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Introduction

This compilation contains selected papers from the 2003 meetings of Western Regional Research Project W-1133. This was the inaugural meeting of W-1133—given that upon rechartering its prior designation of W-133 was changed. The objectives of W-1133 are:

1. Estimate the economic benefits of ecosystem management of forests and watersheds

2. Estimate the economic value of changing recreational access for motorized and non-motorized recreation

3. Calculate the benefits and costs of agro-environmental policies

4. Estimate the economic values of agricultural land preservation and open space

This year's meetings were held from 22 February through 24 February at the Excalibur Resort in Las Vegas and were attended by 45 professionals who represented land grant universities, non land grant colleges and universities, and federal and state agencies. Thirty presentations were made and the contents of this volume are representative of the topics discussed.

This meeting marked the loss of our long-time administrative advisor, Enoch Bell. We will miss his guidance and support, and we wish him well in retirement.

Comparing Consumer's Surplus Estimates Calculated from Intercept and General Survey Data

by

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Comparing Consumers' Surplus Estimates Calculated from Intercept and General Survey Data

Abstract

A sample for use in estimating consumers' surplus was generated by visiting and recruiting individuals at lakes and reservoirs. This produces a choice-based, or "intercept" sample. Such sampling remains common in applied work such as transportation, retail sales and marketing, and examination of voting behavior. It is cost-efficient, allowing focus on individuals of interest, but it produces an endogenously stratified sample, and potential avidity bias, i.e. individuals are overly avid in their consumption of a good as compared to the general population. We have a unique opportunity to use an exogenous source of data (a random digit dial telephone survey sample, stratified by county) and compare welfare measures based on this sample to those based on our intercept sample. Following a suggestion by Manski and Lerman we then make adjustments in intercept participation probabilities by calibrating model parameters. We then reexamine the resulting welfare estimates. The calibrated intercept survey results produce welfare estimates that are somewhat different than for the telephone survey. The differences are shown to be due to differences in the distribution of predicted demand (visits). To our knowledge, prior to this research no one has applied Manski and Lerman's idea to actual data, and we are not aware of any research that has gone the extra step to examine welfare measures.

Key words: choice-based sampling, multinomial logit, recreation demand modeling
JEL Codes: C81 (Methodology for Collecting, Estimating and Organizing Microeconomic Data); H41 (Public Goods)

Comparing Consumers' Surplus Estimates Calculated from Intercept and General Survey Data

1. Introduction

In this manuscript we investigate potential biases from using sample data generated from an "intercept" recruitment scheme, all in the context of a multi-site random utility model of recreation demand. Here the word intercept means the process of making direct contact with an individual at a certain place, a form of sampling. Congress recently debated over the issues of extrapolating from samples to a population in connection with the 2000 census. Various sampling methods are used in the calculation of most all statistical estimates, but as seen in the congressional debate, the procedures are rarely understood. The use of sampling will no doubt remain an issue, especially as research budgets most often preclude methods that might be used to obtain data on populations, or even data on simple random samples of individuals. There are many situations where the individuals are recruited in person. These include retail sales studies (common in marketing – see O'Kelly), where buyers of goods are surveyed to determine market areas for stores (Applebaum). The buyers are contacted at stores in shopping malls because of low response rates in doing random household samples. Choice-based samples are also used in public transportation studies, where commuters are found and surveyed at bus-stops and train stations (see Manski and Lerman), and studies of voting behavior, where voters are often surveyed as they exit polling places.

In-person recruitment is increasingly used in studies of demand for natural resources and "non-market" goods. Outdoor recreation is a very popular activity in the United States; it is quite common for half of many state populations to engage in it. The U.S. Department of Agriculture estimates that outdoor recreation in national forests contributes about $100 billion annually to the gross domestic product (the National Recreation Lakes Study Commission estimates this contribution to be about $350 billion in total), and that more than two-thirds of all Americans participate in some form of outdoor recreation. Despite this frequency of participation, recreation studies are rarely funded with research budgets that allow extensive sampling.[1]

Simple random sampling (SRS) of the population is thought to produce unbiased, or at least consistent statistical estimates. Unbiased sample data should mimic the population of interest (the intended population group) quite well, i.e. it should be "representative" of the population. Randomly sampling all households, when the target (intended) population is a smaller subset of the larger general population requires screening the subgroup from the general population. Even with two thirds of the national population engaging in outdoor recreation, a random sampling strategy dependent on draws from all households could spend one third of the effort just finding these recreational users. More sampling money will be spent finding people who recreate in states with lower than national average participation in recreation, and more still if the focus is on a particular type of recreation, or mainly concerns one or more specific recreation destinations.

Alternatives to simple random sampling exist. As early as 1977 researchers noted that "choice-based" sampling (focused, non-random or uneven sampling dependent on choices having been made) may achieve economies of scale and might be an order of magnitude less expensive than "comprehensive" interview surveys; Manski and Lerman use the example of contacting and interviewing shoppers at shopping malls rather than randomly sampling from households. Research teams therefore often resort to data collection methods that generate sample data and avoid the screening step, but inherent in the data sets are potential statistical biases.

A popular technique in recreation modeling is to use on-site, or intercept survey methods, where interviewers contact survey candidates while at recreational areas. There are many specific advantages of using the intercept method over other survey methods to collect recreation data, including: (1) the initial contact allows some in-person interaction that may help clarify complex survey issues for the respondent; (2) visitors from any origin who visit the site can be identified (e.g., perhaps representative of the population of non-resident visitors); and (3) information about

[1] Exceptions are some large statewide efforts such as the Michigan recreation study (Lupi et al.), the Montana statewide recreation models of Morey et al., or the ARCO-funded Montana fishing study by Desvousges and Waters; and nationally important survey efforts conducted in conjunction with the National Survey of Fishing, Hunting, and Wildlife (see Waddington and Meier) and the National Acid Precipitation Assessment Program (Englin et al.).

who actually uses the resource can be used to develop an efficient stratification plan to reach the target population with a survey of the general population, focusing on geographical regions where most activity will take place. Because of these advantages many recreation researchers have relied on this sampling approach (see Table 1 for examples) and no doubt will continue to do so. However, there are possible biases, discussed in section 2, and these are shown in this manuscript.

In what follows, we demonstrate the potential biases in intercept data using an exogenous data source for comparison. The intercept sample model is estimated with a conditional multinomial logit model - a now common specific version of the Random utility model or RUM.[2] In the application we estimate probabilities of recreating at several Sierra Nevada waters and the per-choice-occasion values individuals have for these waters.

2. Literature Review and More Background

Diagee Shaw (1988) demonstrated that on-site sampling may introduce several types of statistical or sample bias in a recreation context.[3] There are two main possible problems with intercept samples: truncation (all non-users are truncated from the sample), and endogenous stratification (frequent users are more likely to be in the sample than occasional users). Shaw's work, as well as most related literature, generally does not consider the issues in a multi-site random utility model.[4]

Cosslett (1981a, 1981b) and Manski and Lerman briefly noted sampling some issues in a framework that could be adapted to the RUM. Morey, Shaw and Rowe also considered some sampling issues in the RUM context. More recently McFadden (1999) greatly extended Shaw's (1988) discussion of on-site bias to encompass a situation where there is an intercept recruitment

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[2] One of the first applications is by Caulkins, Bishop and Bouwes; this was done about the same time as the work by Bockstael et al. in their report for EPA; and other more recent examples of RUMs for recreation can be found in Morey, Shaw and Rowe (1991), Lupi et al., and Shaw and Ozog.

[3] Recognition that uneven sampling can produce biased estimators is as old as sampling theory (Cochrane), and the use of weighting procedures in travel cost or travel demand samples has also been discussed (Ben-Akiva and Lerman).

[4] Shaw's focus is on continuous or Poisson distributed trips. This work was later extended to the negative binomial distribution demand specification [Englin and Shonkwiler (1995)]. Cameron et al. (1996 or 1999) model the influence of mail survey response on demand equations which are basically assumed continuous (i.e. demands are normally distributed). There has also been considerable debate on response rates and sampling in the contingent valuation literature (see Mattsson and Li).

followed up with a mail survey, which is the data collection strategy we pursued. He does not use data to explore the empirical issues. The focus of an empirical multi-site RUM model study is Nevada's Walker Lake, and the data are discussed in the next section, as they drive the development of the model.

3. Data

Our data appear to be unique, and relate to a policy issue involving a lake that is drying up in Nevada. Walker Lake, a terminus lake on the eastern side of Sierra Nevadas, has been characterized as effectively "dying" because of upstream withdrawals and problems with salinity in the lake. Continued recreational access at Walker Lake depends on maintaining water levels to support the fishery there (see details in Brussard; Fadali; Fadali et al. 1998; or Eiswerth et al.). Concerns about the lake inspired research on the values that recreational users might have for increasing water levels there. A small project and sampling budget precluded using a professional survey research firm and developing huge samples. Instead, university graduate students recruited a modest number of recreational users and implemented an intercept and telephone survey.

The survey team was sent to selected waters to recruit individuals encountered on the site for a very short follow-up mail survey (complete details can be found in Fadali's thesis, or in an earlier version of this manuscript (Shaw et al. 1999). The follow-up allows more survey time to collect information on trips other than the one observed. As Table 1 illustrates, this "follow-up" survey method has also been used in many recreation studies. In our case at least some detailed information on each of the individual's seasonal water-based recreation trips can be collected in this follow-up survey.

During approximately the same time frame for the intercept survey a sample of households in the general regional population was contacted by telephone. The sample was stratified by counties in the region of Walker Lake, but otherwise obtained using random digit dialing. The telephone respondents were asked a few questions about recreation in the region, beginning with the simple question of whether they had engaged in outdoor recreation at waters in the region of interest at all. Because of time constraints for the total length of the telephone interview, fewer questions were asked about recreation than could be asked using the longer mail survey questionnaire. Sampling rates for this telephone survey varied by county, with highest attempted contacts being in the counties nearest Walker Lake and other regional waters; stratification was adopted to ensure some non-zero participation at the waters of interest. We note that the stratification scheme is not simply to oversample small population counties, as is common in sampling, because of spatial relationships.

4. The Model

4.1 Basic Recreation Demand Model

Assuming a random sample, a simple conditional multinomial logit (MNL) model can be estimated. The MNL is perhaps the most commonly applied and most simple of the RUMs; the recreation valuation literature is now replete with applications, often extended to include a nest structure and a variety of other modifications. The MNL applied in recreation modeling is conditional, on the total number of recreation trips. These trips are assumed to be fixed over the period, and the number of trips a person takes in this period may vary. The model should not be confused with the unconditional MNL that allows each alternative to have its own slope parameter[5]. We use the simple MNL to focus on the sampling issues, and note that the benefits of using many of the more complicated variations of the RUM would be negated by using uneven samples. The log likelihood function for the MNL can be summed over N individuals and J alternatives as:

$$\log \ell = \sum_{i=1}^{N} \sum_{j=1}^{J} y_{ij} \ln \pi_{ij} \qquad 1$$

Where y_{ij} are the choices (trips in our case) by person i to alternative (site) j, and π_{ij} are the alternative choice probabilities that are derived assuming the errors follow the extreme value distribution, such that (suppressing the ith subscript):

$$\pi_j = \frac{\exp(\alpha_j + \beta X_j)}{\sum_{s=1}^{J} \exp(\alpha_s + \beta X_s)} \qquad 2$$

[5] Issues with fixed trips relate to calculation of seasonal welfare measures and are covered in Shaw and Shonkwiler, as well as in Lupi and Tomasi. We do not calculate seasonal welfare measures here.

Where s = 1,…,4 for the constant term, to exclude a fifth alternative. The destination choice set is imposed on all of the individuals in the sample by the researchers, and is thus assumed exogenous.

Ben-Akiva and Lerman remind us that there is actually a missing term in the log likelihood in equation [1]. If j is the choice, y_{jn} is a variable indicating the choice of observation n, and x is the vector of characteristics of the observational unit, then the actual log likelihood is:

$$\ell = \sum_{n=1} \sum_{i \in C_n} y_{in} \ln Prob(i \mid x_n, \theta) + \sum_{n=1} \ln prob(x_n) \qquad 3$$

The right-hand-side (RHS) term is implicit, but can only safely be dropped with simple random sampling (SRS). As departures from SRS are often overlooked, no attention is paid to this term. A key point is that sampling procedures other than simple random sampling may indeed lead to this term's involvement in identification of the likelihood, calling for weights and other considerations in modifying the basic MNL model.

4.2 Weights and Survey Sampling Issues

The interception of users at recreation sites generates a choice-based sample, complicated by use of the follow-up survey information. The most rigorous treatment of these intercept and follow responses would follow the more complex strategy suggested by McFadden (1999). Unlike a pure intercept sample, where only the probabilities of being in the sample can be influenced by the individuals' participation or avidity rate, the probability of all trip patterns recorded in the subsequent mail survey questionnaire may also be dependent on the fact of being intercepted in the first place.

McFadden (1999) derives formal intercept and follow probabilities, but does not use data in his analysis. Let D be the number of occasions a survey team visits a site, M be the number of times a recreational user could take a trip, K be the number of trips actually taken, and π be the probability the user takes a trip to site J. The probability of a person being intercepted on a single trip during the season is simply equal to $\pi K*(D/M)$, because the chance of a trip being taken when screening is occurring is D/M, and there are K such chances (presuming K trips are taken).

In our on-site sampling efforts, because of the timing of recruitment of participants and weather patterns (high water precluded water-based recreation at a number of sites in 1996) we are confident that the likelihood of multiple interception was low; in fact, we have only a negligible number of records of this occurring in the sampling effort. Assuming McFadden's approximation formula for a single intercept trip [as above, it is = $\pi K^*(D/M)$] is appropriate, a clear result of the above is that frequent trip-takers are oversampled relative to the population, and the distribution of trips will be skewed upward. With this in mind, McFadden suggests that one may effectively discard the intercept observation itself, and treat the remaining M-1 observations for an individual as if they were obtained by random sampling.

4.3 Treatment of Different Sample Groups

As stated above, the mail survey group data is composed of several types of sample data, but attention here is focused on the potential differences between the intercept group and the Telephone Survey group. We rely on the telephone survey sample to provide the "population" estimates. This extra source of information is what makes this analysis empirically feasible.

Telephone Survey

The telephone survey sample is a general, but stratified sample because of different sampling rates used in calling people who live in different counties in the Walker Lake region. The basic tenet of the travel cost model, that people who live near resources use them more, is well known and we therefore assumed that people in counties located far from the Walker Lake region were less likely to visit the region's waters, and attempted contact with a lower percentage of these county residents. Otherwise, this sample is an exogenous random sample of the general population, because we assume that individuals cannot determine the sample (county strata) they are in, at least in the short run. Asking about visitation to water-based recreation sites allows calculation of an estimate of the portion of the general population who recreate, information that cannot be gleaned from the intercept sample.

