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Modeling a Share or Proportion with Logit or Tobit: The Effect of Outcommuting on Retail Sales Leakages*

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Abstract

In this study the effects of commuting and demographic variables on the amount and distribution of outshopping were modeled using household-level survey data in which the proportion of expenditures within specific categories of goods were reported across neighboring retail market areas. The effects on the propensity to shop outside the core study area were estimated using the two-limit tobit and logit models. Influences on the relative distribution of that outshopping were modeled by multinomial logit. The multinomial logit and tobit models were shown to produce similar estimates, with empirical results indicating that retail sales leakages are increased for outcommuters for certain types of goods.

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1. INTRODUCTION

In this study, the effects on outshopping behavior of commuting and income level are estimated by two-limit tobit and logit models, with additional estimation of the distribution of outshopping across competing market areas by multinomial logit. The tobit model is specified as given in Maddala (1983) and applied following Harris and Shonkwiler (1994). The multinomial logit with the dependent variable as a share or proportion is specified as defined in Greene (2003), but it appears that there is no previous application of this model in the regional studies literature.

Socio-economic variables in the form of a share or proportion often are subjected to transformation prior to estimation, which may introduce bias or diminish the efficiency of the estimated coefficients. For example, least squares regression may be applied to proportion data following a logit transformation, which requires that zero values be transformed by the addition of some small constant (McDowell and Cox 2001). Commonly seen in the regional studies literature is maximum-likelihood estimation by the logit model in which the dependent variable is transformed using a rule that assigns a binary value (Leistritz et al. 1989; Pinkerton, Hassinger, and O'Brien 1995). The binary dependent variable used in the logit model presented in this paper has been produced by such a transformation.

In contrast, the two-limit tobit and the multinomial logit models are estimated using all the information in the proportion data and might be expected to be more efficient than the logit model in which the information has been reduced to a binary form. The two-limit tobit accommodates excess zeros and ones and models non-limit observations using the Normal distribution. The use of the two-limit tobit implies that the latent variable underlying the distribution of the observed variable, shares of expenditures, may take values less than zero or greater than one. This is useful in the study of the propensity for outshopping, which as a function of preferences is not bounded as are shares of expenditures. The multinomial logit model with a share dependent variable incorporates more information than the more restrictive binary categorization of the consumer as an outshopper (inshopper) or not and, by using the distribution of shares of household retail expenditures across competing market areas to capture the presence and amount of outshopping, may enable additional insights into consumer behavior. A case study of the effect of outcommuting on consumer behavior in Carson City, Nevada is presented as an application of the models.

2. STATISTICAL METHODS

2.1 Determinants of Outshopping by Two-Limit Tobit

The dependent variable for the case study that follows is the proportion of household expenditures for a specific category of retail goods for each of three neighboring market areas, which are described in detail in section 3. The dependent variable exhibits relatively large numbers of observations at both the zero percent and 100 percent extremes of the possible range of values, implying double truncation. The two-limit tobit model is well-suited to such data and in this study is estimated by maximum-likelihood within the GAUSS programming environment. To facilitate use of the tobit, the dependent variable has been reduced to a single value representing the proportion of expenditures within the Carson City market area only.

The likelihood function for the nth observation (n = 1, 2 … N) of the two-limit tobit model is given by:

$$(1) \qquad L_n = \Phi\left[\frac{L_1 - \boldsymbol{\beta}'\mathbf{x}_n}{\sigma}\right]^{d_{n0}} \left[\frac{1}{\sigma}\phi\left(\frac{y_n - \boldsymbol{\beta}'\mathbf{x}_n}{\sigma}\right)\right]^{d_{n1}} \left[1 - \Phi\left(\frac{L_2 - \boldsymbol{\beta}'\mathbf{x}_n}{\sigma}\right)\right]^{d_{n2}}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, $\phi(\cdot)$ is the standard normal probability density function, $\boldsymbol{\beta}$ is the vector of regression coefficients, σ is the standard deviation, $\mathbf{x}_n$ is the matrix of independent variables, and y_n is the observed value of the normally distributed dependent variable. For each observation, one of the exponents d_{nj} (j = 0, 1, 2) will take a value of one, depending upon whether the value of the observed y_n is equal to the lower limit, is in the interval between limits, or is equal to the upper limit, respectively, and all other exponents will take a value of zero. The lower and upper limits of the censored distribution, L_1 and L_2, have been set equal to zero and ten, as the data have been scaled to take values between those two limits, inclusive.

