Evidence of Changes in Preferences Among Beef Cuts Varieties: An Application of Poisson Regressions

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The U.S. beef industry has focused much of their marketing efforts in providing a wide range of improvements in terms of variety, quality, convenience, and product consistency. Often this occurs through efforts to achieve some differentiation by marketing base on specific product attributes (e.g., Coleman Natural Beef, Harris Ranch Beef, Angus Beef, etc). Clearly, consumers must understand these attributes. Meat products in general, and in our case beef cuts, can be differentiated according to how consumers perceive product attributes, how these attributes affects the product's performance, and how important these attributes are to potential consumers. Demand for convenience, nutrition, and variety should be reflected through both total consumption and the number of beef cuts purchased in any one buying occasion. That is, the number of beef cuts (e.g., hamburgers, steaks, roast, etc.) purchased in a food shopping experience provides one indicator of consumers' preference set for beef in its widening range of forms (Van Osselaer and Alba, 2000). While recognizing that the number of cuts is but one of several measures of consumers' meat preference, this study specifically focuses on the desire for variety through measuring the number of beef cuts actually purchased in each buying event. As an initial step, we have limited this part of the research just to measuring the likelihood of buying one, two, three, or more numbers of cuts in each setting without dealing with the type of cuts and the pounds. Clearly, after measuring the desire for variety; the next step is to determine what fulfills that desire (i.e., beef form) and how much.

Previous studies have shown that demographics and health concerns are important demand drivers along with prices, competing foods, and information (Economic Research Services, 1994; Ward, 2004). For example, if health is an important issue for the consumer while shopping for beef products, he or she will more likely make a purchase depending on how the attributes of the available beef cuts are associated with the nutritional considerations. Likewise, any reduction in searching costs by offering greater varieties should contribute to a greater number of beef cuts purchased. Martinez and Stewart (2003) suggest that time-pressed consumers purchase more on convenience, while looking for quality, variety, and value. Barkema (2001) indicated that consumer demand for food is shifting toward products that are easy to prepare while also promising safe eating, improved nutrition, and greater consistency.

Are consumers' purchasing habits for beef consistent with the expectation of desiring more convenience, having more options, and having the ability to match the products with specific health concerns? Using a sample selection model, consumers' preferences for beef cuts are measured using a combination of limited dependent variable models. In an initial step, a logit model is specified to generate a sample that includes only meat consumers. Then, in the second step, Poisson regression models are introduced to calculate the probabilities of the number of purchases. Step one generates the regime choice as a binary outcome, while in the other generates the count variable, which represents levels of consumption among beef cuts (Green, 1994).

Household Consumption Diaries

Using household consumption diaries from a database maintained and marketing by the National Panel Diary Group (NPD), a total of 95,559 households reported their meat consumption activities on a two-week (wave) purchasing cycle covering the periods from September 1992 through August 2000. NPD is a private data management system where households are moved in and out of the sample in order to maintain a demographically representative sample. Since households move in and out of the base, the household demographics are the differentiating characteristics among households, not the specific household identity. That is, we are not pooling cross sections over time since the cross sections change frequently within the data set.

Figure 1 illustrates the distribution of consumer beef cuts purchased among the 95,559 households reporting since 1992. An estimated 14.1 percent of the households indicated no beef consumption during a reporting wave. Among those average households consuming some beef, 27.1 percent only purchased one beef cut in a buying occasion and 26.6 percent purchased two types of cuts. As would be expected, the remaining percentages drop off rapidly.

The average distributions should differ across households, possibly over seasons and over time. Therefore, identifying and measuring the effects of household demographics and time is of primary interest. For example, are changes in the varieties of beef reflected with changes in the distribution shown in Figure 1?. In the left columns of Table 1 we have identified several variables that profile the household characteristics and measure the change through time. DCUT represents the number of beef cuts purchased. Income (INC), household size (HWZ), age of the respondent (AGE), presence of children (CHD), education level (EDU), and occupation (OCC) correspond to a set of explanatory terms representing household demographics. Geographic characteristics of the respondent and adjustments across time are captured with the region of the country (STA), market size (MSZ), seasons (MTH) and years (YRS). All these variables are binary and are included in the subsequent models using the restrictions that the sum of the coefficients for each dummy equals zero to deal with the singularity issue with dummy variables (Ward and Ferrara, 2005).

Estimating Purchasing Frequencies

Purchase processes are generally assumed to be a renewal process. Variables that report a frequency are often treated using count data models (Long, 1997). Count data models have been applied in various research disciplines such as agricultural economics, political science, and medical sciences. Examples include the number of times that shoppers decide to purchase irradiated meat products (Rimal et al, 1999), modeling household purchases (Pelzer et al, 1991), and estimation food expenditures on bulk purchases (Peña and Ruiz, 1998). Such studies involve truncated data sets because only those who consume beef at least once are included in the analysis (Okoruwa et al, 1998). In contrast to these studies, the current database includes those households who also did not purchase beef in a particular buying occasion.

The objective of this research is to estimate the demand for beef cut varieties using a limited dependent variable model that accounts for both participation and consumption decisions. For this purpose, it is useful to consider the process as two separate choice events: first, the decision of whether or not to consume meat products and second, conditional on consumption, the decision of the number of beef purchases during that particular period.