The stratified sample cannot be used without some adjustment using weights. We adopt a simple adjustment strategy where the telephone survey data is estimated using weighted maximum likelihood. The weight (w_g) is constructed using the number of Telephone sample individuals contacted in that gth county versus the actual population there. Oversampled county observations are given less weight in estimation and undersampled county observations are given more. The weights are normalized so that they sum to 364, and the average per-person weight is approximately equal to one.

The Pure Intercept Sample

We can create the equivalent of a "pure" intercept survey sample by dropping all follow-up trips, as suggested by McFadden (1999). I.e., if all trips we know an individual takes because of his reporting on the follow up survey are dropped, this leaves only the intercept trip itself, which is akin to a pure intercept data collection procedure.

Calibrated Intercept and Weighted Exogenous Sample Maximum Likelihood (WESML)

Finally, we can adjust the probabilities of visiting the five sites for the mail survey sample using two methods, calibrated intercept, and weighted exogenous sample maximum likelihood (WESML). First, the calibrated intercept method is an adjustment process that takes into account the nature of the estimation of the non-random sample. We follow the suggestion of Ben-Akvia and Lerman for the method of calibration, which in turn follows earlier proofs by Manski and Lerman and independently by Cosslett (1981a, 1981b). Manski and Lerman and others demonstrate that an exogenous sample maximum likelihood procedure for a choice-based sample when the choice model is a conditional multinomial logit will yield consistent estimators for all parameters except the constant terms for each alternative. Using their notation, a sample likelihood of a general stratified sample with no overlap across strata can be written as:

$$\ell^* = \prod_{g=1} \prod_{n=1} \prod_{j \in C_n} \left[\frac{f(j, x_n) H_g}{W_g} \right]^{y_{jn}} \qquad 4$$

where as before, j is the alternative chosen, **x** is the vector of attributes for observation n, H_g and W_g are sample and population shares, respectively. Cosslett (1981b) lays out all the assumptions and the proofs in general cases. He also discusses specific cases such as when the density function, f( ), follows the extreme value distribution, which generates the MNL, and he notes that the MNL model parameters are not identified when population shares are unknown. However, if the population shares are known, as is assumed true in our case, then each inconsistent alternative constant term may be calibrated to yield a consistent estimate by using the log of the ratio of sampling fractions

(H_g) to population weights (W_g). In more formal terms each of the calibrated or consistent estimators is found using:

$$\alpha_j = \hat{\alpha}_j - \ln(H_g / W_g) \qquad 5$$

where the estimated constant on the right-hand side is obtained using maximum likelihood on the pure intercept sample data.

The second method, WESML produces a consistent, but not generally efficent estimator. Manski and Lerman also show that consistent parameter estimates can be achieved by maximizing the WESML likelihood function:

$$L_{WESML} = \sum_{g=1} \sum_{n=1} \sum_{j \in C_n} y_{jn} \frac{W_g}{H_g} \ln Prob(j \mid x_n, \theta) \qquad 6$$

The estimates resulting from this second method are compared to the calibrated intercept below.

Several of the above-mentioned authors discuss the weights in terms of shares of people who fall into subgroups (our counties, g). In our case the observational unit is a recreation trip, because all trips within the MNL are assumed independent from one another. The weights can therefore be constructed using trip proportions. Therefore we let H_g be the fraction of the sample's trips drawn from the five choices (waters of interest) and W_g is the share of population trips for each of the waters, assuming the Telephone survey sample adjusted trips are the same as the population's trips. W_g is weighted with the county population adjustments mentioned above, and otherwise assumed to reflect the true population trips.

The calibration idea is intuitive. Suppose that the fraction of total sample trips at water 1 is 10 percent, then $H_1 = .10$. Suppose the population share of trips going to water 1 is lower, at 5 percent, and $W_1 = .05$. If the estimated site-specific constant for water 1 is 1, the calibration factor is ln(.10/.05) and we subtract 0.693 from the constant, reducing the probability of visitation there because the intercept sample visits there more frequently than the population does. If the proportions are the same, the ratio equals one, and ln(1) = 0, so there is no calibration, and if the intercept group visits a site less than the population the correction factor is negative, and the constant is increased (we subtract a negative number, or add it to the constant).

We therefore subtract $\ln(H_g/W_g)$ from the α_j terms in the site choice probability equations to examine differences in probabilities of visits, as well as in welfare measures. This calibration method is applied to the intercept model, including the intercept trip. Once parameters are calibrated, any results involving the parameters will be influenced. This includes welfare measures based on the MNL, discussed below. As neither Cosslett (1981a, 1981b) nor Manski and Lerman discuss welfare measures in their analyses, there is no claim in the literature about what should happen to these estimates following calibration. In addition, these authors simply make an argument about consistency of the calibrated constant, but make no claim that the probabilities will perfectly match in any small sample. We therefore expect that the calibrated intercept probabilities and consumer surplus estimates will be closer together than the uncalibrated ones.

4.4 Welfare Measures

Of particular interest in non-market valuation is the implied welfare measure, or consumer's surplus for the population. Our focus is on per choice occasion welfare measures, and we are aware of the differences between these and seasonal welfare measures.[6] Specifically, we examine the individual's WTP to prevent loss of access to Walker Lake. In our RUM the parameters estimated for the travel cost (p_{ij}) model of site-choice probabilities enter into calculation of the welfare measures. The welfare measure is calculated using the difference of the logsum of the conditional indirect utility functions (V_j), where in the case of the simple linear RUM, we have this conditional on choosing site j (assuming no other explanatory variables explain site choice), and the indirect (V_j) is simply a function of a site-specific alternative constant term and p_j. The consumer's surplus takes the form $CV = 1/\beta[\ln A^1 - \ln A^0]$, where the first term is the inverse of the travel cost parameter, or the inverse of the constant marginal utility of income. A^1 is defined by the denominator in the probability equation (see equation 2) at price levels p^1 and similarly, A^o is defined at price levels p^o.

[6] See the issues in Shonkwiler and Shaw.

The problem comes when we make inferences about representative individuals in the usual fashion, i.e. by taking the sample mean of the estimated CVs. Laitila does not specifically consider the RUM-based welfare measure, but notes the following. Let the estimator of the CV using random sampling be CV^{RS}. Under random sampling, for the individual i:

$$CV^{RS} = n^{-1} \sum CV(\mathbf{x}_i; \theta,\beta)$$

is an unbiased and consistent estimator. However, it is not consistent under choice-based or on-site sampling because the distributions of x in the subpopulations from which the samples are taken are different from the usual one. He goes on to show an estimator how to derive a consistent estimator of CV with choice-based sampling such as we have, but this laws of large numbers to hold (see Laitila, p. 22). The parameters with an estimated positive influence in the welfare formulas that are upwardly biased will lead to overestimates of welfare loss. We also expect that the travel cost parameter is negative, and if this parameter is biased and smaller (less important in reducing the probability of a site visit) than it should be, the CS will be larger than the unbiased CS, ceteris paribus.

5. Results

The simple RUM corresponding to equations [1] and [2] is estimated using the follow-up mail survey questionnaire data, and similarly, using data from the telephone survey. So that the model for the two main sample data sources can be comparable to each other, the set of explanatory variables for both models were limited by the amount of data that was collected using the less extensive telephone survey. The specification of the conditioning variables vector **x** is done to simply include a variable measuring the travel cost to and from five recreation sites the individual visits. A match in data collected for the two samples was attempted by limiting the respondents to the same twenty-one county area in the region.

The probability of recreating at five sites (j = 1, ..., 5) in the region (Walker, Topaz and Pyramid Lakes, Lahonton Reservoir, and Boca/Stampede Reservoir) is estimated using the basic model adding four site-specific constant terms (the terms that are α_k) that help explain variation in the probabilities of visiting the waters or specific sites, noting that all five could not be identified (see Cosslett 1981b).

Table 2 has the estimated parameters for the general telephone survey model (GTS - see column two), the on-site survey sample with the uncalibrated intercept trips only in (column three), the WESML estimates on the intercept trips, the intercept trip model with follow-up trips only, i.e., dropping the intercept trip taken (column four), and the calibrated intercept model (column five). All models yield a travel cost parameter which is negative and significantly different than zero, with slight differences. If there were no other parameter influences, this indicates that there would be some differences remaining in the CV estimated from each model. However, the models also each allow for site-specific dummy variables to influence the probabilities, which in turn influence consumer's surplus.

In the specification the site-specific constants are the only variables used to supplement the travel cost variable, and for this reason White's (1982) standard errors, which are robust to specification problems, are reported in Table 2. The Pyramid Lake dummy and Topaz Lake dummy is positive in the GTS and calibrated intercept models respectively, but otherwise the sites other than the base case (Walker Lake) have lower relative constants. Recall that the calibration method requires subtraction of the log of the sample fractions from the intercepts. In the base case the intercept is zero, so the calibrated intercept is of course negative, but all that matters are the relative magnitudes.

Table 3 reports the estimated or predicted mean sample probabilities (top half), and the actual mean shares of trips taken to each of the five sites (see bottom half). The probabilities could be expected to exactly match in large samples because of Cosslett's proof about the consistency of MNL estimates, and should be closer together here. In all cases except the calibrated model, the rounded predicted mean probabilities are exactly or close to equivalent to the actual shares of trips taken to each site. For example, the weighted telephone survey estimates provide a perfect match between the predicted mean probabilities and actual mean shares, except for rounding.

The calibration and weighting methods are expected to reduce the probability of visiting the waters where the intercept method may oversample recreational visits. This is easy to see by comparing the calibrated and WESML mean probability for Lake Lahonton. After calibration, the adjusted estimates almost exactly match the mean Telephone survey probability of 19 percent, while the corresponding pure intercept mean is 28 percent. Where the intercept underpredicts the mean, as in Lake Topaz visits, the calibration and WESML methods pull the average probability up. Finally, note that by using calibration or WESML, the Walker Lake mean probability falls a great deal from the intercept model, moving in the direction of the predicted mean Telephone survey probability of 9 percent. While all this supports the entire adjustment exercise, the economic analysis of interest is in the calibrated consumer's surplus estimates.

Consumer's Surplus

Table 4 presents estimated consumer's surplus for all five models, considered for "elimination" of each site. Prior work on the topic of weighting does not include this comparison of consumer's surplus. The average consumer's surplus estimate is different for nearly every sample group and every site. The intercept trips only group (see column three) for Walker elimination has the largest average WTP per choice occasion of almost \$10.[7] The Boca/Stampede and Pyramid Lake eliminations for the Telephone Survey are the largest across groups. Pyramid Lake is the largest sized lake in the group of lakes in the model, and the closest to the city of Reno, Nevada, which provides some intuition for this result.

The average weighted WTP per choice occasion differs by an extent for the calibrated intercept and Telephone Survey models but move toward each other except for the Pyramid Lake elimination. Otherwise, when the WTP is too "low" in the pure intercept sample as compared to the Telephone survey group, the calibration procedure increases the mean CS. The WESML procedure leads to an increase in the Boca and Topaz situations. This is what we might expect, presuming that we are correctly concerned about bias in the CS estimates using the pure intercept. Not everything can be seen in the simple examination of the mean CS estimates, but the calibration procedure appears to be effective in that the means are moving in the "right" direction. The WESML method helps in a few instances, but not all.

Discussion

Differences in consumer's surplus estimates between the calibrated and WESML intercept models and general/weighted Telephone survey model remain for several reasons. First, the calibration and WESML methods do not lead to an exact match in the two groups' mean

[7] If one believes in ordinal, rather than cardinal welfare measures, then we cannot say how much higher in absolute terms.

probabilities, which in turn has implications for the estimates of consumer's surplus. There is no reason why they should match, as the statistical argument is one of consistency in the parameters, a large sample property. The MNL model produces consistent estimates of parameters in large samples when using SRS data, but we have but one sample here and do not use perfect SRS data, though we are not sure anyone has such data.

6. Conclusions

The applied work here demonstrates the potential bias from use of an intercept survey sample, which is a very commonly used type of sample data. To our knowledge, though theoretical discussions of the general problem now exist (e.g. Laitila does not use any data or simulations) the actual empirical effects of this bias on RUM-based welfare measures have not been considered before. We see that for our sample, use of an intercept survey method alone can generate substantial bias in welfare measures as compared to more random sampling techniques. Our study also demonstrates some benefits from using an exogenous sample to compliment an inexpensive mail survey. We used a stratified sample of households drawn from the general population, contacted by telephone. One could use the Telephone Survey alone (not conduct a mail survey), but the number of questions that can be asked and the amount and complexity of information conveyed is limited by the research budget. In addition, telephone surveys are not without their problems in communicating complex information and obtaining adequate responses.

Unless one has good prior knowledge on where people live who consume goods (for our case, who visit waters or recreational resources of interest), there is no way to generate a good, but inexpensive sampling plan. Thus, the intercept method has its value even when Telephone sampling is the intended strategy. We are quite sure that researchers will continue to use it because it is so inexpensive, is relatively easy to implement, and allows interactions between the survey team and the respondent. However, the message that we provide here is that even careful adjustments using calibration or weighting will not mimic general population consumer's surplus estimates. Simulation method might further shed light on discrepancies.

An alternative to the intercept, while a more expensive strategy to accomplish this analysis, would be to start with a simple random sample of the general population, perhaps via random digit dialing. This then requires identifying the target group through some screening process, and then making an attempt to follow them throughout the season in order to collect the necessary data on the individual's subsequent consumption (here - trips) taken during throughout the entire season. One might ask each person to keep a diary of their consumption patterns. Either a telephone, or mail survey, or both could be used to collect the necessary follow-up information. In complex situations we may slightly favor a mail survey in order to better communicate information. However, a combined analysis like this could cost in the range of the hundreds of thousands of dollars.

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Table 1: Studies Involving the Intercept Sampling Method*	
Study Authors	**Method Used/Data**
Bockstael, McConnell and Strand	Intercept recruitment/marine recreation
Cameron and James	Intercept Survey only/marine recreation
Herriges and Kling	Intercept Survey only/marine recreation
Kaoru, Smith and Liu	Intercept Survey only/marine recreation
Kling and Thomson	Intercept Survey only/marine recreation
Lin, Adams and Berrens	Intercept Survey/river recreation
Morey, Shaw and Rowe	Intercept Survey only/marine fishing
Morey et al.; Morey and Waldman	Intercept recruitment with follow/river angling
Schumann	Intercept survey

* These examples are studies that may combine some aspect of intercept sampling with other survey methods.

Table 2: Estimated Parameters[1]

	Model Approach				
Variable	**General/Telephone Survey**	**Intercept Trips (uncalibrated)**	**WESML (Intercept)**	**Follow-up Trips Only**	**Calibrated Intercept**
Travel cost	-0.048 (0.0075)*	-0.064 (0.013)*	-0.089 (0.013)*	-0.073 (0.013)*	-.06
Boca/Stampede Dummy	-0.599 (0.2174)*	-1.84 (0.504)*	-0.509 (0.799	-1.68 (0.542)*	-0.86
Lahonton Dummy	-0.437 (0.237)*	-0.840 (0.457)	-1.03 (0.903)	-1.47 (0.509)*	-1.21
Pyramid Dummy	0.259 (0.239)	-0.418 (0.405)	-0.282 (0.830)	-0.76 (0.485)	-0.476
Topaz Dummy	-0.037 (0.158)	-1.53 (0.478)*	0.184 (0.787)	-0.521 (0.413)	0.591
Walker Dummy	NA	NA	NA	NA	-.963
Sample Sizes[2]					
Number Obs.	364	113	113	113	113
Trips	2,257	113	1,591	1,591	113

* indicates significance at the five percent level or better.