Assuming an underlying latent variable y_n* such that:

$$(2) \qquad \begin{aligned} y_n &= L_1 \text{ if } y_n^* \le L_1 \\ y_n &= y_n^* \text{ if } L_1 < y_n^* < L_2 \\ y_n &= L_2 \text{ if } y_n^* \ge L_2 , \end{aligned}$$

the expected value of y_n in the interval between L_1 and L_2 is:

$$(3) \qquad \int_{L_1}^{L_2} y \frac{1}{\sigma}\left[\frac{\phi((\mathbf{y} - \boldsymbol{\beta}'\mathbf{x}_n)/\sigma)}{\Phi_{2n} - \Phi_{1n}}\right] dy ,$$

where Φ_{1n} and Φ_{2n} represent the cumulative distribution function of the standard normal, evaluated at $(L_1 - \boldsymbol{\beta}'\mathbf{x}_n)/\sigma$ and $(L_2 - \boldsymbol{\beta}'\mathbf{x}_n)/\sigma$, respectively. An alternative expression for the conditional expectation, which does not require integration over the dependent variable, has been defined by Maddala (1983) as:

$$(4) \qquad E\left(y_n \mid L_1 < y_n^* < L_2\right) = \boldsymbol{\beta}'\mathbf{x}_n + \sigma \frac{\phi_{1n} - \phi_{2n}}{\Phi_{2n} - \Phi_{1n}} ,$$

where ϕ_{1n} and ϕ_{2n} represent the probability density function of the standard normal, evaluated at $(L_1 - \boldsymbol{\beta}'\mathbf{x}_n)/\sigma$ and $(L_2 - \boldsymbol{\beta}'\mathbf{x}_n)/\sigma$, respectively. Either expression may be used to estimate the change in the expected value of y_n given a change in a conditioning variable x_{nk}.

2.2 Determinants of Outshopping by Logit

The binary dependent variable for the logit model was created by assigning all proportions less than or equal to 0.5 a value of zero, and all proportions greater than 0.5 a value of one. The motivation for the logit model is not dissimilar from that of the two-limit tobit in that we may define y* to be an unobserved latent variable, which represents the propensity to shop within the Carson City market area. The latent variable y* is assumed to be linearly related to the observed independent variables through the structural model:

$$(5) \qquad y_i^* = x_i\beta + \varepsilon$$

and is linked to the observed dependent variable y by the measurement equation:

$$(6) \qquad y_i = \begin{matrix} 1 \text{ if } y_i^* > \tau \\ 0 \text{ if } y_i^* \le \tau \end{matrix}$$

where τ is the threshold value. Letting P_i and $1 - P_i$ be the probabilities that the dependent variable equals 1 and 0, respectively, the probability of observing y_i may be expressed as:

$$(7) \qquad P(y_i \mid x_i) = P_i^{y_i}(1 - P_i)^{1-y_i}.$$

The probability of observing all N values for the dependent variable y, given the values of the explanatory variables X_{ik}, is the product:

$$(8) \qquad L = \prod P_i^{y_i}(1 - P_i)^{1-y_i}.$$

If it is assumed that the cumulative distribution function of ε is logistic, then substitution of the cumulative logistic function for P_i in equation (4) will produce the likelihood function for the logit model:

$$(9) \qquad L = \prod \left(\frac{e^{\hat{b}_0 + \sum \hat{b}_k X_{ki}}}{1 + e^{\hat{b}_0 + \sum \hat{b}_k X_{ki}}} \right)^{y_i} \left(\frac{1}{1 + e^{\hat{b}_0 + \sum \hat{b}_k X_{ki}}} \right)^{1-y_i}.$$