For this research, a count-identification model for beef consumption is estimated jointly using a zero-inflated Poisson regression (ZIP) for the frequencies and using a truncated logit regression for the consumption of beef products. The joint modeling is accomplished by assuming that conditional on independent variables ($x_i's$) the dependent variables ($y_i's$) are stochastically different. Under this scenario, the dependency (beef consumer) is captured through the ($x_i's$), and the joint-likelihood factors provide a component for consumption and another for count or number of purchases (Cameron and Trivedi, 1998).

A major objective in the analyses of truncated data is to estimate the underlying (latent) population demand for beef cut products. Following Green (2003), the analysis includes a logit model that determines whether a zero or a nonzero consumption outcome occurs and it is given by using "i" to denote the observations:

$$y_i^* = f(x_i \beta) + u_i \tag{1}$$

Let $y_i^*(Pounds)$ be the count variable of interest and define the indicator variable for the Poisson regression as:

$$DCUT\begin{cases} = y_i & if \quad y_i^* > 0 \\ = 0 & if \quad y_i^* \leq 0. \end{cases} \quad and \quad DDCUT\begin{cases} = 1 & if \quad DCUT = 0 \\ = 0 & if \quad DCUT > 0 \end{cases} \tag{2}$$

where x_i is a row vector that represents the full set of demographic and non-demographic variables that might affect the frequency of purchase (see Table 1); β is a vector of parameters, and u_i is the residual term (Gujarati, 2003). The response variable is qualitative in nature and can take only two values: 1 or 0 thus, consumption is only observed if $y_i^*(Pounds)$ is greater than zero. Once the sample selection is performed, the Poisson regression model is used to examine the non-linear relationship between the frequency of purchase, the variety of purchase, and the factors that may influence consumers' preferences. In general, the probability of an individual not consuming beef; and consequently not buying one or more beef cut varieties is:

$$\Pr[DDCUT_i = 1] = \frac{\exp(x\delta)}{1+\exp(x\delta)}. \tag{3}$$

Using a more detailed specification proposed by Cameron and Trivedi (1998) and Greene (2003), the number of beef cuts purchased and the probability distribution can be formulated as follows:

$$\Pr(DCUT_i = y_i | x_i) = \frac{e^{-\lambda_i}(\lambda_i)^{y_i}}{y_i!}, \qquad y_i = 1,2,\ldots..k \tag{4}$$

where $\lambda_i = \exp(x\beta)$ letting y_i denote the number of cuts DCUT.

To be more specific, we assume that individual quantity demanded y_i is a random draw from a Poisson distribution with a mean λ_i which in turn, is assumed to be a function of parameters β and a vector of individual specific explanatory variables x_i (Haab and McConnell, 1996). In equation (4) the equation $\ln\lambda = \sum_{j=0}^{k}\beta_{ji}x_{ji}$ corresponds to a set of dummy variables with their respective coefficients along with the intercept. Given the limited space, Table 1 includes the Poisson coefficients for the second stage of the model along with the supporting t-values. Almost all variables are statistically significant and have the expected signs (i.e., when the signs could by hypothesized). Since, the variables can be statistically significant but numerically unimportant, we will use the results from Table 1 to concentrate on the probabilities of each level of beef purchases (i.e., counts) and express the response to each variable relative to the average.

The estimation of the mean predicted probability is of particular importance in order to compare the observed proportions of the sample at each count, and summarize the predictions of the model. The predicted probabilities for the average consumer can be computed for each observation and for each count (DCUT) that is of interest (Long, 1997) as follows:

$$\overline{\Pr}(y_i = DCUT) = \frac{1}{K}\sum_{i=1}^{K}\hat{\Pr}(y_i = DCUT \mid x_i) = \frac{1}{K}\sum_{i=1}^{K}\frac{\exp(-\hat{\lambda}_i)\,\hat{\lambda}_i^{y_i}}{y_i!} \tag{5}$$

Poisson regression models show a very restrictive but convenient theoretical characteristic, that is, its conditional mean is equal to its conditional variance which represents the main property of the model. As a result, the conditional mean of (y_i) measures the average consumption given the probability of observing a positive consumption,

$$(E[y_i \mid x_i\beta]) = (Var[y_i \mid x_i\beta]) = \lambda_i\,. \tag{6}$$

However, many times this assumption is not satisfied and the variance is greater than the mean, which is often the case when zero event counts are dominant or represent a large number of observations of the sample set. Individuals show unobserved heterogeneity when expressing their experiences regarding an event in particular, and this heterogeneity leads to overdispersion; that is, the actual variance of the process exceeds the nominal Poisson variance even after regressors are introduced (Cameron and Trivedi, 1998). To account for the over-dispersion, we can use a Negative Binomial as a Gamma mixture of Poisson random variable that accounts for over-dispersion by adding a parameter alpha. The negative binomial distribution adds a quadratic term (α) to the variance function $(\lambda + \alpha\lambda^2)$ representing the overdispersion. As such, the key to modeling the effect is to introduce the unobservable into the model which, in the case of the negative binomial arises if it is assumed that the unobserved heterogeneity, λ_i, has log gamma distribution. Selectivity would arise if the unobserved heterogeneity in this conditional mean is correlated with the unobservable in the sample selection mechanism (Green, 2006). Following Cameron and Trivedi, 1998, the negative binomial model takes the form:

$$\Pr(DCUT_i = y_i | \lambda_i, \alpha) = \frac{\Gamma(y_1 + \alpha^{-1})}{\Gamma(\alpha^{-1}) y_i!} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda_i} \right)^{\alpha^{-1}} \left(\frac{\lambda_i}{\alpha^{-1} + \lambda_i} \right)^{y_i}, \alpha \geq 0, \; y_i = 1,2,\ldots..k \qquad (7)$$

This reduces to the Poisson if $\alpha = 0$. The larger the value of α the more variability is in the data that is associated with the mean λ_i.