[1] Note that White's standard errors, which are robust to specification errors, are reported in parentheses.

[2] Telephone survey trips were 3,081 originally, but 2,257 after weighting.

Table 3: Estimated Probabilities, Actual Shares

	Model Approach				
	General/Telephone Survey	**Intercept Trips (uncalibrated)**	**WESML (Intercepts)**	**Follow Up Trips Only**	**Calibrated Intercept**
Predicted Probabilities					
Boca/Stampede	.24	.09	.21	.12	.20
Lahonton	.19	.28	.19	.24	.20
Pyramid	.29	.31	.26	.34	.29
Topaz	.18	.07	.16	.12	.15
Walker	.09	.25	.18	.18	.17
Actual Shares					
Boca/Stampede	.24	.09	.09	.12	.09
Lahonton	.20	.28	.28	.24	.28
Pyramid	.29	.31	.31	.34	.31
Topaz	.18	.07	.07	.12	.07
Walker	.09	.25	.25	.18	.25

* N = 364 for Telephone Survey, and N = 113 for Intercept Survey.

Table 4: Consumer's Surplus					
	General/Telephone Survey	**Intercept Trips (uncalibrated)**	**WESML (Intercept)**	**Follow-Up Trips Only**	**Calibrated Intercept**
Elimination of Boca/Stampede	$6.56	$1.54	$2.88	$1.83	$3.74
Elimination of Lahonton	$4.77	$5.61	$2.69	$4.02	$3.67
Elimination of Pyramid	$7.95	$6.54	$3.93	$6.54	$5.99
Elimination of Topaz Lake	$4.80	$1.33	$2.96	$2.36	$3.35
Elimination of Walker Lake	$2.63	$9.85	$6.67	$6.61	$5.76

An External Validity Test of Intended Behavior: Comparing Revealed Preference and Intended Visitation in Response to Climate Change

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An External Validity Test of Intended Behavior: Comparing Revealed Preference and Intended Visitation in Response to Climate Change

Abstract

We compare revealed preference and survey response estimates of visitor trip making behavior from climate change. The revealed preference is estimated from a time-series regression analysis of past visitation as a function of historic weather variability. We find no statistical difference between the revealed preference regression estimates and survey intended behavior estimates of the total number of National Park visits. The mean estimates of the change in visitation are within 12% of each other.

An External Validity Test of Intended Behavior: Comparing Revealed Preference and Intended Visitation in Response to Climate Change

I. Statement of Problem

Evaluating the demand for new products and potential effects of new government policies often requires an analysis of what consumers would do under changed circumstances. Occasionally the demand for the new product or new policy can be quantified using an econometric analysis of past data, but frequently consumer intended behavior surveys are required. These surveys describe the new product or new policy (e.g., extended bus operating hours) and ask the consumer the quantity (if any) they would purchase at a particular price. The key question often asked by marketing managers and policy makers is whether these survey responses yield valid estimates of behavior. However, there are often very few opportunities to externally validate survey responses. Usually the survey must be conducted because there is no past data or the available data do not allow extrapolation to the new product or policy. In this paper we report on one of these rare cases where actual behavior can be used to test the validity of survey responses. The application is changes in recreation visitation to a National Park resulting from potential changes in climate. Both the methodological testing and subject matter are of some interest as very few studies have evaluated the effect of climate on recreation visitation. Our case study area, Rocky Mountain National Park near Denver, Colorado, is typical of many large, high elevation National Parks in western North America.

There have been only a few studies that have combined stated-preference visitation data with revealed-preference travel cost data to measure changes in intended visitation (Whitehead *et al.*, 2000; Grijalva *et al.*, 2002). Chase *et al.* (1998) used contingent visitation to measure the hypothetical impact on visitation demand of alternative entrance fee levels at three national parks in Costa Rica. Only Grijalva, et al. 2002 has been able to perform an external validity test of the intended visitation behavior. She found that rock climbers stated changes in visitation behavior due to climbing area closures matched the aggregate actual visitation behavior the next year when the closures took place.

Revealed Preference Regression Model

We model total visitation *(Vi)* to Rocky Mountain National Park (RMNP) in month *i* as a function of climate and demographic variables *(Xi)*. The specified model takes the form:

$$V_i = \beta_0 + \beta_1 S_i + \beta_2 T_i + \beta_3 P_i + \beta_4 Pop_i + \beta_5 SVDV_i + \varepsilon_i \qquad (1)$$

where S_i represents average snow depth for month *i*, T_i represents average maximum temperature for month *i*, P_i represents total precipitation for month *i*, Pop_i represents average monthly population for 12 counties along Colorado's urban Front Range, $SVDV_i$ represents a dummy variable for school vacation months (for which $SVDV = 1$ for July and August), and ε_i represents the normally-distributed disturbance term.

Monthly visitation data was obtained for the years 1987-99. In this paper we concentrate on peak (May-October) season visitation since nearly 90% of the annual visitation to RMNP occurs during this time period. The Natural Resources Ecology Laboratory at Colorado State University provided the historic climate data for the regression, as well as climate forecasts associated with two widely used global circulation models (GCM's) known as CCC and Hadely.

Intended Visitation Survey Data

A visitor survey was designed that compared the historic average temperature, precipitation and snow depth to what these variables would be like with the CCC and Hadley global climate change scenarios. This was done in side-by-side tabular form that was developed from two focus groups, and refined through pretesting with visitors in RMNP. The survey design used graphical and numerical representations of the climate scenarios. Icons and symbols that proportionally represented hypothetical changes were included to give a more descriptive presentation of climate scenarios. A copy of the survey is available from the lead author.

The intended visitation questions asked the respondent a series of closed-ended questions regarding **if** their *number of visits* and *length of stay* would change under each climate scenarios; and if so, how many more (or fewer) trips or days would they have visited a year.

Survey data was collected during the summer of 2001. Visitors were selected randomly at five different types of areas in RMNP over a total of 40 sampling days. Visitors were given a mail back survey packet at the sampling sites. Mail-returned surveys were chosen because of the complexity of the climate scenarios and the amount of time required to complete the questionnaire. There were 1,378 attempts to distribute surveys, and 112 were refused. Thus, a total of 1,266 surveys were distributed. Reminder postcards were mailed to survey recipients one week after the day of distribution, and replacement copies of the survey were mailed three weeks later to non-respondents. At the end of the survey collection period, 967 surveys were returned, which amounts to a 70% response rate (or a 76% response rate, net of refusals).

Hypothesis Tests

External validity of intended behavior surveys and revealed preference regression would be evidenced by failing to reject the null hypothesis:

$$\text{Ho: } V_{est}\,(\text{Regression}) = V_{est}\,(\text{Survey}) \tag{2}$$

Where Vest is the peak season park visitation estimate with each method.

The construction of confidence intervals allows for tests of the statistical difference between revealed preference and survey estimates of visitor use with the two climate scenarios. The formula for calculating confidence intervals for visitor use estimates based on the regression equation is: $(1\text{-}\alpha)100\%\ \text{Confidence Interval} = \text{Vest} \pm t_{\alpha/2}\, se[1+W'(Z'Z)^{-1}\, W]^{0.5}$ (3)

A 95% confidence interval was used for this analysis; *se* represents the standard error of the regression. The *Z* matrix represents the explanatory exogenous variables, while the *W* matrix represents future value of those variables with each climate forecast (e.g., CCC). Thus, the matrix $[W'(Z'Z)^{-1}\, W]$ reflect future values of temperature, precipitation and snow depth with each climate scenario. The new standard error for resulting visitor use estimates Vest is therefore represented by $se[1+ W'(Z'Z)^{-1}\, W]^{0.5}$ (Mendenhall, 1990).

Since the intended visitation estimate for the change in annual visitor days is based on the survey responses to two intended behavior questions (regarding the change in the number of trips and the length of stay), the standard error must reflect the variance of the product of the two distributions. Thus,

$$Var\,(XY) = E(X^2)\,E(Y^2) - \mu_X^2\,\mu_Y^2 \tag{4}$$

$$= Var(X)\,(Var(Y) + (Var(X)\,\mu_Y^2) + (Var(Y)\,\mu_X^2) \tag{5}$$

Substituting this derivation for *Var* (XY), the standard error of the joint distribution (*se)* is calculated as follows:

$$se = sd\,(XY)\,/\,\text{sqrt}\,(n) \tag{6}$$

$$= \text{sqrt}\ Var\,(XY)\,/\,\text{sqrt}\,(n)$$

$$= \text{sqrt}\,[Var(X)\,(Var(Y)) + (Var(X)\,\mu_Y^2) + (Var(Y)\,\mu_X^2)]\,/\,\text{sqrt}\,(n)$$

where *sd* = the standard deviation. The standard errors for each of the two climate scenarios were calculated according to Equation 6.

Results

With the CCC climate scenario involving a 2.4 degree increase by 2020, about 8.6% of the respondents indicated that their visitation behavior would change. The application of their responses to baseline RMNP visitation data yields a mean estimate of 1,357,888 **additional** visitor days, as provided in Table 1 below.

Table 1: Survey Results – CCC Climate Scenario

RESULTS: CCC SCENARIO	CHANGE NUMBER OF TRIPS	CHANGE LENGTH OF STAY
% Respondents who would change their visitation behavior	8.60%	11.54%
Average additional trips per visitor	+0.14 trips per visitor	+0.10 days per trip
Total Visitation	3,186,323	
Projected New Visitation	3,618,856	
Change in Visitation (%)	13.57%	
Change in Visitation (#)	432,533	
Average length of stay (days)	3.04	
Mean Change in Annual Visitor Days	1,357,588	

The Hadley climate scenario was included in Survey Version B, and 11.1% of the respondents to that survey indicated that their behavior would change under the hypothetical climate scenario. The application of their responses to baseline visitation data yields a mean estimate of 1,002,080 **additional** visitor days, as provided in Table 2.

Table 2: Survey Results – Hadley Climate Scenario

RESULTS: HADLEY SCENARIO	CHANGE NUMBER OF TRIPS	CHANGE LENGTH OF STAY
% Respondents who would change their visitation behavior	11.11%	13.49%
Average additional trips per visitor	+0.10 trips per visitor	+0.13 days per trip
Total Visitation – 1999	3,186,323	
Projected New Visitation	3,502,426	
Change in visitation (%)	9.92%	
Change in visitation (#)	316,103	
Average length of stay (days)	3.04	
Mean Change in Annual Visitor Days	1,002,080	

Monthly Visitor Regression Results

The results of the regression analysis of historic monthly visitation as a function of climate variables is presented in Table 3 below. The model has a fairly high explanatory power and the key climate variables are significant at conventional levels.

Table 3: Visitation Regression Results

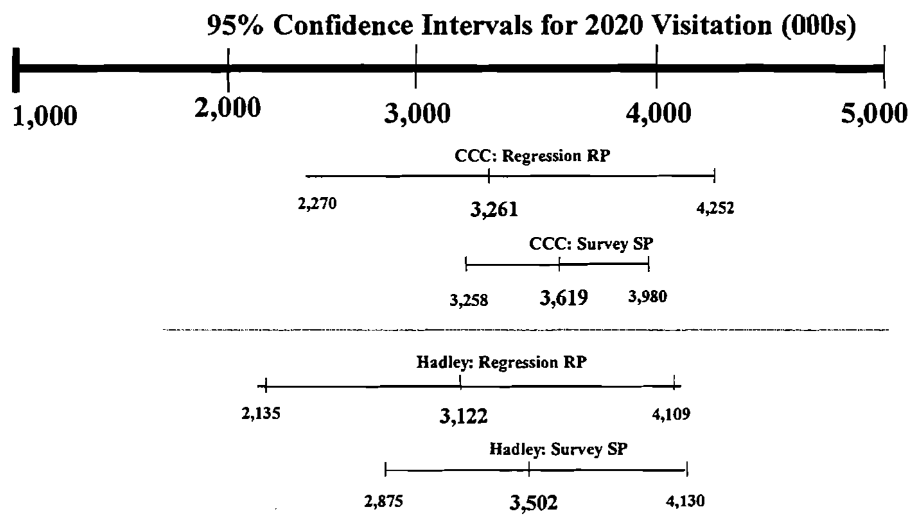
Regression Variables	Peak Season (May-October)		
	Coefficient	**Std. Error**	**t-Statistic**
Intercept	-639,549.7	162,598.1	-3.9333
Snow depth	-386.3	71.0	-5.4388
Maximum temperature	18,457.7	3,330.1	5.5427
Precipitation	846.4	302.9	2.7947
Population	0.022	0.050	4.3088
School Vacation DV	200,961.4	27,049.0	7.4295
R^2	0.8840		
Adjusted R^2	0.8741		
Durbin-Watson	2.4566		

Comparison of Revealed Preference Regression and Survey Estimates

Using 2020 climate forecasts and the baseline year regional population level, we are able to isolate the effects of changing climate variables in the forecast of future visitation. Under the revealed-preference regression approach, visitation is estimated to increase 11.6% under the CCC scenario versus 13.6% for the survey responses, a fairly close correspondence. For the Hadely climate scenario, the regression estimate is 6.8% versus 9.9% for the survey.

Figure 1 below illustrates the 95% confidence intervals for the visitation forecasts for the CCC and Hadley scenarios under both the revealed preference and survey (stated preference) analytical methods. As is evident, the estimates from the stated and revealed preference methods are not statistically different from one another. The mean estimates of the change in visitation are within 11% of each other for the CCC climate scenario and 12% for the Hadley climate scenario.

Figure 1: Comparison of Confidence Intervals for Regression Revealed Preference (RP) and Survey Stated Preference (SP)



Conclusions

We compared visitor survey responses to a revealed preference regression to estimate the effects of climate change on visitation to Rocky Mountain National Park. A comparison of the results of the survey intended visitation analysis with that of the revealed preference regression analysis indicate that the two approaches produce mean estimates of peak season visitation within 12% of each other, not a statistically significant difference. Thus it appears that carefully constructed intended behavior surveys can produce estimates approximating that obtained from actual behavior.