The log-likelihood function is therefore:

$$(10) \qquad \ln L = \sum y_i \ln\left(\frac{e^{\hat{b}_0 + \sum \hat{b}_k X_{ki}}}{1 + e^{\hat{b}_0 + \sum \hat{b}_k X_{ki}}} \right) + (1 - y_i)\ln\left(\frac{1}{1 + e^{\hat{b}_0 + \sum \hat{b}_k X_{ki}}} \right).$$

Maximization of the log-likelihood functions for all three models has been performed with GAUSS software. The GAUSS program employs the Berndt, Hall, Hall, and Hausman (1974) (BHHH) estimator in a Newton-Raphson optimization and includes a derivation of the marginal effects.

2.3 Determinants and Distribution of Outshopping by Multinomial Logit

A multinomial logit model is used to estimate the proportionate distribution of retail market participation across neighboring retail market areas. Both the logit and multinomial logit models may be motivated within the context of the random utility model. For the multinomial logit, the nth (n = 1, 2 … N) consumer's utility U_{ij}, derived from the choice of shopping location j (j = 1, 2 … J) may be expressed as:

$$(12) \qquad U_{nj} = \mathbf{X_n}\boldsymbol{\beta}_\mathbf{j} + \varepsilon_{nj} \,,$$

where $\mathbf{X_n}$ is a vector of characteristics associated with the consumer, $\boldsymbol{\beta}_\mathbf{j}$ is the vector of slope coefficients for choice j, and ε_{nj} is the residual error term. The utility derived from choosing alternative j is assumed to be the maximum among the J choices, and by assuming the J residual errors to be independently and identically distributed with Type I extreme value distribution, the probability of the consumer making that choice can be modeled as:

$$(13) \qquad \mathrm{Prob}\left(Y_i = j \mid \mathbf{X_n}\right) = \frac{e^{\boldsymbol{\beta}_\mathbf{j}'\mathbf{X_n}}}{1+\sum_{k=2}^{J} e^{\boldsymbol{\beta}_\mathbf{k}'\mathbf{X_n}}} \,.$$

Note that because the probabilities across alternatives sum to one, the coefficient vector for one of the alternatives must be normalized to zero to allow estimation of the model. As shown in expression (13), $\boldsymbol{\beta}_1 = 0$.

The likelihood function for the multinomial logit is the product of the J probability terms, with an exponent d_{nj} defined for each, which is assigned a value of 1 if alternative j is chosen by individual n and a value of 0 otherwise. Taking the log of that likelihood function produces:

$$(14) \qquad \ln L = \sum_{n=1}^{N}\sum_{j=1}^{J} d_{nj} \ln\left[\mathrm{Prob}\left(Y_i = j\right)\right].$$

The multinomial logit log-likelihood function in expression (14) may be modified to accommodate data in which the individual's choice among alternatives is reported as a share that is allotted to each of the alternatives by applying the transformation $d_{nj} = s_n p_{nj}$ (Greene 2003), where s_n is the total number of shares and p_{nj} is the proportion of that total. This type of multinomial logit model is particularly appropriate for our data, reported as a share of expenditures distributed to each alternative market area.

Previous studies of outshopping that have used the logit model have categorized respondents as outshoppers or inshoppers to allow estimation using the binomial logit. Leistritz et al. (1989) describe grouping respondents into three categories: non-outshoppers, presumably those respondents who reported no purchases outside the local market area, as well as outshoppers for two different groups of goods. Pinkerton, Hassinger, and O'Brien (1995) describe collecting responses to a Likert-type scale, then converting the categorical values to a binary value.