While the full results are not reported in Table 1, a negative binomial (α) coefficient was included showing an alpha (α) parameter consistent (almost zero) with the Poison regressors, hence the negative binomial parameter estimated equals the Poisson estimates (β) and the LR test statistic take a value equal to zero. As a result, the conditional mean is correctly specified and there is not overdispersion (see Table 1). Poison estimates yield consistent parameter estimates, with nearly all t-values showing highly significant results which, indicating the statistical importance of each of the variables included in the model.

Poisson Beef Cuts Model Estimates

While almost all demographic variables in Table 1 show statistically significant impacts, numerically not all of them are expected to have an important effect on the likelihood of buying one or more beef cuts. The large sample size allows high levels of significance among coefficients with almost 65% of them being significant at the 5% level or lower. Estimates also show a small R^2 coefficient, which doesn't represent a concern in this model considering the number of observations. The log likelihood value for frequency of purchase (-118,569) lead to the inference of a significant systematic relationship between the independent variables and the number of beef cuts purchased (DCUT), and consistent with the LR test, all coefficients are significantly different from zero at the 0.05 significance level.

The significance and numerical effect of parameter estimates from the models used in this study are particularly noteworthy, and tend to confirm that there is no evidence of change in consumers' aptitudes or preferences toward purchasing one or more beef cuts over time. As parameters' coefficients indicate, the quantity of cuts purchased among beef consumers are more likely to be affected by factors related to the number of people living in the household, the profession of the respondent, his/her age and education.

For instance, at lower levels of education coefficients clearly show the negative effect on the number of cuts purchased which, might signalize the strong effect of income-education on the quality and quantity of beef purchased, assuming that people with higher levels of education have higher income levels and assuming that more beef varieties implicitly refer to different quality levels. These results also indicate that a single respondents or couples have a negative propensity to purchase more than one variety. Conversely, estimated coefficients on household size of more than three are positive and statistically significant, suggesting that in the case of large families, the household's head might be interested in large number of beef cuts to satisfy the preferences in terms of variety, convenience, and quality.

On the other hand, the effects of the respondent's age are consistent and indicate that the impact of people aged 40 years and younger is small when purchasing for more than one beef cut. However, the estimated coefficients on age for respondents aged 40 years and older have a positive sign, indicating a strong relation between age and the number of cuts (i.e., two or more cuts). Outputs from all other variables included in this research indicate that almost all of them have a significant impact on the frequency of buying beef products but, considering their small numerical value, they are not discussed in detail. In general, the estimates reported here are very revealing in terms of life styles and might explain the tendency among beef consumers to relate a particular beef product with certain attributes that are expected while shopping beef cuts for a particular occasion.

Probability of Beef Cuts Purchase

Results from equation (5) show the predicted change in the conditional mean if the k^{th} regressor changes by one unit. Thus, for the average consumer, the likelihood of buying beef products is more than 85 percent (probability of zero consumption is 14.1 percent) and that the probability of buying one, two, three, four, or five beef cut varieties are 27.1 %, 26.6 %, 17.7 %, 9%, and 3.7 % respectively (Figure 1). In order to show the impact of each variable included in Table 1 and equation (5), a useful approach is to express the likelihoods for each beef cut relative to the average probability for each category in order to interpret the range and extension of the response (Ward and Ferrara 2005). To facilitate the interpretation of the probabilities, a ranking of the impacts of each variable is presented in Figures 2 and 3 showing the differences between the most negative effect and the most positive effect of each variable while holding all other variables to their mean values. The differences were then sorted in descending absolute magnitude, thus giving a quick way to rank the impacts of each variable included in the Poisson regression thus showing the variables creating the largest impacts on beef buying to those variables with the least impact.

At this point of the analysis it is important to reiterate that even the fact that almost all the variables included in the model showed statistically significant impacts, numerically the range of effects on the likelihood of the number of cuts purchased were quite small relative to the average probability. However, results clearly show the importance of the household size, occupation (profession), and age in terms of purchase probabilities. In the case of two cuts purchase, this sequence is altered due to the larger effect of education comparing to the age of the respondent but, in general the numerical effect of this demographic is almost imperceptible. Reading the figures, the "number of people in the household" is ranked first (most likely to influence) in all categories with ranges fluctuating within 8 percentage points, as in the case of one beef cut, to 1 percentage point in the two beef cut category. These results are somehow expected because of the difference in preferences among household members and in particular when young and older people coexist. Next, occupation of the respondent can impact the likelihood of purchasing from 1 to 5 percentage points, depending on the number of cuts considered. For one cut, this range is five points; for three and four cuts, 3 points; and for two and five cuts, one point. Note that respondents with higher level of responsibility (manager and proprietors) and more education (professionals and students) are more likely to purchase less variety which, might entail an inclination for a particular beef cut that contain the attributes to satisfy their expectations in terms of health and safety. Age of the respondent present relative low significance when buying one or more beef cuts yet, it might imply that older people have a positive tendency to purchase more variety, in particular cuts with characteristic of convenience and lower fat levels. Individuals over 40 years of age have an increasing probability of purchasing more than one variety. A study by Capps et al in 1988, suggest that consumers older than 30 years of age are more likely to try lean meat products than consumers from 20 to 29 years of age. Therefore, consistent with our results, older people seem to be more health conscious in their eating habits than younger people. Regarding the effects of occupation, the results interestingly suggest some consistency in the probability of buying more beef cuts for respondents in low skilled professions. The estimated coefficients on these categories have a positive sign and coefficients are highly significant. In contrast, respondents in professions that require more training and education show negative effect on the probability of buying more than one beef cut.

