less need to be concerned about market exit across any of the outlet alternatives.

Pricing is important, and the models show both the direct price effects and the indirect price effects through volume discounting. Beef prices were shown to drop as the cut sizes are increased. Price discounting was empirically linked to four cut sizes giving a maximum discount of nearly 30% for some beef types. The price discounting component, when using the logit estimates, was shown to be a relatively small part of the impact of the purchase sizes. That is, consumers were shown to switch outlets when buying larger beef sizes, even after removing the price discounting component from the model. Clearly, the need to buy larger sizes drives households to become more mobile in their outlet decisions, and the willingness to shift outlets is greater than what would be attributed to just discounted prices. Although we have not identified the other factors, it is clear that consumers seek other outlet alternatives with the motivation to switch tied to both price and nonprice considerations. This is usually true only when buying the large cut sizes. Price discounting is important, but is clearly not the driving force.

These empirical models are particularly important for dealing with issues associated with competitiveness and the likelihood that consumers are or are not willing to make changes. Furthermore, the models provide the bases for management strategies when considering targeting specific groups of consumers based on demographics. Impacts associated with competitive pricing have been shown, and the results generally indicate that potential gains are greater when targeting consumer profiles compared to relative competitive pricing. There were more changes in outlet mobility associated with demographic differences than with variations in prices. However, in every case the potential for change was uniquely tied to the purchase size.

NOTES

1. Seasonality was defined such that the four seasonal coefficients sum to zero. Then each seasonal coefficient was estimated where: Quarter 1: $\beta_{j0} - \beta_{j13} - \beta_{j14} - \beta_{j15}$; Quarter 2:

$\beta_{j0} + \beta_{j13}$; Quarter 3: $\beta_{j0} + \beta_{j14}$; Quarter 4: $\beta_{j0} + \beta_{j15.}$ Hence, β_{j0} represents an overall average across seasons instead of just one of the four quarters.

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