Shortcomings to such approaches include ad hoc decision rules regarding which respondents are classified as inshoppers or outshoppers and the loss of information in the transformation to a binary variable. The approach described in this study seeks to minimize the effect of both shortcomings in that the use of a proportion variable requires no subjective categorization of the respondent and it preserves the maximum amount of information possible.

3. CASE STUDY: THE EFFECT OF COMMUTING ON RETAIL SALES LEAKAGES

3.1 Introduction

Our case study employs data from a survey of Carson City, Nevada residents. Nevada has experienced dramatic population growth during the past decade; and the Reno metropolitan area is the second fastest growing region in the state, increasing by a third with the addition of approximately 85,000 new residents during the 1990s (U.S. Department of Commerce 2001). With that growth, the Reno metropolitan area has been expanding into nearby rural communities. Forty-five minutes to the south, Carson City (population 52,457) still exists as a separate city. However, with the average commute distance of employees of Reno firms increasing as new housing is built at the expanding periphery of the metropolitan area, Carson City has become increasingly attractive as a source of residential housing. Contributing to the trend is a planned freeway extension from Carson City to Reno, which should reduce commute time. U.S. Census data (2000) show that approximately 14 percent of Carson City workers commute to work in Washoe County, a number that is expected to increase with the continued growth of the Reno metropolitan area; and as outcommuting increases, so may the potential for increased retail sales leakages. Although expanding employment in urban centers generally produces higher incomes in the surrounding areas, as those distinct municipalities are subsumed into bedroom communities for the larger city, agglomeration effects are likely to result in much of the retail trade sector being lost to the urban center (Parr and Denike 1970), impacting the tax base of the peripheral communities. Exacerbating this effect for Carson City is the growth of shopping opportunities in southern Reno, the area closest to Carson City. The need clearly exists, therefore, for strategic planning to address the changes that are expected to occur in the retail sector and for studies with which to inform that process.

Responding to Walzer and Schmidt's (1977) finding that proximity to a large employment center results in lower local retail sales, Shields and Deller (1998) noted the difficulty in discerning whether proximity is capturing commuting effects or agglomeration effects. Since the residence locations for all respondents in our data set are virtually equidistant from the urban center, agglomeration effects will be constant across observations. The effect of commuting on outshopping is then explicitly estimated free from any variation due to agglomeration effects. In the two previous studies known to explicitly model the effect of commuting upon outshopping, Pinkerton, Hassinger, and O'Brien (1995) and Shields and Deller (1998) found the effect of employment outside the community to be negative and significant for most categories of goods and services.

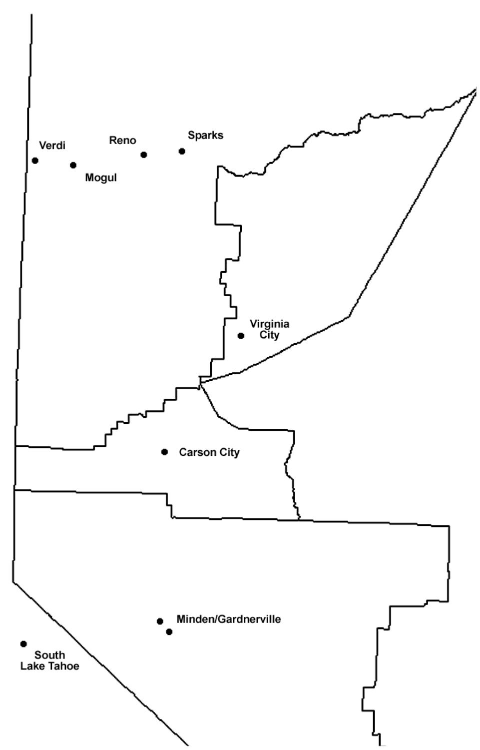
3.2 Data

Data were obtained by telephone survey from a sample of 120 employed Carson City heads-of-households between the ages of 21 and 65 selected by Random Digit Dialing. Respondents were asked how household expenditures for several individual categories of retail goods and services were distributed among six neighboring regions in the Carson City/Reno area (see Figure 1) as a proportion of total household expenditures for each category. Demographic and work-related data were also obtained.