Beyond education, the impact of all other demographics and seasonal changes is relatively low with an average range between 1 and 2 units, and in the extreme case of the category for two beef cuts this range is almost zero.

Total effects of household size and occupation of the respondent variables on probabilities of purchasing beef cut varieties is clearly shown in Figure 4. As expected, in the case of household size, as the number of household members increase the probability of purchasing increase almost ten percentage points, while for household' head occupation the overall probability to affect the number of beef cut purchases varies between 83 percent (sales professionals) and 87 percent (retired respondents).

Finally, it is possible to compare the effect of those two variables across the five types of beef cuts by comparing the full range of probability change as illustrated in Figures 5 and 6. In the case of household size, with the exception of one beef cut, the probabilities of buying two or more cuts increase as the number of people living in the house increase. While, the likelihood of buying one beef cut shows a decrease of a 10 percentage point range across households' categories, Figure 5 clearly illustrates an increase of 4 to 11 percentage points when considering the likelihood of purchasing two or more beef cuts. In Figure 6 the effect of occupation presents a different trend in terms of the direction of the change in probabilities. In this case, retired respondents show the highest probability of buying two or more beef cut varieties and sales professionals the lowest, while this tendency is reverse for one beef cut purchase.

Concluding Remarks

What do these results mean for the beef industry and for consumers demand for variety within the context of the beef industry? Considerable efforts to provide variety within the product category is one way to potentially influence demand for the category such as beef. In the beef industry even the increasing role of brands is apparent where branding has almost doubled (Ward and Ferrara, 2006). As initially shown in Figure 1 the single cut is only around one-fourth of the total, thus pointing to the propensity to buy more than one cut in a buying occasion. Yet, the time dimension to the model points to little change in the probabilities across the decade of the 90's and, in fact, the probabilities of not buying beef even increased slightly. Furthermore, among those buying some beef the likelihood of buying just one cut actually increased although by a very small amount. The main story, however, is that the models point to very little change over time in terms of the distributions of count or number of cuts, and equally important is the fact that the impact of all the demographics on buying beef cut varieties is small. This is surprising given the growth with brands within the beef category and given the fundamental differences among consumers as reflected with age and income. Achieving growth in demand through varying the number of cuts appears to be quite limited to the extent that growth and the number of cuts are correlated. Again, we emphasize that the measure does not account for the pounds nor the type of cuts, just the numbers of cuts. Clearly, that is a logical extension to the analysis.

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Table 1: Demographic characteristics and coefficient estimates

Description	Variable	Name / Range	Poisson Coef. (Frequency)	t-value
Intercept			0.67191	127.162
INC: income per household (dollars)	INC1	0-24,999	0.00601	1.74381
	INC2	25,000-49,999	0.02041	7.1124
	INC3	over 75,000	-0.00030	-0.09443
	INC4	50,000-74,999*		
HWZ: household size (Number of members)	HWZ1	1	-0.21651	-53.5636
	HWZ2	2	-0.00727	-2.28741
	HWZ3	3	0.09229	27.3823
	HWZ4	4 or more*		
AGF: age of female head (years)	AGF1	Under 25	-0.04339	-4.9172
	AGF2	25 to 40	-0.03183	-7.63724
	AGF3	40 to 65	0.05186	14.1529
	AGF4	Over 65*		
CHD: presence of children(<18)	CHD1	Yes	-0.04687	-8.20437
	CHD2	None < 18*		
EDF: female head education level	EDF1	High school or less	-0.06515	-21.1174
	EDF2	Post graduate	0.03984	11.5785
	EDF3	College graduate	0.02761	7.13616
	EDF4	Some college*		
OCC: occupation householder	OCC1	Professional	0.01524	0.757587
	OCC2	Proprietor, manager	-0.02071	-3.88721
	OCC3	Clerical	-0.00570	-1.06386
	OCC4	Sales	-0.07640	-10.023
	OCC5	Craftsman	-0.01676	-2.20445
	OCC6	Operative	0.04554	8.52224
	OCC7	Military	0.00957	1.59624
	OCC8	Service worker	-0.01387	-0.89894
	OCC9	Farm related jobs	-0.00446	-0.56349
	OCC10	Student employed	-0.05997	-3.76614
	OCC11	Laborers	0.07735	6.43658
	OCC12	Retires, unemployed*		
STA: Regions (based on census)	STA1	New England	0.04351	7.01564
	STA2	Middle Atlantic	0.02947	7.11567
	STA3	East North Central	-0.01041	-2.59509
	STA4	Pacific	-0.01164	-1.99667
	STA5	South Atlantic	0.01013	2.59085
	STA6	East South Central	-0.02645	-4.4275
	STA7	West South Central	-0.01891	-3.68935
	STA8	Mountain	-0.00582	-0.87087
	STA9	West North Central*		
MSZ: Market Size (number of people)	MSZ1	50,000-249,999	-0.04793	-9.69358
	MSZ2	250,000-499,000	0.02803	6.42188
	MSZ3	500,000-999,999	0.02310	5.20861
	MSZ4	2,500,000 or more	0.00858	2.51394
	MSZ5	1,000,000-2,499,999	0.01116	3.24035
	MSZ6	Non market size*		
MTH: months	MTH1	Jan	0.04360	7.99677
	MTH2	Feb	0.00665	1.21613
	MTH3	Mar	0.04192	7.65656
	MTH4	Apr	-0.00875	-1.59424
	MTH5	May	-0.00186	-0.34669
	MTH6	Jun	-0.01266	-2.37025
	MTH7	Jul	-0.01958	-3.62112
	MTH8	Aug	-0.00977	-1.81572
	MTH9	Sep	0.00543	1.00234
	MTH10	Oct	0.02107	3.81695
	MTH11	Nov	-0.04365	-7.43509
	MTH12	Dec*		
YRS: Years (1992: 2000)	YRS1	1992	0.00844	0.897219
	YRS2	1993	0.02055	4.55507
	YRS3	1994	0.02768	6.21516
	YRS4	1995	0.01483	3.31003
	YRS5	1996	0.01485	3.31477
	YRS6	1997	0.00677	1.49636
	YRS7	1998	-0.02123	-4.68136
	YRS8	1999	-0.03224	-7.06163
	YRS9	2000*		
alpha (α): Negative binomial coefficient	-------	------	0.00050	0.09454