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Growth Equilibrium Modeling of Urban Sprawl on Agricultural Lands in West Virginia

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Growth Equilibrium Modeling of Urban Sprawl on Agricultural Lands in West Virginia

Abstract

With dynamic economic and social changes, increasing pressure is exerted on natural resources management. Agricultural land resources particularly face growing pressure of conversion to non-agricultural uses from population and development demands for land. The continual conversion of agricultural land may have implications in terms of the loss of prime farmland, irreversible landscape changes, deteriorating environmental quality, and interference with rural lifestyles. This study models urban sprawl on agricultural land in a growth equilibrium modeling approach. The primary research focus is on the development of econometric model to address agricultural land conversion. Application of the model on West Virginia data indicates that population and employment growth induce reallocation of agricultural lands, with population accounting for a significant pressure on agricultural land conversion. Poor agricultural performance and urban adjacency significantly induce conversion and facilitate sprawl at urban fringes. Results also indicate that Federal and NGOs land conservation programs have the potential to significantly reduce changes in agricultural land density.

I. INTRODUCTION

Throughout history, there has been an intricate relationship between mankind, natural resources and the environment. Over time, this intricate relationship has been changing in response to varying natural, social, political, technological, and economic forces.

Recent exponential population growth and dynamically changing economic activities over space have resulted in concern about the nature and health of our relationship with the natural world. Heated debates on issues of land use systems, land degradation, environmental pollution, energy supply, wildlife extinction, and reduced natural resource stocks on the one hand and land use planning, environmental management, alternative renewable energy planning, wildlife protection, and natural resource management policy issues on the other are all indications of the urgency of reconsideration of (and precautious approaches to) the relationship between economic agents and natural resources.

One of the natural resources facing demographic, economic, and technological pressures is agricultural land. Consequently, today there are growing concerns and issues of land use systems and preservation. Pressure on agricultural land often arises from population growth and attendant land demands, competing alternative economic activities over space, and growing global demand for food and fiber. Though increasing global food and fiber demands have been met with agricultural technologies in many instances, the competition for land between different economic activities has resulted in conflict of interest and eventual conversion of land between different uses.

New spatial features create frictions among economic sectors in their competition for land. This, however, increases social costs in terms of increasing costs of amenities due to scattered and unplanned rural development, frictions in land use, deterioration of environmental quality, disruption of local production methods and farming practices, and transformation of rural landscapes into urban type developments. Suburban developments also affect the value of agricultural land and the effectiveness of the agricultural sector in meeting its various demands.

The intent of this research is to develop a conceptual model that captures the impact of regional changes in growth of employment and population on agricultural lands. The model is tested on West Virginia data.

II. SUBURBANIZATION TRENDS AND AGRICULTURAL LANDS

In the last two decades, defined acres of urban land increased by 40 percent between 1980 and 1997 in the U.S. (Vesterby and Krupa 1997). Similarly, Vesterby and Krupa (1997) reported that urban areas in the U.S. increased by 49.3 percent from 1945 to 1997. Particularly, urban areas in the Appalachian Region grew by 5.1 percent during this period. Uses of land for transportation increased by 2.6 percent in the U.S. and by 0.3 percent in Appalachia from 1945 to 1997. Meanwhile, cropland decreased in Appalachia by 7.0 percent with a loss of 6.0 percent in crops and a gain of 0.6 percent in pasture. According to Pimentel and Giampietro (1994), over the next 60 years urbanization will diminish U.S. arable land base by 470 million acres.

USDA's report in 1990 concerning the extent of agricultural land conversion indicates that in the United States, 60% of land removed from agriculture in sub-urban areas comes from cropland and that 90% of the croplands likely awaiting conversion to non-agricultural uses in 50 years is expected to be prime farmland (USDA, 1990). The Natural Resource Conservation Service also reports that for the 5-year periods of 1982-87, 1987-92, and 1992-97, prime farmland conversion accounted for about 30 percent of the newly developed land (NRCS, 2001).

A series of studies in West Virginia on land use, taxes, and land use values have been done in the past (Dufresne and Colyer 1975; Colyer and Templeton 1977; Ferrise and Colyer 1980, 1984; Tall and Colyer 1989). Some of the studies have indicated increased use of land for residential, commercial, and industrial uses and for transportation, public utilities, community facilities, and government installations (State MRP Land Use Committee 1976; Tall and Colyer 1989).

The Census of Agriculture (1992) also reported that the total number of farm acres in West Virginia declined by over three percent from 3.37 million acres in 1987 to 3.27 million acres in 1992.

A substantial amount of land in and around the small towns and their constituent counties located near large centers, particularly in the eastern Panhandle, is being used for second or retirement homes, campground and weekend recreational use, or has been purchased as speculative investments. Most of these developments seek flat, well-drained land. However, the quantities of such land, which are usually used for farming, are severely limited in most West Virginia communities. As a result, such losses of land make it difficult or impossible to maintain rural land for agricultural uses because returns to land in agriculture are low relative to other uses in West Virginia (MRP, 1976).

This problem demands on understanding of urbanization trends, causing factors as well as possible modeling approaches to provide relevant insights for regional land use planning and management.

III. THEORIES OF SUBURBANIZATION

Understanding the forces behind land conversion to non-agricultural uses is particularly relevant in modeling and predicting land use changes. Pressures on agricultural land can generally be seen from the rural agricultural sector point of view as well as from city pressure point of view. Both of these perspectives can help explain the origin and effect of factors leading to conversion.

With increases in urban population and residential and employment preference towards the edge of cities, the conversion process becomes eminent unless interrupted by policy measures. Behind the forces of population and employment changes across time and space, however, there are a number of theories that attempt to identify the factors affecting the suburbanization process.

Studies attribute the suburbanization and land conversion process to "rural renaissance" [pull factor] and "urban flight" [push factor], a shifting economic base, and a change in employment opportunities (Dissart and Deller 2000; Power 1996; Lewis, Hunt and Plantinga 2002).

One class of theoretical explanation for suburbanization underlines fiscal and social problems associated with central cities: high taxes, low quality public schools and other government services, crime, congestion and low environmental quality. These problems lead residents to migrate to suburban places (Mieszkowski and Mills, 1993).

In the context of the United States, different historical explanations of push factors are generally attributed as causing suburbanization pressures during different decades. During the 1950s, it was claimed that home mortgage insurance by the federal government was responsible for suburbanization. In the 1960s, the interstate highway system and racial tensions were popular explanations of decentralization. More recently, crime and schooling considerations have been prominent explanations of urban decentralization (Mieszkowski and Mills, 1993).

Alternative explanations of suburbanization also rest on the rural qualities and endowments [pull factors] as a factor of migration and inter-temporal land use changes vis-à-vis increasing urban disamenities. For private housing demand for land, open space is often attributed as a principal attractor of urban and suburban residents to exurban areas. Rural environment provides scenic views, recreational opportunities, and a near absence of disamenities associated with development, such as traffic congestion and air pollution (Irwin and Bockstael, 2001).

The urban push factors (urban disamenities) as well as the rural pull factors (natural amenities) interact to influence the migration patterns of households and businesses. Though whether population follows employment or employment follows people is an ongoing debate, the interest here is the influence of inter-temporal and spatial population and employment changes on regional land use changes.

In a simultaneous fashion, population and employment changes play a major role in affecting land use patterns over space and in affecting the conversion of land away from agriculture. Decentralization of residential places is followed by decentralization of employment. Firms move to suburbs following changes in residential location preferences. However, this further stimulates a change in population across regions (Mieszkowski and Mills, 1993).

In a competitive land market, the price for land equals the present discounted value of the stream of future rents. Thus, it is expected that if rents from development exceed agricultural rents in the future, the higher rents from future development will be capitalized into the current price of agricultural land (Plantinga and Miller, 2001). Hence, as the development pressure intensifies following the out-migration of population and businesses to suburban areas, more land will be put into use for housing and development purposes as these economic activities might provide a better bid than competing agricultural and other rural economic activities.

IV. CONCERNS OF ECONOMIC INTEREST

Suburbanization and consequent agricultural land use changes have been concerns of economic research. The decision making process of households and businesses and their location preferences have been investigated according to economic behavior, resource reallocation and consequent policy implications (Dissart and Deller, 2000).

Migration and employment growth patterns in suburban places and development pressures have socio-economic implications that have a multitude of economic implications.

One argument for growing concern over development of agricultural lands is that agriculture is valued as a way of life and provides scenic benefits, jobs, and income opportunities for many rural communities. But rapid development continually threatens the livelihood of the farming population and the amenity benefits provided by land in farming. Moreover, agriculture is considered as one of the most important parts of American culture and history that needs to be preserved (Barkley and Wunderlich, 1989).

Concern is also focused on the interference of development of adjacent agricultural lands on the efficiency of farming practices. Many studies measure the direct effects of the loss of farmland in terms of output reduction and income losses. Indirect impacts on the farming community could also include regulatory restrictions on farming practices with suburbanization, technical impacts, and speculative influences. When farmers become uncertain about the future viability of agriculture in their area, farmland production falls, as does farming income. Ultimately, the critical mass of farming production needed to sustain the local farming economy collapses (Berry 1976; Daniels and Nelson 1986; Daniels 1986; Lapping and Fitzsimmon 1982).

Resource-based rural land use change is dynamic, shifting from one use to another as economic factors favor different resource uses at different times. However, urban uses are an absolute use category because the conversion of agricultural land to urban uses is irreversible. Once the land is paved over or built-upon, it is most likely lost forever to non-agricultural uses. This irreversibility component of land use changes also poses allocational and policy concerns to land use systems.

Recently, attention has focused on preserving local benefits from agricultural lands such as open space, environmental quality, and impediments to urban sprawl. Many of these benefits have public characteristics and, as a consequence, will tend to be undersupplied by private producers (Plantinga and Miller, 2001).

Irwin and Bockstael (2001), in their estimation of open space spillovers using a hedonic pricing model of residential property sales suggest that the positive amenity value associated with open space may not be identified.

In addition, there is value attached to open space, green surroundings, and the peace and serenity some associate with agricultural land (Bowker and Didychuk 1994; Kline and Wichelns 1996; Ready et al. 1997; Rosenberger and Loomis 1999; Rosenberger and Walsh 1997). The problem for surrounding communities is that the cash-driven marketplace often does not recognize these amenities (Gardner 1977). Society as a whole loses if these amenity values are reduced through development.

Vesterby, et al. (1994) raise issues revolving around the value of land that may fail to be accounted for in the valuation process. Aside from issues of productivity of the agricultural sector impacted by conversion processes, urbanization of rural land raises issues at the State and local levels with regard to protecting watersheds, maintaining air quality, providing open space, preserving rural life styles, preventing urban sprawl, and preserving local economies. These values are usually not internalized in the market price of farmland. Hence, the trend in land use changes poses serious policy considerations as they entail multifaceted socio-economic implications.

V. POLICY ISSUES

From a policy perspective, the conversion of agricultural lands to non-agricultural (development) uses has been a critical public issue. In every state and at every level of government, land use has become a subject of impassioned debate. Some states have provided locally initiated mechanisms for the protection and enhancement of agricultural land. Many people feel government should take action to identify and preserve rural areas where agriculture is recognized as an important land use and to take steps to improve the future prospects of retaining rural land for agricultural production, open space benefits, and rural character and heritage values (Kline and Wichelns 1994).

Debate also mounts on the efficiency of the price mechanism in fully accounting for the non-market values of agricultural land preservation. Competing demands for land may lead to an inefficient amount of agricultural land in the future (Lopez et al. 1994). Thus, if the state government wishes to preserve farmlands and keep farm families on their farms, it is essential to understand the impact of residential, commercial, and industrial growth upon agricultural land, and policy responses to these changes.

A desire to preserve farmland often conflicts with the pressure for continued and expanded development. This often excretes a greater challenge to land use policy and remains a central problem in striking an appropriate balance between development and preservation. In the case of West Virginia, level land is a rare resource. As a result, such losses of land make it difficult or impossible to maintain rural land for agricultural uses as returns to land in agriculture are low relative to other uses in West Virginia.

VI. THEORETICAL MODEL

Understanding the underlying economic motives of economic agents and capturing behavioral friction across space is a complex undertaking and a critical requirement in the modeling process of land use. In a circular flow process, consumers (households) do not only supply factors but can also demand them from a factor market. Similarly, producers not only demand factor inputs, but they can decide to supply a factor market. Taking land as a significant input exchanged in the factor market, households (landlords) can supply land to the market for sale or rent the resource to generate a flow of financial returns. However, households can also demand land to maintain higher utility from the flow of services of land to consumers. Similarly, businesses demand land as an input of production (both farm and non-farm businesses) to produce profit-generating outputs as well as to maintain locational cost and revenue advantages. However, as industry cost structures, technology, preferences of consumers, government policies, environmental requirements, etc., change, they may find it cost effective to relocate, hence supplying the present land holding back to the factor market. This is consistent with the assumption that firms are spatially mobile to maintain location equilibrium.

It can be noted from the circular flow chart (Figure 1) that there are immense interdependences among sectors. The simultaneous decisions of consumers and producers, both in the product and factor markets, affect the value of products and resources and their consequent distributional structure. Any change in the factor or product market by an exogenous event or endogenous decision factor affects the decision by different sectors in the economy, which in turn affects the efficiency and distribution of resource use.

Suburban and rural land, as indicated earlier, can be demanded for direct use by consumers and by agricultural and non-agricultural producers. Consumers' demand for land can be motivated by a number of factors. As indicated in figure 1, consumers (households) tend to demand more sub-urban and rural land as population pressure and urban congestion intensifies and as the quality of life including natural amenities tend to be valued higher by households for housing and recreational purposes. Households can also be attracted to suburban areas for employment as there are growing small business enterprises across the urban fringe and emerging rural economies.

The demand of rural and suburban land for agricultural land purposes is motivated by fertility and location factors affecting the profit of farmers, the agglomeration of farms in the farm environment, and the farming tradition maintained for generations. However, with intensified competition over suburban land on the one hand and lesser per acre return of agricultural enterprises on the other has led to the conversion of land to other non-agricultural uses. This implies that the agricultural sector is not only a source of demand for land, but is also a net supplier of rural land for other competing uses.

Non-agricultural producers are similarly motivated by locational convenience to maximize profits. Transportation costs and agglomeration economies can attract firms to a given location that generates better locational returns. Non-agricultural firms consider regional labor cost savings and market size in their location decision. Growing suburban population, transport savings and labor advantages can motivate firms to relocate to locations where such advantages are prevalent. This exerts pressure on the suburban land markets and increases the price of land.

In most cases, land demanded for different purposes in the suburban area satisfies certain qualities. Starting from locational convenience and nearness to big markets, it could provide positive environmental externalities and physical characteristics that could be of interest to developers. As the gravity over land intensifies, the value increases in the factor markets enabling one sector to outbid competing sectors. This gravity can enhance the conversion of agricultural lands to urban uses and contributes to further suburbanization. Though it is theoretically relevant to view firms as being mobile over space, the mobility of resources back to certain sectors is ambiguous. Though the relative strength of sectors in terms of bidding power can determine the flow of land resources, land taken away from agriculture is often irreversible.

From the established general framework, specific relationships in a regional growth frame can be generated for the modeling purpose. Generally, the changes in spatial land use features may be captured by aggregate changes in population and employment densities. The growth of population in suburban areas and metropolitan cities as well as the spread of small businesses and recreational and administrative land requirements can exert pressure on the current use of land.