The six retail trade areas in the survey were defined as Carson City, Douglas County, South Lake Tahoe, North Lake Tahoe, Reno/Sparks, and Other. Of these, only Carson City and Reno/Sparks contained a sufficient number of observations to be used as individual alternatives in model estimation. Consolidation of the remaining four areas into one (denoted Other), however, allowed modeling of information on purchases outside the Carson City and Reno/Sparks areas. Likewise, many of the retail purchase categories (e.g., Accounting, Legal Services) contained too few observations to be used for estimation of parameters and were dropped from the data set. Descriptive statistics for the remaining four categories are shown in Table 1.

FIGURE 1

Carson City/Reno Study Area



Descriptive statistics for the explanatory variables included in the empirical model specification are shown in Table 2. Income information was collected as a categorical set of ranges in order to minimize nonresponse. The effects of commuting are modeled through a set of binary place-of-work variables.

TABLE 1

Mean Expenditures by Retail Category and Market Area, Carson City Households

		Carson		**Reno**		**Other**	
Retail Category	**Obs.**	**Mean**	**S. D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Clothing/Shoes	112	.6317	.3385	.3330	.3372	.0353	.1118
Gen. Merchandise	115	.8276	.2510	.1083	.1939	.0641	.1769
Grocery Stores	120	.8998	.2402	.0682	.2006	.0319	.1275
Restaurants	119	.7646	.2596	.1992	.2517	.0361	.0752

TABLE 2

Descriptive Statistics for Conditioning Variables

Variable Name	**Description**	**Frequency**	**Mean**	**Std. Dev.**
Income	1 = under $20,000 2 = $20,000 - $39,999 3 = $40,000 - $59,999 4 = $60,000 - $79,999 5 = $80,000 - $99,999 6 = $100,000 and above	7.27% 22.73% 29.09% 15.45% 8.18% 17.27%	3.46	1.54
Works in Carson City	1 = employed in Carson City 0 = otherwise	78.33% 21.67%	.7833	.4137
Spouse works in Carson City	1 = spouse employed in Carson 0 = otherwise	38.33% 61.67%	.3833	.4882
Works in Reno	1 = employed in Reno 0 = otherwise	10.00% 90.00%	.1	.3013
Spouse works in Reno	1 = spouse employed in Reno 0 = otherwise	5.83% 94.17%	.0583	.2354
Works in Other	1 = employed in Other 0 = otherwise	11.67% 88.33%	.1167	.3224
Spouse works in Other	1 = spouse employed in Other 0 = otherwise	55.83% 44.17%	.5583	.4987

3.3 Empirical Specification

The empirical specification estimated by the econometric models may be expressed as:

$$\begin{aligned} U_{jn} &= \beta_0 + \beta_1 \text{Income}_{jn} + \beta_2 \text{Works in Carson City}_{jn} \\ &\quad + \beta_3 \text{Spouse Works in Carson City}_{jn} + \beta_4 \text{Works in Reno}_{jn} \\ &\quad + \beta_5 \text{Spouse works in Reno}_{jn} + \varepsilon_{jn}\ , \end{aligned} \tag{15}$$

where U_{jn} is the latent unobservable indirect utility realized by the nth consumer for the jth alternative, reflected in the observable distribution of purchases across the (j = 1, 2 … J) alternative retail market areas in the multinomial logit model and the observable proportion of purchases within the local retail market area in the two-limit tobit model. The commuting variables form the core of the model, consistent with our effort to explain the effect of commuting upon shopping behavior. Implicit in this specification is that the coefficient on employment in Carson City or Reno is relative to employment in Other. Income is the only demographic variable to be included. Additional demographic variables, including age, gender, education level, and length of local residence, collectively failed to achieve significance when tested against the restricted model by likelihood-ratio test.