***Normalized on the last category of each explanatory variable**
Period: 1992:9 - 2001:8
N. of obs. = 95,559
N. pos. obs. = 80,839
% Positive obs. = 0.845676

R-squared = .077776
Scaled R-squared = .048904
Overdispersion test = 190.32
Log likelihood = -118569
LR = 3003.12

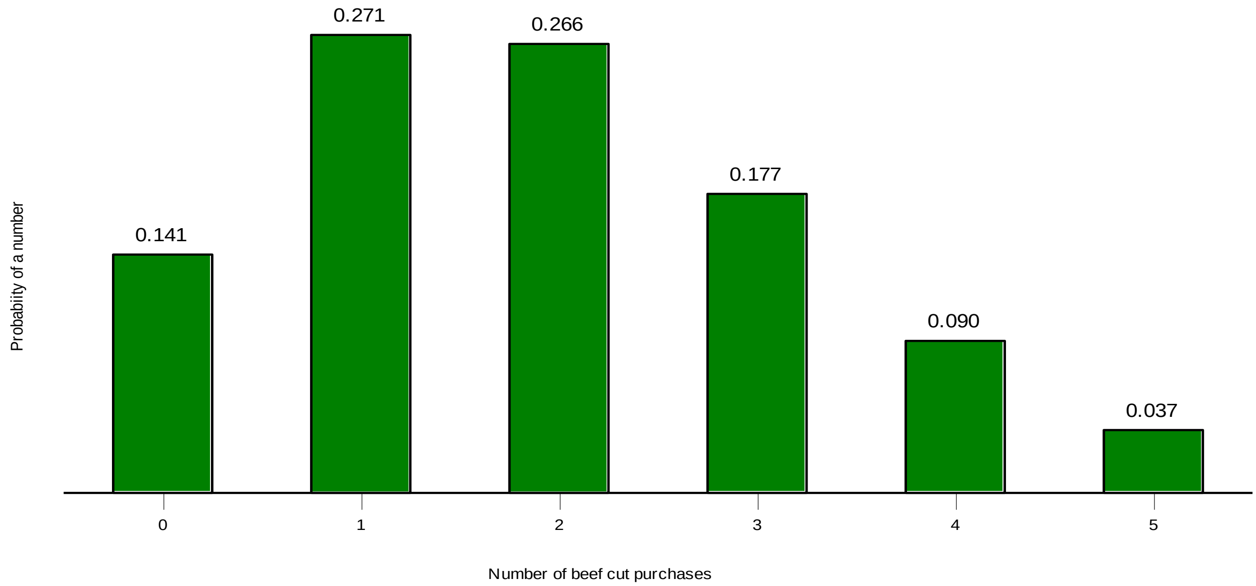

Figure 1: Average probability of buying one or more beef cuts across income categories.