To capture the impact of inter-temporal employment and population density changes on agricultural lands, a growth equilibrium modeling is introduced. Growth equilibrium models were developed to simultaneously explain employment and population changes for a region. These types of models capture the direct and indirect linkages between population and employment migration patterns and other exogenous factors important in explaining these migration patterns. In their early applications, these models were used to resolve the debate over whether people follow jobs or jobs follow people (Carlino and Mills 1987). Beginning with Roback (1982), this modeling strategy was used to identify the direct and indirect linkages between population and employment migration and amenity factors (Knapp and Graves 1989). Roback's (1982) application investigated the linkages between crime rates and urban migration. More recent applications include migration linkages with natural amenities including climate and topography (Carlino and Mills 1987; and Clark and Murphy 1996), wilderness (Duffy-Deno 1998), natural amenities and recreation supply (Deller et al. 2001) and forested public land (Lewis, Hunt and Plantinga 2002).

This paper expands the modeling approach to agricultural land use changes in a regional growth framework. The theoretical model is developed following basic assumptions. It is assumed that consumers maximize utility by the consumption of a vector of goods and services. Consumers consume goods and services as well as location and non-market amenities, and are assumed mobile over locations that maximize utility. The consumption of the vector of consumer choices is limited by income (budget). Households migrate until utilities are equalized at different alternative locations.

Producers are assumed to maximize profit from the production of goods and services. Firms select locations to capture locational cost and revenue advantages, minimize the cost of transportation, benefit from agglomeration and regional labor cost differences. Firms enter and leave regions until competitive profits are equalized across regions.

It is also assumed that firms and households adjust to disequilibrium over time. In a general equilibrium framework, population and employment are affected not only by each other, but also by a variety of other variables that affect numbers of jobs consistent with competitive profit rates and number of people consistent with equalized utility levels among places. In principle, many such variables might be simultaneously determined in such a general equilibrium model, along with population and employment (Carlino & Mills, 1987).

Following the spirit of the Carlino-Mills model, this research work expands on the regional growth model to investigate the simultaneous interaction of employment, population, and agricultural lands and to model the impact of growth on agricultural land conversion.

In a general equilibrium framework, population and employment are affected not only by each other, but also by a variety of other variables that affect numbers of jobs consistent with competitive profit rates and number of people consistent with equalized utility levels among places. In principle, many such variables might be simultaneously determined in such a general equilibrium model, along with population and employment (Carlino & Mills, 1987).

Thus, maintaining similar behavioral assumptions of economic agents and distributed-lag adjustment specification procedures, the simultaneous interaction of equilibrium employment and population and their interaction with agricultural lands can generally be modeled as:

(1) $P^* = f(E^* | \Omega^{P})$

(2) $E^* = f(P^* | \Omega^{E})$

(3) $A_gL^* = f(P^*, E^* | \Omega^{A_gL})$

where P^*, E^*, and A_gL^* refer to equilibrium levels of population, employment, and agricultural lands respectively; Ω^P, Ω^E, and Ω^{AgL} refer to a vector of other exogenous variables having a direct or indirect relationship with population, employment and agricultural lands respectively.

The functional expressions (equations 1, 2, and 3) can be expanded to growth equilibrium expressions as:

(4) $P^* = \Psi_P E^* + \Phi_P \Omega^P$

(5) $E^* = \Psi_E P^* + \Phi_E \Omega^E$

(6) $A_gL^* = \Psi_P E^* + \Psi_E P^* + \Phi_P \Omega^P + \Phi_E \Omega^E + \Phi_{AgL} \Omega^{AgL}$

Equations 4 and 5 indicate that the equilibrium level of population depends on the equilibrium level of employment and a vector of exogenous variables that can possibly influence equilibrium population. Similarly, the equilibrium level of employment depends on the equilibrium population and a vector of other exogenous variables that can possibly affect employment. Equation 6 indicates that the equilibrium level of agricultural land is influenced by the regional equilibrium levels of population and employment and by other exogenous factors that interact to influence the conversion of agricultural lands.

Following Deller, et al.'s (2001) linearized expression of the equilibrium conditions, equations (4), (5) and (6) can linearly be represented as:

(7) $P^* = \alpha_{0P} + \beta_{1P} E^* + \sum \delta_{1P} \Omega^P$

(8) $E^* = \alpha_{0E} + \beta_{1E} P^* + \sum \delta_{1E} \Omega^E$

(9) $A_gL^* = \alpha_{0AgL} + \beta_{1AgL} P^* + \beta_{2AgL} E^* + \sum \delta_{1AgL} \Omega^{AgL}$

Population and employment are likely to adjust to their equilibrium values with substantial lags (Mills & Price, 1984). Similarly, agricultural lands are assumed to likely adjust to their lagged values. The rate and level of agricultural land conversion in the base year is likely to influence the behavior of agricultural land conversion in the current year; or conversely, equilibrium levels of agricultural land adjust to previous period conversion patterns. Thus, a distributed lag adjustment equation can be introduced as:

(10) $P_t = P_{t-1} + \lambda_P (P^* - P_{t-1})$

(11) $E_t = E_{t-1} + \lambda_E (E^* - E_{t-1})$

(12) $A_gL_t = A_gL_{t-1} + \lambda_{AgL}(A_gL^* - A_gL_{t-1})$

where λ_E, λ_P and λ_{AgL} are speed-of-adjustment coefficients with $0 \leq \lambda_E, \lambda_P, \lambda_{AgL} \leq 1$, and t-1 is a one period lag. This indicates that current employment, population, and agricultural lands are dependent on their one period lagged levels and on the change between equilibrium values and one lagged period values adjusted at speed-of-adjustment values of λ_E, λ_P and λ_{AgL}.

Rearranging terms:

(13) $\Delta P = P_t - P_{t-1} = \lambda_P(P^* - P_{t-1})$

(14) $\Delta E = E_t - E_{t-1} = \lambda_E(E^* - E_{t-1})$

(15) $\Delta A_gL = A_gL_t - A_gL_{t-1} = \lambda_{AgL}(A_gL^* - A_gL_{t-1})$

Substituting the linearized expressions of P*, E*, and A_gL^* equations 10, 11, and 12 into equations 13, 14, and 15 gives:

(16) $\Delta P = \lambda_P(\alpha_{0P} + \beta_{1P}E^* + \sum\delta_{1P}\Omega^P - P_{t-1})$

(17) $\Delta E = \lambda_E(\alpha_{0E} + \beta_{1E}P^* + \sum\delta_{1E}\Omega^E - E_{t-1})$

(18) $\Delta A_gL = \lambda_{AgL}(\alpha_{0AgL} + \beta_{1AgL}P^* + \beta_{2AgL}E^* + \sum\delta_{1AgL}\Omega^{AgL})$

The speed-of-adjustment coefficient (λ) is embedded in the linear coefficient parameters α, β, and δ (Deller, et al., 2001). Noting that equilibrium values of employment, population, and agricultural lands are initial values plus their change between their current levels and their base periods levels, the final equations can be written as:

(19) $\Delta P = \alpha_{0P} + \beta_{1P}P_{t-1} + \beta_{2P}E_{t-1} + \beta_{3P}\Delta E + \sum\delta_{1P}\Omega^P$

(19) $\Delta E = \alpha_{0E} + \beta_{1E}P_{t-1} + \beta_{2E}E_{t-1} + \beta_{3E}\Delta P + \sum\delta_{1E}\Omega^E$

(21) $\Delta A_gL = \alpha_{0AgL} + \beta_{1AgL}P_{t-1} + \beta_{2AgL}E_{t-1} + \beta_{4AgL}A_gL_{t-1} + \beta_{3AgL}\Delta P + \beta_{4AgL}\Delta E + \sum\delta_{1AgL}\Omega_{AgL}$

Equations 19, 20, and 21 indicate that population and employment changes are dependent on initial levels and change of population and employment interchangeably as well as a vector of factors affecting the change of population and employment in a county (or region). The change in agricultural land is affected by the initial levels of employment, population, and agricultural land density, changes of employment and population from one period to the other, and by a vector of other exogenous variables influencing agricultural land density changes. In such a system, the simultaneous interaction of employment and population and their effect on agricultural land conversion can be identified.

VII. EMPIRICAL MODEL

Following the developed growth equilibrium model, the empirical model can be specified by integrating variables of research interest. This research has focused on the theoretical development of a growth equilibrium model to measure the effect of growth on agricultural lands. The model is tested on West Virginia data.

Empirically, the changes in population, employment and agricultural land densities are affected by a vector of variables aside from simultaneous interdependencies among the growth equilibrium empirical model variables. Equations (25), (26), and (27) specify integrating a vector of variables that are hypothesized as having a direct influence on the dependent variables.

The empirical model is specified as:

$$(22)\quad \Delta P = \alpha_{0p} + \beta_{1P}P_{t-1} + \beta_{2P}E_{t-1} + \beta_{3P}\Delta E + \delta_{1P}HWYDEN_{99} + \delta_{2P}UNERT_{t-1} + \delta_{3P}MEDHVA_{t-1} + \delta_{4P}MEDINC_{t-1} + \delta_{5P}PCTAX_{t-1} + \delta_{6P}NEARDIST_{99} + \delta_{7P}OWNOCC_{t-1} + \delta_{8P}P20KADJ_{1993} + \delta_{9P}PFEDL_{92} + \delta_{10P}PWATERAC_{92} + \delta_{11P}PFORESTL_{92} + \delta_{12P}DAG_{t-1} + \delta_{13P}PINMIGRT + \delta_{14P}POUTWORK$$

$$(23)\quad \Delta E = \alpha_{0E} + \beta_{1E}P_{t-1} + \beta_{2E}E_{t-1} + \beta_{3E}\Delta P + \delta_{1E}HWYDEN_{99} + \delta_{2E}UNERT_{t-1} + \delta_{3E}PAGEMP_{t-1} + \delta_{4E}PMIEMP_{t-1} + \delta_{5E}PCNEMP_{t-1} + \delta_{6E}PSVEMP_{t-1} + \delta_{7E}PCTAX_{t-1} + \delta_{8E}NEARDIST_{99} + \delta_{9E}DAG_{t-1} + \delta_{10E}P20KADJ_{1993} + \delta_{11E}AGSLAC_{t-1} + \delta_{12E}INCFM_{t-1} + \delta_{13E}PCOUNTY + \delta_{14E}PINMIGRT + \delta_{15E}POUTWORK$$

$$(24)\quad \Delta A_gL = \alpha_{0AgL} + \beta_{1AgL}P_{t-1} + \beta_{2AgL}E_{t-1} + \beta_{3AgL}\Delta P + \beta_{4AgL}\Delta E + \delta_{1AgL}HWYDEN_{99} + \delta_{2AgL}PAGEMP_{t-1} + \delta_{3AgL}INCFM_{t-1} + \delta_{4AgL}PCROP_{t-1} + \delta_{5AgL}PPAST_{t-1} + \delta_{6AgL}NEARDIST_{99} + \delta_{7AgL}DAG_{t-1} + \delta_{8AgL}P20KADJ_{1993} + \delta_{9AgL}AGSLAC_{90} + \delta_{10AgL}DCONSERV + \delta_{11AgL}POUTWORK$$

Table 1 (attached at the end) provides the definition of the variables specified. The model specification identifies direct and indirect interaction of different variables of interest and their effect on the change in the dependent variables. The change in population density is simultaneously determined by changes in employment and initial population conditions as generated from the interaction growth model. Highway density, distance from a metropolitan area, and adjacency to urbanized areas variables try to capture the direct effect of accessibility on population changes. It is expected that the more accessible a county is, the more (higher) the population density change.

Median housing value, percentage of houses that are owner occupied, and median household income in the sample counties can also be thought of as directly influencing demographic attributes. These variables try to capture population changes derived from housing and property values in spatial location decisions and a sense of community. It can be argued that an increase in median household income and a reduction in property values expand the utility maximizing goods bundle, including housing and recreational site choices. This tends to positively influence population growth.

Per capita tax rates and unemployment are also specified to capture their direct influence on population. Labor mobility attributes in terms of in-migrating and out-migrating labor is also introduced. Generally, a higher unemployment rate can be expected to reduce population in two ways; indirectly through reducing people coming to a specific location in search of job (employment effect) captured by ΔE in the population equation and directly through its effect on crime rates and safety affecting individual location decisions for housing and other purposes in that specific location. Generally, the effect of per capita tax on population could be viewed as negatively related. Those counties with higher per capita taxes might see people out-migrating to other locations of light fiscal burden or vice versa. However, it can also be argued that people can also prefer high per capita tax rates if the area is less populated and has the natural amenities intact than places with high population and congestion and less fiscal burdens. In return, it may also depend on how tax revenue is being reinvested in a community. The sign has to be empirically determined to conclude on both possibilities.

Finally, the listed agricultural variables are related with population changes through the provision of natural amenities, federal land preservation, and intensity of the agricultural activity that have a direct bearing on property values and employment opportunities that directly and indirectly affect population changes.

Similarly, employment density changes are affected by initial employment conditions as well as change in population for the study period as determined in the simultaneous equation system. A vector of other relevant variables also directly interacts with employment growth.

Again, highway densities, distance from metropolitan or urban areas and adjacency to urbanized areas capture the effects of accessibility on employment changes. Generally, the more accessible or exposed a county or specific region is, the more the expected employment growth will be. Extension of highway infrastructure makes the temporary in-migration of labor and supply decisions of distant labor easier. These have a direct bearing on employment changes.

The decomposition of employment into different sectors identifies the influence of each employment sector on the overall employment change in West Virginia. Interrelationship of sectors should carefully be noted to capture the impact of employment change of one on the overall employment. For instance, a growing service industry can attract employment from other relatively less paying sectors. This can lead to employment cuts by other employers to raise the wage and salary. Similarly, the effects of these different sectors are in part reflected in their overall mobility. For example, the services sector may be much more mobile than the other sectors. The construction sector typically expands and contracts based on the demand for their products. Resource-dependent sectors (agriculture, mining) have limited mobility, as they require location-specific inputs (land, minerals) in their production processes. Though the actual impact can separately be studied in an impact analysis framework, the interrelationship of different employment sectors and their influence on overall employment is recognized.

The direct relationship between per capita taxes and unemployment rate with employment growth is analogous with the effect on population. Higher tax structures can discourage new businesses and can motivate relocation of businesses and employees to reduce tax burdens. Similarly, counties with tax incentives can attract more new businesses. Hence, the level of imposed tax is generally inversely related with employment creation. Consideration of other factors of positive importance to businesses and households can offset the negative impact of higher taxes and induce them to move to areas of high fiscal burden if savings from other attributes of the area are greater. Higher unemployment rates can also directly affect employment growth trends. High unemployment regions attract lesser in-migrating laborers as compared to regions with boosting employment opportunities and high employment growth. This regional unemployment rate differential may affect and explain some portion of the change in total employment variations.