3.4 Two-Limit Tobit Results

Estimation results from the two-limit tobit model are shown in Table 3 for the purchase categories of Clothing, General Merchandise, Grocery, and Restaurant. Standard errors for all estimated parameters have been calculated following White (1982) to preserve robustness in the presence of distributional misspecification.

Income is negatively signed and significant for all categories. The sign is opposite that reported in Harris and Shonkwiler (1994), who reported a positive income coefficient for all categories, but is intuitively appealing as it is likely that with additional income, consumers might be more likely to travel to Reno for the greater selection of goods and the availability of higher-quality goods. The commuting variables vary in significance, with the most consistently significant variables being those related to the spouse's work location. A spouse working in Carson City results in an increase in local purchases significant at the .05 level across all purchase categories except Restaurant. For households with spouses working in Reno, a strongly negative effect is present for local purchases from grocery stores and restaurants, also significant at the .05 level. The manner in which gender might affect the spousal variables was investigated while determining the best specification for the empirical model but found to have no significant effect.

3.5 Logit Results

Parameter estimates achieving significance from the logit model are presented in Table 4. Note that none of the variables achieved significance in the General Merchandise category. Also, the Works in Reno variable is not shown because it did not achieve significance for any of the categories of retail purchases.

TABLE 3

Estimated Coefficients from Tobit Model, by Retail Purchase Category

Variables	Clothing	Gen. Merch.	Grocery	Restaurant
Intercept	8.418 (2.011)[a]	10.820 (1.682)[a]	10.774 (2.038)[a]	9.680 (1.456)[a]
Income	-1.640 (.340)[a]	-0.805 (.370)[b]	-0.817 (.478)[c]	-0.358 (0.189)[c]
Works in Carson City	3.494 (1.825)[c]		4.217 (2.476)[c]	
Spouse works in Carson City	2.637 (1.076)[b]	2.623 (1.095)[b]	3.485 (1.731)[b]	
Works in Reno/Other				-3.155 (1.789)[c]
Spouse works in Reno/Other			-5.440 (2.484)[b]	-3.165 (1.283)[b]
sigma	4.173 (.404)[a]	4.038 (.543)[a]	5.030 (.827)[a]	3.138 (.338)[a]

Numbers in parentheses are White's standard errors. [a]Significance at the .01 level. [b]Significance at the .05 level. [c]Significance at the .10 level.

TABLE 4

Estimated Coefficients from Logit Model, by Retail Purchase Category

Variables	Clothing	Gen. Merch.	Grocery	Restaurant
Intercept		2.216 (1.302)[c]	2.429 (.862)[a]	
Income	-0.874 (.243)[a]			
Works in Carson City	1.346 (.775)[c]			
Spouse works in Carson City	1.753 (.713)[b]			
Spouse works in Reno/Other			-3.041 (1.086)[a]	-1.948 (0.958)[b]

Numbers in parentheses are White's standard errors. [a]Significance at the .01 level. [b]Significance at the .05 level. [c]Significance at the .10 level.

Fewer parameter estimates achieve significance in the logit model compared to the two-limit tobit or multinomial logit models, although the signs and magnitudes of those that do are comparable to the estimates from the other models. The poor performance of the logit in this case is at least partly due to the naïve transformation rule, which does not account for the distribution of expenditures being skewed toward Carson City. This effect is likely to be present in any transformation of categorical data as well and can be compensated for in this case by oversampling observations in which the dependent variable takes a value of 0, followed by the application of a weighted endogenous sampling maximum likelihood estimator described in Greene (2003). Since the logit is presented here for purposes of comparison only, a weighted transformation has not been included.