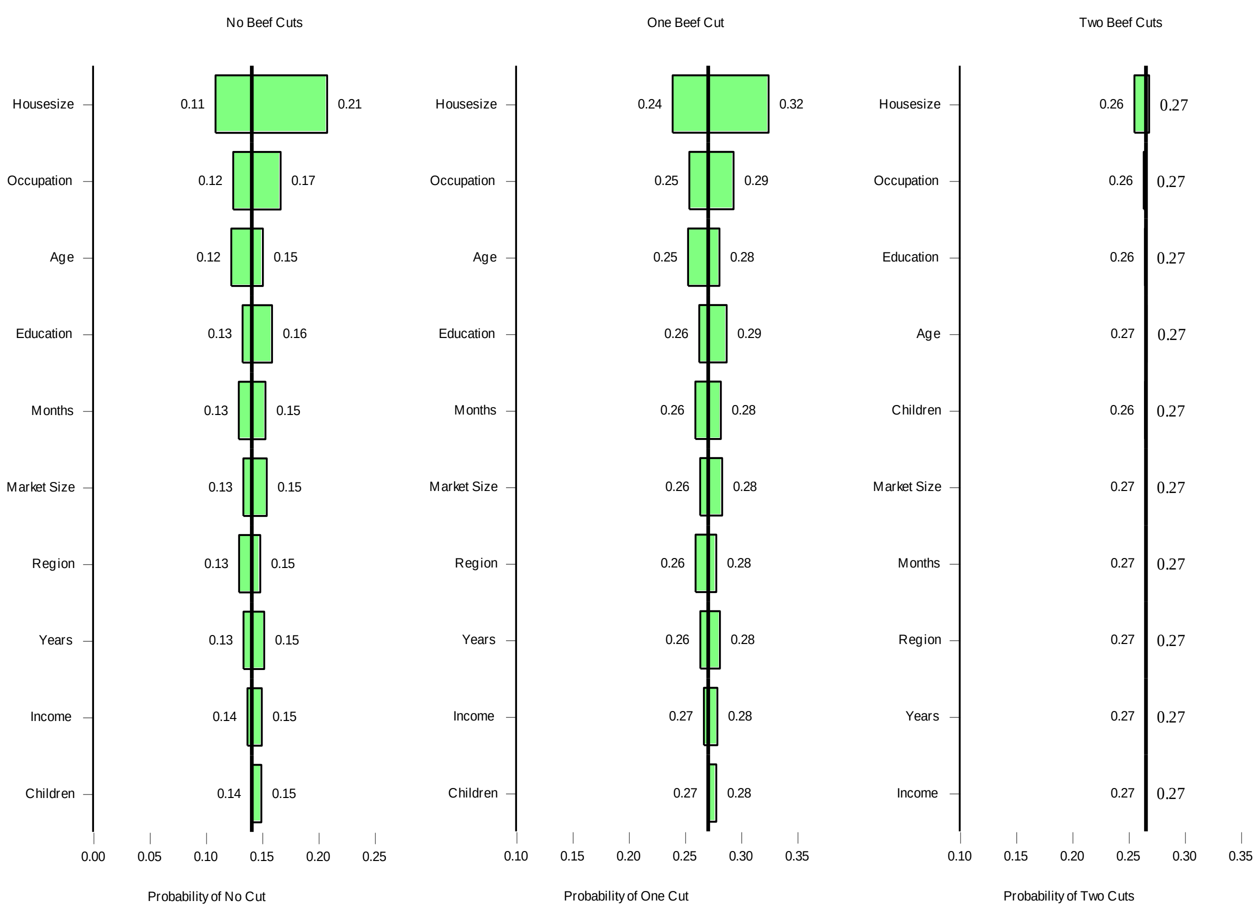

Figure-2: Range from the average probability of zero, one or two beef cut purchases