Another source of change in employment densities arises from the agricultural sector. Agricultural sales volume, average farm income (agricultural sales plus all transfer payments), and agricultural land density measures are specified to capture the competitive ability of agriculture in retaining its land use as measured by its profitability and use of land. Not only is the agricultural sector important for farm employment opportunities and off-farm employment opportunities through agricultural sector's backward and forward linkages with other sectors, a decline in agricultural land density and the shrinking of the sector may result in a direct cut of farm employment opportunities as well as related off-farm employment. This directly and indirectly affects the change in employment density.

Finally, much research focus is placed on the change in agricultural land densities. From the model specification, it is clear that all those factors simultaneously affecting employment and population densities will indirectly influence the change (conversion) of agricultural lands. The initial employment and population states and their density changes over the study period will greatly determine the agricultural lands converted to other uses.

Highway density, distance measures, and adjacency to urbanized areas are specified to capture accessibility influences on agricultural lands. Though these variables have an indirect bearing on agricultural land conversion through their interaction with population and employment densities, they also have a direct spatial effect on the change in agricultural lands. It is expected that the more the agricultural sites are accessible or have improved communication and transportation facilities, the higher will be the conversion rate of agricultural lands to other uses.

Decomposing total agricultural lands into selected crop and pasturelands in the model tries to isolate the relative impact of those agricultural uses on total agricultural land densities in each county. It is expected that these changes will significantly explain some portion of the changes in agricultural land densities. That is, farmers tend to allocate prime land for crop production. This breakout may enable the identification whether prime farmland is being lost at a greater rate than marginal farmland. The model further specifies that initial agricultural densities will have a bearing for the end of period densities. Some studies indicate that farmers' decisions to sell land not only depend on their farm situation but also on the decision of other farmers (speculation effects) in previous years. Hence, initial period land densities will capture some inherent conversion decisions.

The change in agricultural land densities is also expected to be partially explained by initial period agricultural employment and average farm incomes. Changes in farm employment not only affect the agricultural land density through its effect on employment changes (simultaneously determined in the model) but it is also positively related with agricultural land. Increasing agricultural employment share might indicate feasibility of the sector in a region given certain circumstances. Hence, rapid changes in agricultural employment could be linked with the size and dominance of the sector. However, it should also be noted that increased mechanization could reduce employment while improving competitiveness of the sector. The final relationship between the two could be blurred. Thus, agricultural sales per acre are included to capture the total value of agricultural production per acre in a region.

Finally, to determine the influence or significance of conservation practices on the conversion of agricultural lands, a conservation variable is introduced to measure the marginal effect of land conservation efforts on agricultural land density changes.

Descriptive Statistics

To estimate the empirical model, relevant data was collected for all 55 counties in West Virginia for 1990 and 1999. The characteristics of the data are indicated in the summary provided by table 1.

VIII. RESULTS AND DISCUSSIONS

The result of the estimation is provided in Table 2. Results are estimated for the population, employment, and agricultural density changes. The system of equations model is estimated using two econometric techniques. The simultaneous equations system of employment and population is separately estimated, as the change in agricultural land is not endogenized in the population-employment system. It is argued that changes in agricultural lands may not be a reasonable predictor of changes in population and employment across space; though they may have a degree of influence on such variables. However, the changes in population and employment growth have a significant direct bearing on agricultural land conversion. The simultaneity test undertaken, using Hausman's Specification Test, showed significant simultaneity between changes in employment and population, but not with changes in agricultural land. Hence, the 2SLS is used to overcome estimated coefficient bias and inconsistency and address the simultaneity introduced in the structural model. Hence, agricultural land density changes are estimated using an Ordinary-Least-Squares estimation technique while the simultaneous interaction of employment and population are captured through a Two-Stages-Least-Square econometric technique.

Changes in population density in the study decade is significantly associated with some exogenous variables. The percentage of houses that are owner occupied ($OWNOCC_{t-1}$) is significantly associated with population density changes. The result indicates that higher population density changes are occurring in counties with higher rates of owner occupancy. This may result in two ways. First, that a higher rate of owner occupancy indicates that people decide to stay in that location for an extended period of time, which positively affects the population density in the location of settlement. However, beyond this obvious physical relationship one can infer that higher rates of owner occupancy is normally observed, among many groups, with in-migrating high income families and retired (senior) citizens. The spread of new retirement houses and recreational and residential facilities in some parts of West Virginia is one justification for the result.

There is also a significant positive relationship between changes in population densities and unemployment rates (UNEMPRT90). Intuitively, regions of high unemployment attract fewer people through the employment and crime effects. The unexpected negative sign in the population density model, however, may mean that across the 55 sample counties in West Virginia, population density changes are higher in counties with higher rates of unemployment. Generally, rural counties face higher rates of unemployment and subsequently lower land prices.

Furthermore, the positive relationship between unemployment and population density changes might indicate that the change in population is little affected by unemployment considerations but rather by other factors. Again, the groups that are less averse to unemployment are affluent and senior citizens.

Studies associate positive relationship between population growth and pressure on natural amenities. In a structural simultaneous equations model, for instance, Duffy-Deno (1997) measured the pressure exerted on endangered species due to changes in population and employment. A similar result is indicated between changes in population density and natural amenities – proportion of a county's area in water (PWATERAC) and proportion of total land in forests (PFORESTL) in this study. The model indicates a significant negative relationship between population change and forested counties and a negative but insignificant relationship with density of county surface water.

The relationship between population density changes and proportion of count's land base in federal ownership (PFEDL) indicates a significant inverse relationship. An increase in federal land will negatively affect population density changes, i.e., federal land preservation programs can slow population growth in some regions. This can happen in many ways. One possible way is that preservation programs, by limiting the encroachment of residential land to federal land reserves, physically limit the spread of population pressures (as in south-western West Virginia). Another way a federal land preservation program may affect population growth is through the effect on the value of land. By physically limiting the economic supply of land to other uses, preservation programs can increase the market value of private land, hence reducing the incentive to purchase land. This can push development and housing demands of land to neighboring counties where land prices are not as high.

The result also estimates a significant positive relationship between population density changes and median housing value (MEDHVA90). The positive relationship may imply that higher population density changes are occurring in areas of higher median housing value in West Virginia. This may be due to the fact that regions of high population experience high demand for properties. This can raise property values in the face of higher demands from increasing population through time. However, it may also be argued that areas of growing housing and property value, *ceteris paribus*, attract less population in-migration and hence slowdown the density change in population. The data set does not account for the fact that though property values are increasing in population centers in West Virginia, it could be true that they are relatively cheaper when compared to surrounding metropolitan and urbanized areas. For instance, the housing value in the Eastern Panhandle is increasing at a significant rate but still faces increasing demand. One reason for this could be the fact that though property values are increasing, they are cheaper when compared to the adjacent metropolitan D.C. area, making the Eastern Panhandle a substitute for the high property values in D.C. Since this study is concentrated in West Virginia, economic activities in the surrounding states are not included in the dataset. The result may thus be attributed to data limitations.

Distance and adjacency measures have weakly captured the influence of distance and location on population density changes. Moreover, the insignificant influence of a change in employment on population density changes reinforces the conclusion that, in the case of West Virginia, jobs follow people.

The employment model captures significant information concerning employment density changes and their relationship to key variables of research interest. On the influence of access to employment density changes, the result indicates a significant positive relationship between employment changes and improved access. Specifically, a significant positive relationship is observed between employment growth and highway density (HWYDEN99) while a weak positive relationship is estimated for the relationship with the distance from nearest metropolitan county (NEARDIST) measure. Consistent with theoretical expectation, the significant positive relationship between employment and improved access implies that locations endowed with better access (for example, interstate highways) attract more employment opportunities as access reduces the costs of transportation and exposes new markets separated by transportation barriers. The result indicates an insignificant relationship between adjacency to urbanized areas and changes in employment densities.

The change in employment is decomposed into different sectors of interest to capture the sources of employment density changes. The relevant sectors of analytical interest are the percentage of employment in agriculture (PAGEMP90), mining (PMIEMP90), construction (PCNEMP90), and service (PSVEMP90) sectors. The results from the model indicate that construction, mining, and agricultural sector employment have a positive but highly insignificant relationship with changes in total employment. The agricultural sector in particular poorly explains total changes in employment density in West Virginia. This may imply that these sectors account for an insignificant variation in employment density changes in the state. However, a change in employment density is significantly and directly related with counties dominated by the service sector. The growing percentage of employment in the service and construction industry might infer the spread of service based new industries and emerging construction activities in the state. Growth in the service sector may generate new employment opportunities. This can negatively influence employment in the agricultural sector.

The result indicates a positive and significant relationship between proportion of land owned by a county and changes in employment density. The result may indicate that counties with significant land ownership saw significantly positive changes in employment. This may be due to the fact that such counties might provide land incentives to encourage employment opportunity growth and development to overcome poverty and development bottlenecks in the state.

Incorporating labor mobility aspects into the employment density model, a significant positive relationship is estimated between total employment changes and the proportion of resident county jobs held by people outside a county. This indicates that a high change in employment density is associated with counties that draw workers from neighboring areas. Intuitively, employment density changes are concentrated in areas with growing employment opportunities that attract labor, including from adjacent counties. However, these counties may not have significant pressure on land if workers are not demanding housing in the counties where their jobs are located.

The significant positive relationship between population changes (POPDIFF) and employment density change provides further information to the previous result on whether people follow jobs or jobs follow people argument presented in the previous section. The conclusion that jobs follow people in the case of West Virginia is also reinforced in the employment model. A change in population significantly influences employment growth.

Distance, adjacency, tax and agricultural land density measures appear to be weak predictors of changes in employment density in the case study.

The agricultural density model estimates a negative relationship between changes in agricultural land density and access measures. The result indicates that agricultural land density is negatively related with highway densities (HWYDEN). It is evident that access improves the growth of employment in a region, as confirmed by the employment model in the last sections. At the same time, it also tends to diminish agricultural land densities due to increased pressure. Though as expected, the statistical significance is weak. Similarly, agricultural land density changes fade away as distance away from urbanized areas increases. This indicates that pressure to farming activities is exerted more at the urban fringes and suburban areas. However, this conclusion is statistically weak.

A more appropriate measure of the influence of location on agricultural land conversion may be the adjacency dummy proxy (P20KADJ) that measures the influence on rural communities of being adjacent to urbanized areas as compared to not being adjacent to urbanized locations. The result, at a 5 percent significance level, indicates that those counties that are adjacent to urbanized areas experience higher changes in their agricultural land density as compared with those counties that are not adjacent to urbanized locations. This result can be related with the finding in the population density model that agricultural lands density is negatively related with changes in population density. Generally, higher population pressure is expected in urbanized and suburbanized locations that have more pressure on land for growing non-agricultural purposes.

The result indicates a positive relationship between agricultural land density and population density changes. This result indicates that high changes in agricultural land density occur in areas where there are high changes in population density. This result is consistent with the theoretical expectation that the more population changes in locations, the more would be the expected variation or change in agricultural lands. The result is statistically weak.

The agricultural land density model provides interesting information about the nature of the agricultural sector and related tendency to conversion. The relationship between agricultural sales (AGSLAC90) and agricultural employment levels (PAGEMP90) on agricultural land density change is provided in table 2 (attached at the end). Interestingly, the result indicates that agricultural sales and agricultural employment are significantly negatively related with changes in agricultural land density.

The result indicates that the less profitable and competitive agriculture is, the more conversion of agricultural lands to other uses would be expected. This result is clearly intuitive and logically consistent with the theoretical setup that economic agents that can provide a higher bid rent for a given land at a particular distance and location will dominate that location. Conversely, a rise in agricultural sales and employment opportunities should lead to lower agricultural land density declines.

Agricultural lands density changes are positively and significantly related with their initial period densities. This may indicate that counties with significant changes of agricultural lands (conversion) may grow more sensitive than those counties where agricultural land changes have been stable.

Finally, the relationship between non-governmental organizations operation in land preservation and its relationship to agricultural land conversion is established. Local land trusts, the Nature Conservancy, and other non-governmental organizations actively involved in the preservation of agricultural and rural lands have significant influence on agricultural land changes. This may indicate that increased effort to preserve land in the face of pressure significantly contributes to the reduction of changes in agricultural lands densities.

IX. FURTHER RESEARCH

The intent of this research was the development of an empirical model to effectively address agricultural land conversion. The growth equilibrium model provides an initial modeling stage. The empirical study can be improved by incorporating:

Scope: the study focuses on West Virginia and systematically isolates the effects of regional changes of important variables as constant. A broader regional framework will better explain the effect of regional growth on land use changes.

Policy: the influence of policy measure directly and indirectly related with agricultural land has a bearing on land use. West Virginia does not have an explicit policy to address land use and growth management. However, such policies are adopted and implemented in the Northeastern Region and their implication in terms of growth dispersion and other attendant land use implications are not captured. With a broader regional scope, a proper integration of policy variables will help explain the land conversion processes and their marginal effects on limiting or directing growth, and conserving agricultural land.

Spatial measures: it is evident that the location of an activity will have a significant effect on land use. Establishing the proper proxy and/or variable to represent the effect of spatial location on land use is vital. Physical distances, adjacency to urbanized areas, and interstate highway proxies are taken to represent spatial locations. However, such measures can be improved by integrating applied GIS spatial measures and spatial econometrics specification to properly establish the influence of location on land use changes.

Modeling: this study models the change in land uses using a static system of equations growth model applied to a single decade. Initial conditions are compared with values at the end of the decade. However, approaching the problem from a dynamic model may provide a better understanding of how different forces interact in land use changes.

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Table 1. Definition and summary of variables in West Virginia model (N=55)

VARIABLE	DEFINITION	MEAN	:D. DEV.
DPOPDIFF = ΔP	: in population density ($DPOP_t - DPOP_{t-1}$)	0.426	9.724
DEMPDIFF = ΔE	: in employment density ($DEMP_t - DEMP_{t-1}$)	4.391	9.030
DAGDIFF = ΔAgL	: in agricultural land density ($DAG_t - DAG_{t-1}$)	0.007	0.060
$DPOP_{t-1}$	tion density	94.403	102.886
$DEMP_{t-1}$	/ment density	42.665	59.916
DAG_{t-1}	ltural land density	0.225	0.131
$HWYDEN_{99}$	ıte highway density 1999	0.022	0.036
$PCTAX_{t-1}$	ıita local taxes	315.109	126.389
$MEDHVA_{t-1}$	ι housing value	44,614	10,725
$OWNOCC_{t-1}$	occupancy rate for housing	76.81	4.55
$UNEMRT_{t-1}$	loyment rate	11.11	3.98
$P20KADJ_{93}$	etro counties with ≤ 20K adjacent to metro counties	0.25	0.44
$PFEDL_{92}$	tion of land base in federal ownership 1992	4.97	10.22
$PCOUNTY_{92}$	tion of land base in county ownership 1992	0.002	0.006
$PWATERAC_{92}$	tion of land base covered by water 1992	1.36	1.24
$PFORESTL_{92}$	tion of land base forested 1992	67.35	15.17
NEARDIST	:e to nearest major metropolitan area (miles)	62.41	25.44
$PAGEMP_{t-1}$	tion of total employment in agriculture	6.42	5.79
$PMIEMP_{t-1}$	tion of total employment in mining	7.55	8.50
$PCNEMP_{t-1}$	tion of total employment in construction	5.63	2.59
$PSVEMP_{t-1}$	tion of total employment in services	20.95	5.47
$AGSLAC_{t-1}$	ltural sales per acre	83.22	70.24
$PCROP_{t-1}$	tion of agricultural land in cropland	39.64	11.23
$PPAST_{t-1}$	tion of agricultural land in pasture	52.95	13.78
$INCFM_{t-1}$	e farm income ($1,000)	19.87	20.21
$MEDINC_{t-1}$	e median family income	19,557	3,829
$DCONSERV_{t-1}$	' of land conserved by NGOs	0.0002	0.0004
$POUTWORK_{t-1}$	tion of employed residents working outside county of residence	0.33	0.15
$PINMIGRT_{t-1}$	tion of total jobs in a county held by people outside county	0.18	0.08

Notes: t values are for 1999 and t-1 values are for 1990. Nearest major metropolitan areas defined by miles from Washington DC, Charleston WV, or Pittsburgh PA.