3.6 Multinomial-Logit Results

Estimation of the multinomial logit model with share dependent variable requires a greater number of observations than does the two-limit tobit as the total number of parameters to be estimated will be multiplied by the J alternatives that make up the dependent variable in the multinomial logit, as opposed to the single proportion value in the tobit. Also mentioned in discussion of the logit is that the distributional skewness of the data means that in general only a small proportion of the local market area residents sampled will have reported significant expenditures in other market areas, requiring a larger sample than would be needed for an analysis of the local market area only. In this study, observations on clothing expenditures outside of Carson City and Reno are not sufficient to estimate parameters for that category using the multinomial logit. Estimation results for the remaining categories are shown in Table 5. Coefficients for the market areas Reno and Other are shown, with Carson City implicitly defined as the base category.

TABLE 5

Estimated Coefficients from Multinomial Logit Model, by Retail Purchase Category

Variables	Gen. Merch.		Grocery		Restaurant	
	Reno	Other	Reno	Other	Reno	Other
Intercept	-2.083 (.920)[b]	-4.688 (.996)[a]	-2.140 (.604)[a]	-2.992 (1.323)[b]	-1.687 (.699)[b]	-5.392 (1.166)[a]
Income		0.317 (.190)[c]		0.362 (.120)[a]		
Works in Carson City		1.653 (.904)[c]				2.229 (.996)[b]
Spouse works in Carson City		-1.129 (.560)[b]				-0.971 (.392)[b]
Works in Reno			-3.210 (1.496)[b]			
Spouse works in Reno	-1.009 (.601)[c]		2.626 (.813)[a]		1.389 (.593)[b]	

Numbers in parentheses are White's standard errors. [a]Significance at the .01 level. [b]Significance at the .05 level. [c]Significance at the .10 level.

Income exhibits a relatively small effect upon the model and is largely insignificant. Commuting to Reno, however, is more consistently a significant predictor of the spatial distribution of expenditures. Note that unlike the tobit model for which the marginal effects will be signed the same as the estimated coefficients, the marginal effects from the multinomial logit may be signed differently than the coefficients. For that reason and because the error terms are distributed differently for each type of model, it is more useful in examining the results of the two models to compare the marginal effects rather than the coefficients.

4. MARGINAL EFFECTS

In this study, the use of partial derivatives in the estimation of the marginal effects is problematic because the empirical model only contains discrete categorical or binary explanatory variables and derivatives are not readily interpreted within the context of a change in a variable from one discrete value to another. Alternatively, the marginal effects have been estimated as the change in the conditional expectation of y_n resulting from a unit increase in an explanatory variable. Following estimation of each respective model, the explanatory variables were evaluated at the highest and lowest values defined for each variable while holding all other explanatory variables at their median values. The difference represents the marginal effect for the binary variables. For the categorical variables, the difference was divided by the number of discrete values that the variable was allowed to take, resulting in an average marginal effect for a single unit increase.

The marginal effects for all models have been reported as the change in the share of expenditures resulting from a change in an explanatory variable, with total shares equal to 100. This approach allows for direct comparison of effects predicted by the models and avoids the variability inherent in the use of percent change, whereby the same absolute change in an expectation may produce a very large or very small percent change depending upon the base value of the expectation.

Marginal effects for statistically significant variables from the two-limit tobit model are shown in Table 6. Among the largest marginal effects associated with commuting are those within the Restaurant category, where employment in Reno by either the respondent or spouse is associated with an increase in outshopping within that category of more than 25 percent of total restaurant expenditures. Not related to commuting are the effects of Income, which are uniformly negative and largest within the clothing category. The clothing stores in the large shopping malls located on the southern periphery of Reno may be contributing to the magnitude of the effect within the clothing category. Commuting effects are also largest within the clothing category, however, and local employment is strongly associated with local clothing purchases, exhibiting a marginal effect of greater than 30 percent for the respondent. Grocery purchases also show a strong positive response to employment in Carson City and a strong negative response to employment in Reno.