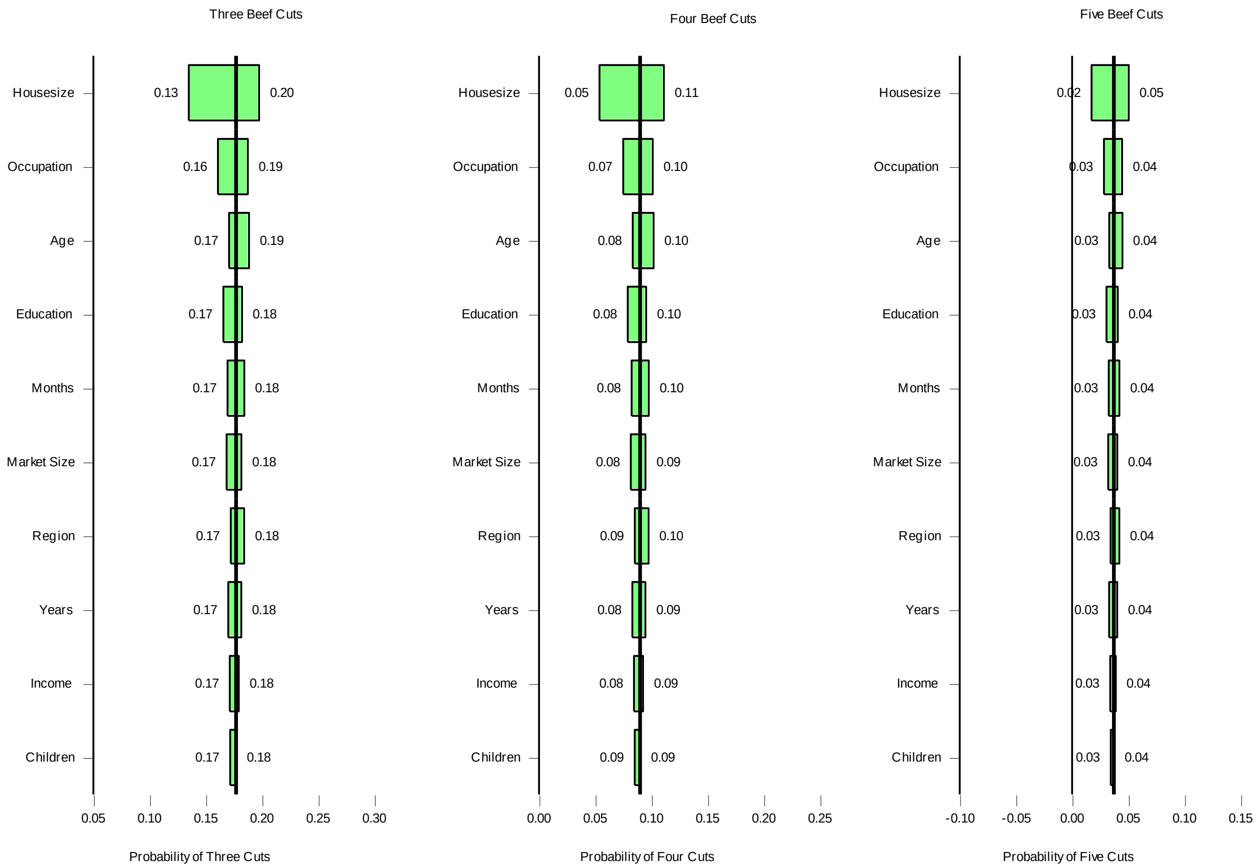

Figure-3: Range from the average probability of more than two beef cut purchases

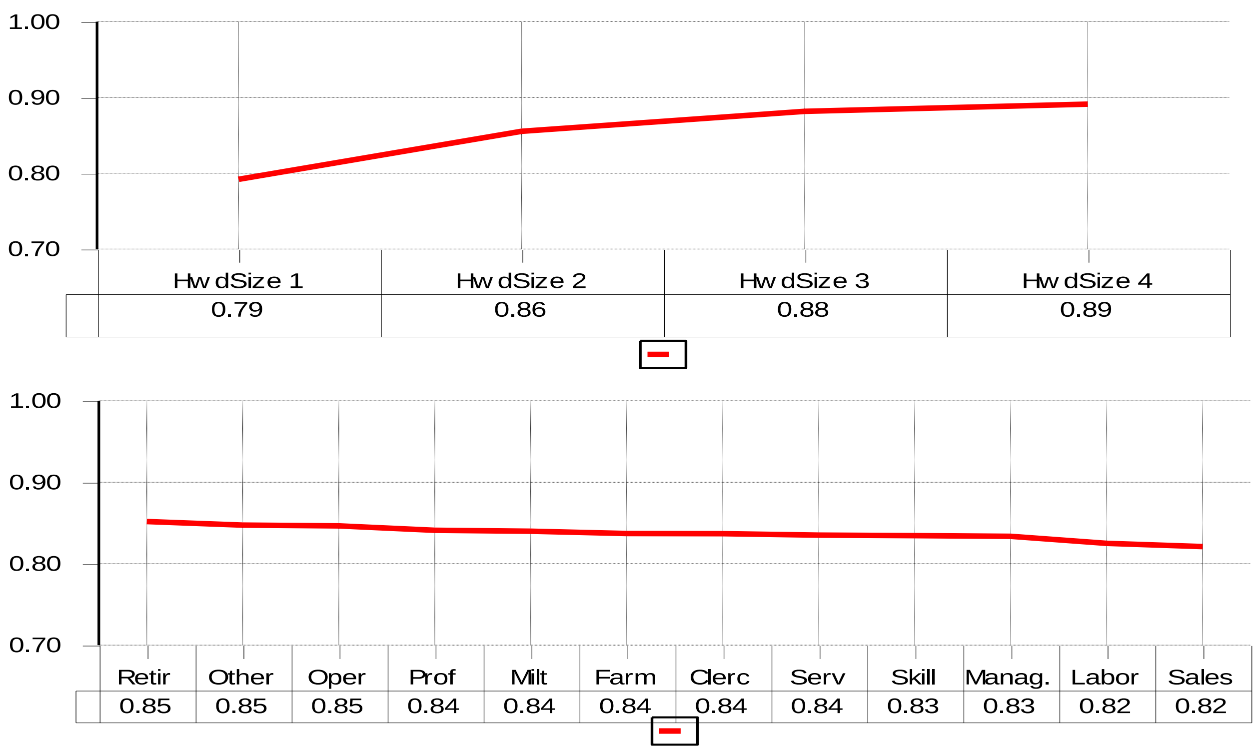

Figure 4: Overall effect of household size and occupation on the probability of buying beef cut varieties