Table 2. Empirical results for system of equations model for West Virginia (N=55)

VARIABLE	ΔP Equation	ΔE Equation	ΔAgL Equation
ΔP	—	0.265**	0.001
ΔE	0.333	—	—
$DPOP_{t-1}$	-0.078***	—	—
$DEMP_{t-1}$	—	0.007	—
DAG_{t-1}	-19.899	0.967	0.168**
$HWYDEN_{99}$	-5.804	157.531***	-0.153
$PCTAX_{t-1}$	-0.002	-0.006	—
$MEDHVA_{t-1}$	0.001***	—	—
$OWNOCC_{t-1}$	0.339*	—	—
$UNEMRT_{t-1}$	0.555**	-0.205	—
$P20KADJ_{93}$	-1.983	-1.742	0.038**
$PFEDL_{92}$	-39.117**	—	—
PCOUNTY	—	154.030**	—
$PWATERAC_{92}$	-92.279	—	—
$PFORESTL_{92}$	-38.395**	—	—
NEARDIST	-0.036	0.005	-0.0002
$PAGEMP_{t-1}$	—	0.004	-0.002*
$PMIEMP_{t-1}$	—	0.079	—
$PCNEMP_{t-1}$	—	0.258	—
$PSVEMP_{t-1}$	—	0.384*	—
$AGSLAC_{t-1}$	—	0.001	-0.00029**
$PCROP_{t-1}$	—	—	0.00034
$PPAST_{t-1}$	—	—	-0.00032
$INCFM_{t-1}$	—	—	—
$DCONSERV_{t-1}$	—	—	-91.568**
$POUTWORK_{t-1}$	8.039	-0.868	-0.0433
$PINMIGRT_{t-1}$	-8.576	23.114**	—
Constant	-17.658	-10.029	0.022
$adjR^2$	0.71	0.65	0.54

Note: significance levels indicated as *@0.01, **@0.05, and *@0.10. ΔE and ΔP equations estimated using a two-stage least squares procedure; ΔAgL equation estimated independently.**

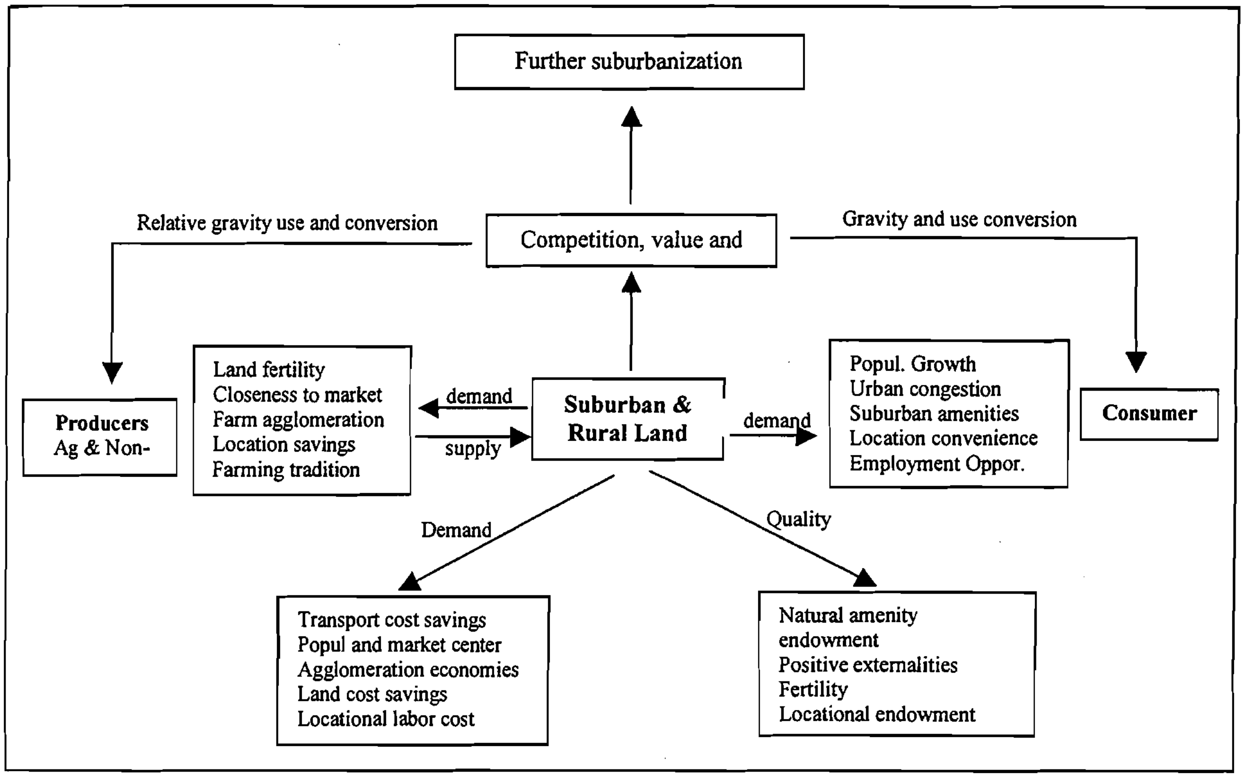

Figure 1. Reduced form circular flow chart for consumers and producers (agricultural and non-agricultural).

Nonlinearity in Valuation

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Abstract

Conjoint techniques are used to assess the relative values and marginal rates of substitution among objectives related to ecosystem management on private lands. Specific objectives that were considered include maintaining apple trees to benefit wildlife, protecting rare ferns to enhance aesthetics and biodiversity, improving recreational trials, harvesting timber, and minimizing management costs. An ordered probit model is used to estimate preferences and nonlinear relationships are explicitly explored.

Introduction

Decisions concerning natural resources are becoming more complex as noncommodity or nonpriced objectives increase in importance on both public and private lands. These objectives, which among others include biodiversity, wildlife habitats, aesthetics, water quality, and recreation, are increasingly important. Pressure to consider a broad range of outputs is acute on public lands where managers are charged with meeting the diverse needs and often conflicting interests of stakeholders. However, privately owned forests comprise nearly three-quarters of the forest land in the United States and are expected to play an important role in providing many forest-related benefits (USDA For. Serv. 1988, 1995). There is concern that these lands may not achieve objectives related to overall ecosystem health and sustainability, nor provide benefits that transcend legal and political boundaries, e.g., biodiversity, water quality, and habitat for certain kinds of wildlife.

Comprehensive multiple-objective models are designed to help guide decisionmaking and help policymakers understand the effects of policy alternatives. Such models require estimates of the relative values or weights to assign the various outputs. Since these goods are not traded in markets, their relative values or weights can be difficult to ascertain. The situation is complicated by the use of different units of measure and the fact that values and relative weighting for many goods and benefits are context specific with respect to time, location, and sociopolitical factors. Further, the relationships may not be linear due to increasing or decreasing marginal rates of substitution.

We used conjoint techniques to solicit landowner preferences for management involving varying levels of timber harvesting, recreational trail improvement, apple tree maintenance to benefit wildlife, protection of a rare species of fern, and cost. We explicitly explore the nonlinear nature of the relationships among the variables. An ordered probit model is used to estimate preferences. The results are used to compute marginal rates of substitution (MRS), or the tradeoffs that landowners are willing to incur to achieve changes in the levels of other objectives.

Analytical Methods

Conjoint analysis is a technique for measuring psychological judgments and is used frequently in marketing research to measure consumer preferences (Green et al. 1988). Respondents choose between alternative products or scenarios that display varying levels of selected attributes. The utility of each attribute can be inferred from the respondent's overall evaluations. These partial utilities indicate the attribute's contribution to overall preference or utility obtained from the bundle of attributes that comprise an alternative. They can be combined to estimate relative preferences for any combination of attribute levels. Conjoint techniques are well suited for soliciting and analyzing preferences for environmental decisions that frequently entail tradeoffs between costs and benefits that are not represented efficiently in market transactions. For example, Opaluch et al. (1993) described an approach that used paired comparisons to rank potential noxious facility sites in terms of social impacts.

Choice experiments can be designed and analyzed in many ways. Respondents may be asked to reveal their preferences by choosing one of two or more options, ranking several options, or assigning numerical ratings to each option. Numerical ratings provide the most information but also place the greatest cognitive demands on respondents. Green (1974), Green and Srinivasan (1978), Louviere and Woodworth (1983), and Louviere (1988) provide information on experimental design in the context of conjoint analysis.

A random utility model may be used to explain preferences. When presented with a set of alternatives, individuals are assumed to make choices that maximize their utility or satisfaction. The utility that the ith individual derives from the jth alternative (U_{ij}) can be represented as:

$$U_{ij} = X'\beta_{ij} + e_{ij} \tag{1}$$

Where X_{ij} is a vector of variables that represent values for each of the five attributes of the jth alternative to the ith individual; β is a vector of unknown parameters; and e_{ij} is a random disturbance, which may reflect unobserved attributes of the alternatives, random choice behavior, or measurement error. A respondent's utility level (U_{ij}) for each alternative is not observed, but a ranking or rating (r_j) is observed that is assumed to proxy for his or her underlying utility.

Following McKenzie (1990, 1993) and others, the analytical capabilities of the conjoint model can be illustrated by assuming that the observed proxy for utility (r_j) can be modeled as a linear combination of the variables representing the attribute levels. Typically, only linear effects are considered but the analyses were modified to include quadratic effects in order to test for nonlinear relationships:

$$r_j = a + b_1x_{1j} + b_2x_{2j} + \ldots + b_nx_{nj} + q_1x_{1j}^2 + q_2x_{2j}^2 + \ldots + q_nx_{nj}^2 \quad (2)$$

The estimated partial utilities are the combined linear (b_n's) and quadratic (q_n's) effects of a discreet change in the level of the associated attribute on overall preference. Relative overall preference for any alternative (combination of attribute levels) can be determined by summing across Equation 2.

The MRS is the rate at which an individual is willing to trade one good for another while remaining equally well off (Nicholson 1978). The MRS or acceptable tradeoff of one attribute for another is determined by the ratio of the marginal responses. Setting the total differential of (2) to the point of indifference and solving yields the marginal rates of substitution or the acceptable tradeoffs for the respective attributes:

$$dr_j = b_1dx_{1j} + b_2dx_{2j} + \ldots + b_ndx_{nj} + 2q_1x_1dx_{1j} + 2q_2x_2dx_{2j} + \ldots + 2q_nx_ndx_{nj} = 0 \quad (3)$$

$$dx_{1j} / dx_{2j} = -(b_2 + 2q_2x_2) / (b_1 + 2q_1x_1)$$

Survey Methods

The Dillman (1978) Total Design Method was used to design a survey that was mailed to 1,250 forest-land owners who hold at least 10 acres of forest land in Franklin County, Massachusetts. In addition to questions on attitudes toward land management and demographics, each respondent completed a conjoint survey. The useable response rate was 61.3 percent.

Forest-land owners in Franklin County were asked to rate four alternative management scenarios for a hypothetical forested property shown in a figure within the survey. The figure included an area of apple trees, a section of rare ferns, and a recreational trail that passed through the sample property. Each alternative was rated on a scale of 1 to 10, with 10 representing alternatives that they would definitely undertake and 1 those that they would definitely not undertake. Ratings of 2 to 9 were used to represent how likely they would be to undertake alternatives that they were not sure of. Each alternative varied by one or more of the following five attributes: the proportion of the apple trees to maintain on the hypothetical property, the proportion of rare ferns to protect, the extent of the trail network to improve, the extent of timber harvesting, and cost. An orthogonal array was used to create a succinct subset of attribute combinations that allows estimation over the entire range of attribute values ($3^5 = 243$ possible combinations). The resulting 18 alternatives were assigned to questionnaires in equal frequency. Each alternative consisted of a unique bundle that included all five individual attributes. Each attribute had one of the three possible levels appearing in parentheses. Alternatives appeared as follows:

--Maintain (none/half/all) of the apple trees shown on the figure that benefit wildlife.

--Protect (none/half/all) of the acres containing a rare species of fern shown on the figure by not harvesting timber in this area or otherwise disturbing the ferns.

--Improve (none/half/all) of the trail network shown on the figure. Improvements, if any, would include the cost of building a footbridge over the stream and clearing scenic vistas.

--Harvest timber from (none/half/all) of the lands shown on the figure. Any harvest would be selective, designed to remove poorly formed and leave some high-quality trees; 25 to 30 percent of all trees would be removed.

--This option would have a net cost to you of $ (50/250/500).

Empirical Results

Seventy-eight percent of Franklin County is forested, most of which is in nonindustrial private ownership. The average respondent owned 60 acres of forest land, and 70 percent of the parcels were less than 100 acres. Approximately 78 percent of the respondents lived within 5 miles of their woodland, 60 percent had owned their land more than 15 years, and one-third had a management plan. About half of the owners were 55 years old or older, and 74 percent had completed at least 1 year of college.

The model was estimated using a polychotomous probit technique developed by McKelvey and Zavoina (1975) to analyze ordinal level dependent variables. The dependent variable (r_j) is the rating for each alternative scenario and was coded from 0 to 9. The explanatory variables (attributes) were coded 0.0, 0.5, and 1.0 to account for the proportions of apple trees to maintain, trail improvements, fern protection, and extent of timber harvesting. Cost was coded in units of $100 (0.5, 2.5, and 5.0). Each respondent rated four alternatives for a total of 2,504 rated scenarios. The results are shown in Table 1.

The estimated signs and relative magnitudes of the coefficients provide information on respondent preferences. As expected, increased levels for each of the attributes except cost had a positive effect on ratings. The magnitude of the positive effects of maintaining apple trees to benefit wildlife and fern protection were greater than those for trail improvements and extending the area available for timber harvesting (which also may be interpreted as lower restrictions on harvesting). Thus, landowners generally placed higher value on the ecological aspects of the alternatives than on the use aspects. These findings are consistent with previous studies that suggest that nonindustrial private forest-land owners place high values on wildlife and other nontimber amenities (Birch 1996, Brunson et al. 1996) and with the attitudinal aspects of this survey (Rickenbach et al. 1998).