Marginal effects for the logit are shown in Table 7 and while signed the same as the marginal effects from the tobit are generally larger. Marginal effects from the multinomial logit with share dependent variable are shown in Table 8. Marginal effects for Clothing could not be estimated due to too few non-zero observations in the Other market area. When estimated with only two market areas, the multinomial logit produced estimates similar to the logit, with the difference attributable to the difference in the form of the dependent variables. The consistently largest marginal effects are associated with Spouse works in Reno, resulting in the loss of 37.7 percent of household grocery expenditures to outshopping, with a 34.0 percent share increase of expenditures in Reno.

TABLE 6

Tobit Share Change in Conditional Expectation

Variables	Clothing	Gen. Merch.	Grocery	Restaurant
Income	-8.72	-4.14	-2.44	
Works in Carson City	30.78		17.22	
Spouse works in Carson City	15.91	12.59	9.23	
Works in Reno				-25.08
Spouse works in Reno			-19.53	-25.16

TABLE 7

Logit Share Change in Conditional Expectation

Variables	Clothing	Grocery	Restaurant
Income	-15.73		
Works in Carson City	29.71		
Spouse works in Carson City	34.70		
Spouse works in Reno/Other		-43.39	-42.99

TABLE 8

Multinomial Logit Share Change in Conditional Expectation

Variables	Gen. Merch.			Grocery			Restaurant		
	Carson	Reno	Other	Carson	Reno	Other	Carson	Reno	Other
Income	-5.12	2.39	2.73	-2.12	0.99	1.13			
Works in Carson City	-0.86	-6.90	7.76				-0.66	-4.17	4.82
Spouse works in Carson City	12.92	-6.92	-5.99				5.55	-2.33	-3.21
Works in Reno				6.62	-4.52	-2.10			
Spouse works in Reno	13.72	-7.48	-6.24	-37.73	33.96	3.77	-27.35	26.04	1.30

A comparison of the marginal effects estimated by the tobit and multinomial logit models shows the direction of the effects to be consistent between the two models and the size of the effects to be similar, with the logit estimates generally larger. The sizes of the marginal effects associated with the commuting variables vary more across models than does the effect of Income, with the largest difference seen for Spouse works in Reno. The positive sign on that variable for the general merchandise category and the negative sign on Works in Carson City are at odds with intuition and likely result from the relatively small data set.

The results of the empirical model for Carson City and neighboring areas show outshopping increasing with income uniformly for all categories of goods. The effect of commuting upon outshopping varies by category of retail good, with the greatest impact across all models observed for grocery and restaurant expenditures when the spouse works in Reno. The marginal effects for the multinomial logit also indicate that the change is distributed primarily to the Reno area.

5. CONCLUSIONS

Both the two-limit tobit model and the multinomial logit with share dependent variable model are useful econometric tools for modeling data that takes the form of a market share or proportion, particularly when censoring exists as may be the case with share data. The two-limit tobit is appropriate for modeling the determinants of shopping behavior for a single market area. Fewer observations are required to obtain coefficient estimates, but the tobit lacks the distributional insights of the multinomial logit, which is appropriate for estimating the distribution of shares over multiple market areas. That feature of the multinomial logit might be further exploited in a geospatial study using GIS techniques based on the respondent's employment address (or neighborhood if necessary to preserve anonymity) and the street addresses of retail businesses.

The findings of this study may be of help to local planners in efforts to preserve the Carson City retail tax base through support and development of retail sectors likely to be impacted by sales leakages due to increased outcommuting. Overall, it appears that commuting to work in Reno results in an increase in the frequent or convenience type of expenditures one might characterize as "after work" shopping, including grocery and restaurant expenditures. Commuting does not appear to be strongly associated with larger or more infrequent expenditures, although income may be.

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