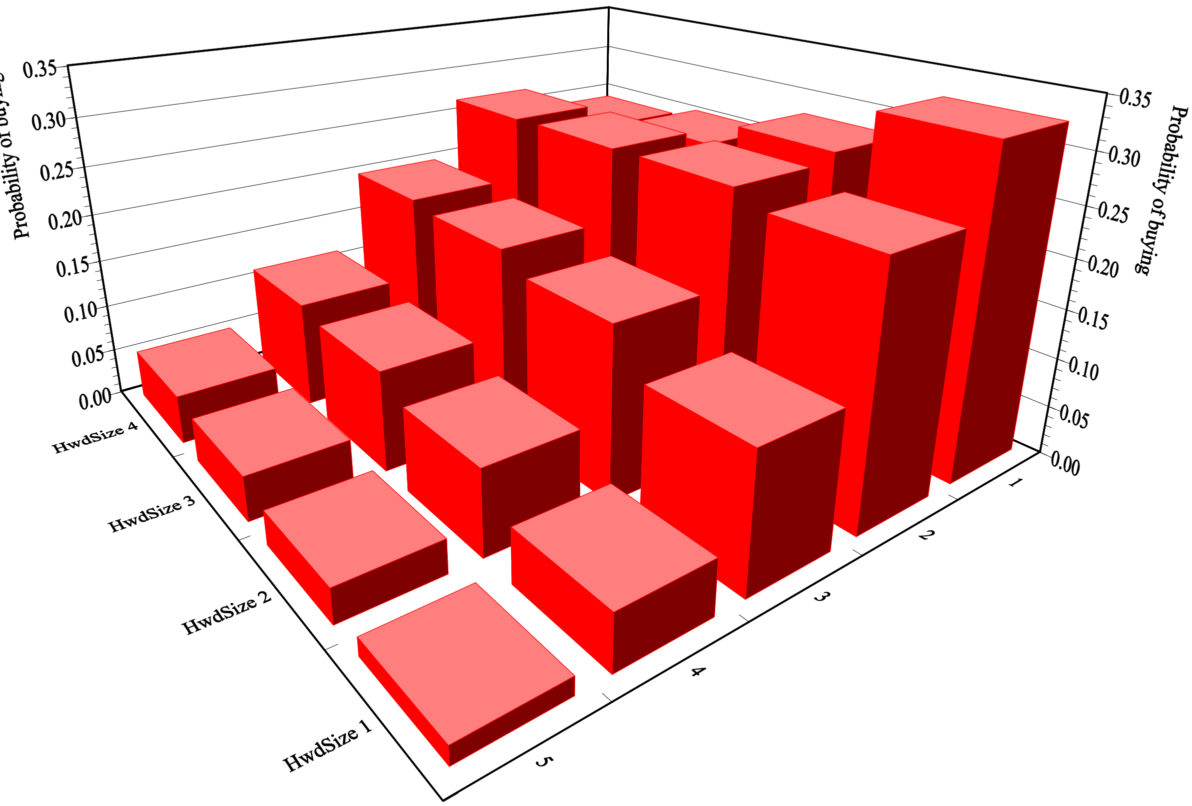

Figure-5: Probabilities of buying one or more beef cuts based household size.

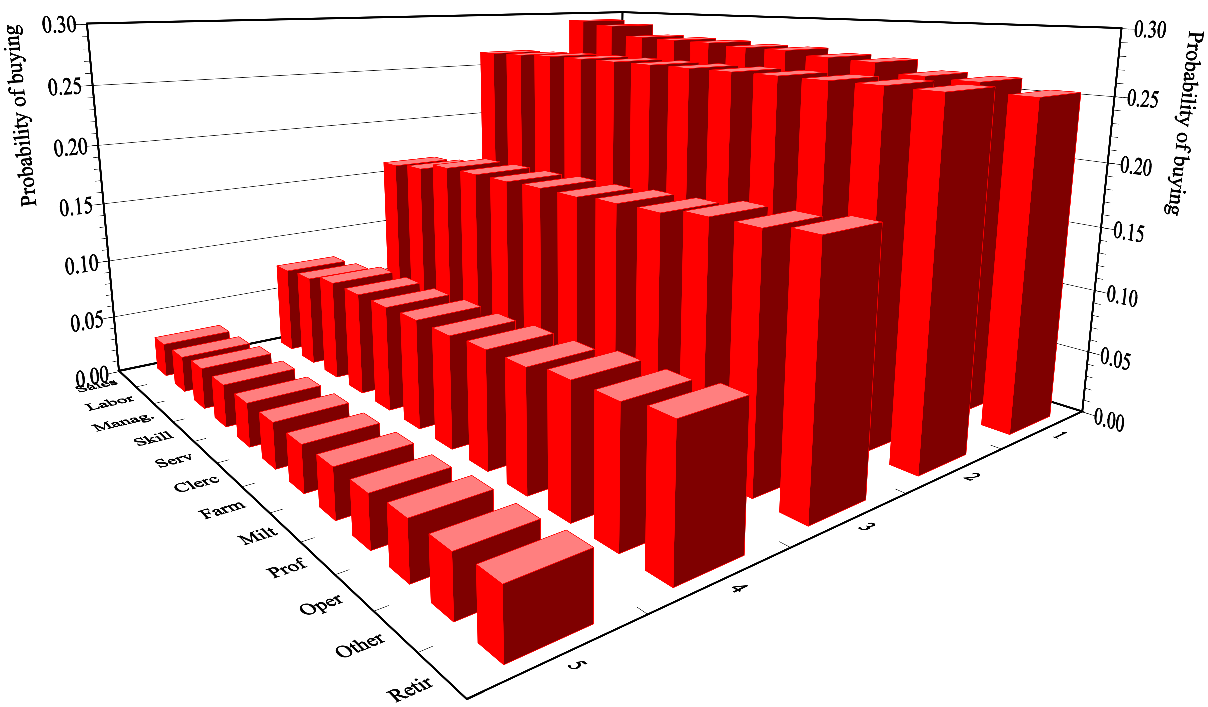

Figure-6: Probabilities of buying one or more beef cuts based on occupations.