A commonly accepted economic precept with intuitive appeal is that one's preference for more of a particular good depends on how much of the good one already has and that willingness to trade among goods depends on the quantities of each good in one's possession. Quadratic effects were examined to estimate these expected nonlinear relationships. The quadratic terms for apple tree maintenance, fern protection, and trail maintenance were negative and statistically significant, indicating decreasing marginal benefits for these attributes. The partial utility or the contribution of an individual attribute toward the total utility provided by an alternative is determined by combining both the linear and quadratic effects at a given attribute level. For example, the partial utilities for fern protection at levels none, half, and all are 0.0, 0.477, and 0.604, respectively (computed as $b_i x_i + q_i x_i^2$). Thus, the increase in utility resulting from an increase in fern protection from none to half is 0.477, while the increase from half to all is 0.127. It appears that marginal increases in utility decreased once respondents believed that a significant portion of the ferns were protected or the apple trees maintained. Although respondents favored initial trail improvements, similar calculations indicate that maintaining the entire trail network versus only half reduced overall utility or preference for an alternative.

Table 1. Ordered probit parameters for a multi-attribute conjoint rating survey (dependent variable = rating, coded 0 to 9, N=2,504).

Variable	Coefficient	Std. error	t-ratio
Constant	-0.1785	0.0701	-2.55
Linear effects			
Apples	1.1019	0.1955	5.64
Ferns	1.3040	0.1871	6.97
Timber	0.2142	0.0521	4.11
Trails	0.8580	0.1863	4.61
Cost	-0.0415	0.0116	-3.57
Quadratic effects			
$(\text{Apples})^2$	-0.5264	0.1836	-2.87
$(\text{Ferns})^2$	-0.6996	0.1784	-3.92
$(\text{Trails})^2$	-0.6570	0.1841	-3.57

All variables were significant at the 1-percent level.
Log-likelihood = -5179.1.

To examine the tradeoffs that respondents were willing to accept among the objectives, marginal rates of substitution can be computed for any two attributes at the selected levels using Equation 3. The tradeoff between cost and attaining management objectives is frequently useful to policymakers. The MRS between cost and the other attributes are shown in Table 2 and illustrate the notion of decreasing marginal benefits. Landowners were willing to incur less additional cost to maintain apple trees or protect ferns as the amounts of these attributes already under protection increased. For example, landowners on average were willing to incur \$23 to protect an additional percentage of the ferns if only 25 percent were currently under protection but only \$6 if 75 percent already were being protected.

Table 2. Marginal rates of substitution, cost (dollars) per 1-percent increase in listed variable at indicated initial level.

Level	Apples	Ferns	Trails	Timber
0.00	26.54	31.40	20.66	5.16
0.25	20.20	22.98	12.51	5.16
0.50	13.86	14.56	4.36	5.16
0.75	7.52	6.13	*	5.16
1.00	1.18	*	*	5.16

* Negative.

The tradeoffs that landowners are willing to accept between two attributes can be determined at any level selected for each attribute by computing the MRS for the attributes directly using Equation 3 or by comparing the MRS between each attribute and cost. For example, if half of the apple trees currently are being maintained, Equation 3 can be used to determine the level at which landowners become indifferent between additional trail improvements and increased apple tree maintenance. The MRS equates to 1 when apple tree maintenance is at 50 percent and trail improvement is about 21 percent. Therefore, landowners would prefer to improve the trail network up to the 21-percent level over additional apple tree maintenance at 50 percent. At this level, landowners would be willing to incur the same additional cost to improve an additional 1 percent of the trail network or to maintain an additional 1 percent of the apple trees.

Summary

Nonindustrial privately owned forests are expected to play an important role in meeting needs for a wide range of forest-related benefits. Estimates of the relative values that landowners place on various nonmarket benefits provided by their land and the costs they are willing to incur to achieve different levels of these benefits are useful to policymakers. The estimates also can be used as inputs for larger decision or optimization models concerned with multiple-objective management on private lands. Conjoint techniques are well suited for assessing the relative values and acceptable tradeoffs (MRS) among various management objectives. Including quadratic effects allows estimation of nonlinear MRS, which economic theory and these empirical results suggest are important. Dennis (1998) also found that nonlinear relationships were significant in analyses of public inputs to National Forest planning.

Landowners in Franklin County, Massachusetts, generally placed higher values on the ecological aspects (fern protection and apple tree maintenance) of management alternatives than on use-related aspects (timber harvesting and recreational trail improvements). Both fern protection and apple tree maintenance exhibited decreasing marginal rates of substitution. Although landowners feel strongly about providing these benefits, their willingness to make tradeoffs between these and other objectives or to incur additional cost depended greatly on current levels at which the objectives were being met.

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Split-Sample Comparison of Experimental Designs for Stated Choice Models with an Application to Wetland Mitigation

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Abstract

A stated choice model is used to estimate wetland mitigation preferences. In a split sample mail survey, a main effects design is compared to a randomized design. Although randomized designs estimate main effects less efficiently, several policy relevant interactions were found to be significant, suggesting some merits of randomized designs.

Introduction

Stated choice methods aimed at valuing the attributes of non-market goods, rather than the goods and services themselves, are increasingly popular among valuation researchers. Stated choice techniques (sometimes referred to as choice experiments or conjoint) can be thought of as an extension of the contingent valuation method for nonmarket goods. Both approaches ask respondents to state a preference over alternatives. Stated choice models are also widely used in marketing applications to estimate preferences over products with attributes that are not currently available and researchable through market data (Carson et al, 1994).

In stated choice studies, respondents are typically presented with descriptions of two or more recreation sites, environmental goods, or environmental programs and asked to indicate which of the alternatives they prefer. By varying the attributes of the alternatives, econometric methods can be used to estimate respondents′ preferences for the attributes. Typically, this is done by estimating a logit or probit model within the framework of a random utility model. This paper uses a study of wetland restoration to address the question of how to define attribute levels and combine the attributes that make up the alternatives that enter a stated choice study.

Experimental Designs

In implementing a stated choice study, one of the fundamental decisions a researcher faces is how to arrange the attributes of the goods to be presented to respondent? This is essentially a question of what experimental design to use. The experimental design is the set of attribute levels, how these are then bundled into alternative goods or programs, and how the alternatives are combined into the choice set presented to a respondent. To fix concepts, refer to Table 1 which depicts a stylized binary choice question. The two alternatives, A and B, are made up of the attributes and are combinations of the available attribute levels. The columns represent the alternatives, and the rows represent attributes. For each attribute, there is a set of attribute levels that are pre-defined by the researchers. The matrix of the pairs of alternatives across all the respondents in referred to as the experimental design.

A typical stated choice study will select the attributes to be valued, and then select the levels of attributes that will be used in the study. While alternatives can then be formed by taking the full factorial combination of each of the levels, this often results in a very large number of alternatives. To reduce the number of alternatives, some researchers rely on fractional factorial designs such as a main-effects plan. An main-effects plan, wherein each of the attributes are combined into alternatives such that the attributes are orthogonal, permits the estimation of the independent effect of each attribute. While such designs are reasonably efficient, they do not permit the estimation of higher order effects such an interactions among variables (Lazari and Anderson, 1994). Estimation of interaction effects requires more complex designs that increase in size. Potential interaction effects might be very important for a policy analysis. In addition, if a researcher is interested in examining non-linear effects for a single variable (attribute) in the utility function, then one must include multiple levels for that variable. While feasible in a main-effects design plan, this too, increases the size of the resulting design plan. The research reported here uses a split-sample survey to assess two alternative experimental designs: 1) a typical main-effects design, and 2) a fully randomized design that permits nonlinear marginal utility and interaction effects.

To generate the fixed design plan, we treat the attribute vectors for alternative A and for alternative B as separate design variables (this approach is discussed by numerous choice modelers including on page 133 of Louviere, Hensher and Swait 2000). In essence, this design approach draws a main-effects plan on the vector of attributes, $X=X^A|X^B$, defined by Astacking@ the vectors for each alternative B see Figure 1. For the other sub-sample of individuals, the stated choice questions consisted of independent random draws from a joint uniform distribution over the integer values spanning the range of attribute levels used in the fixed design. Each draw resulted in a distinct set of attribute levels so that each of the choice scenarios in this sub-sample was unique.

Binary Choice Models: Logit or Probit

Stated choice models and the theory underlying them is well developed in the literature. We briefly review it here. In a typical specification of a random utility model, utility is a function of the attribute values that make up an alternative, and the utility function is assumed to have random errors. When the underlying errors have an extreme value distribution, the probability of a respondent choosing alternative A among the alternatives A and B in choice scenario j is given by:

$$P_j = \frac{\exp(D_j)}{1+\exp(D_j)}$$

The vector of attributes, q, enter the utility function linearly and thus:

$$D_j = \beta_1(x^A_{1j} - x^B_{1j}) + \beta_2(x^A_{2j} - x^B_{2j}) + \ldots + \beta_m(x^A_{mj} - x^B_{mj})$$

where $(x^A_{mj} - x^B_{mj})$ represents the difference in the level of site attribute m between the two alternatives A and B in choice scenario j. Similarly, had the underlying errors been normally distributed we would define the binary choice model using a probit model as a function of D.

That the above parameter vector is estimated on the difference of the attribute vectors for the two alternatives is one of the key features distinguishing designs for binary choice models from designs for the typical linear models with continuous dependent variables. The distinction is worth noting because most of the available design plans are actually derived based on the assumption that good designs for standard linear models are also good designs for binary choice models (Kuhfeld 2000). A truly main-effects design for the logit model, i.e., a design that sought to minimize the number of distinct scenario combinations for identifying the main effects in (1), would need to be based on the attribute differences, as would D-optimal designs (Kanninen 2002, Steffens et al., 2000). Alternatively, the commonly used main-effect plans we examine for the Astacked@ design based on $X=X^A|X^B$ are constructed for identifying the main-effects of X in a simple linear model, but in the context of a logit defined on the difference X^A - X^B, such designs are actually somewhat redundant in terms of minimally identifying the main effects of (1).

Data

We estimated the effects of using alternative design plans within a study of preferences over wetland mitigation projects. In our mail survey, we elicited a choice between an impaired and a restored wetland that were described by attributes which include wetland acreage and wetland habitat quality for various species of flora and fauna. The choice question asked people if a restrored wetland offset the loss of the impaired wetland, and the choice questions and context are the same as presented in Lupi et al. (2002). In the survey, each respondent was given five wetland choice questions. Our stated choice survey was implemented via the mail and received a 46% response rate (despite being conducted during the anthrax attack of late 2001).

The survey was sent to a statified random sample of Michigan residents drawn from the state drivers license data base. The stratification ensured that the geographic distribution across counties for the sample matched that of the state population. Our focus here is on the analysis of the split sample test of the two experimental designs. One subset of individuals was sent a survey booklet with the stated choice questions based on a main-effects design plan for X, while the other subset was sent an individually produced survey booklet with distinct alternatives constructed of random attribute levels.

The variables used in the wetland mitigation choices are presented in Table 2. The variables took between three and five levels each. As a result, our fixed design involves selecting a main-effects orthogonal plan from the full factorial for the Astacked@ X with 4^2 by 3^12 possibilities. The full factorial design for this set of attributes and levels contains over eight million alternatives. Using Addelman=s classic set of design plans, the resulting main-effects plan contains 64 distinct choice scenarios. The resulting data from the fixed-design sub-sample contains 1,463 binary choices over alternative wetland mitigation projects.

The other sub-sample of individuals was sent a survey booklet in which the stated choice questions consisted of independent random draws from a joint uniform distribution over the integer values spanning the range of attribute levels used in the fixed design. Each draw resulted in a distinct set of attribute levels so that each of the choice scenarios in this sub-sample was unique. The surveys for this group were custom-produced on a color laser printer by creating a spreadsheet with thousands of draws from the uniform distribution over the joint parameter values, and using the spreadsheet in a merge file to individually create each distinct randomized booklet. The data resulting from this fully randomized design contains 1,146 binary choices over alternative wetland mitigation projects.

Estimation Results

For the basic main-effects specification of preferences, Table 3 presents the estimated wetland mitigation preference parameters from a random effects probit on the pooled dataset. The negative parameter on the constant indicates that all else equal, people tend not to find that the restored wetland offsets the loss. However, the positive parameter on the acres variable indicates that if the restored wetland was larger people were more likely to choose the restored wetland. The wetland Atype@ variables did not have a significant effect on mitigation choices.

Gaining public access and trails at the restored wetland made people more likely to favor it, although the effect for trails is not significant at the 5% level. The ALow_1@ to ALow_4@ variables represent the low habitat quality for the habitat attributes listed in Table 2 while the AHi@ variables represent the excellent habitat quality for these same attributes. If a restored wetland lowered habitat quality people were less likely to find it acceptable. Conversely, if a restored wetland increased habitat quality, people were more likely to find it acceptable. Put differently, people require an additional acreage premium to compensate them for any declines in habitat quality. The above results are consistent with previous findings from a pilot survey (Lupi et al, 2002). The rho parameter indicates a significant correlation across choices made by an individual.

Interestingly, the habitat variables seem to exhibit a form of non-linearity in their effects. That is, for all of the habitat attributes, the effect of moving from the low habitat quality to the medium quality is about double the benefit of moving from the medium level to the high level. These effects are graphed by the bold lines in Figure 2. However, we must note that the habitat quality variables are not based on an underlying cardinal scale. That is, there is no reason to assume that respondents perceive the distance between the low and medium levels to be the same as the distance between the medium and high levels. For example, in the horizontal axis of Figure 2, when considering the scale fromApoor@ to Aexcellent,@ individuals may simply place Agood@ closer to Aexcellent@ than to Apoor.@ This effect is plotted in Figure 2 and illustrates the difficulty of discerning non-linear effects when dealing with qualitative discrete variables.

Design Performance for Estimating Main Effects

The effectiveness of the two designs for estimating the main-effects was compared. To assess design efficiency, one usually takes some function of estimated covariance matrix to measure the performance of a design. For example, D-optimal designs minimize the determinant of the Fisher information matrix (i.e., the inverse of the covariance matrix evaluated at the estimated parameters). Here, we follow this approach and compare the designs using the ratio of the determinant of the information matrix, *I*, evaluated using $\hat{\beta}$, for each of the two design matrices. The ratio of the measures is,

$$|I(X^M;\hat{\beta})|/|I(X^R;\hat{\beta})| = 0.79$$

where X represents the design matrix for the design being evaluated (the main-effects plan, *M*, or the randomized plan, *R*). Both matrices must be evaluated at a parameter vector so the estimated parameter vector was selected as this is our best estimate of the true parameters. The resulting ratio equals 0.79 suggesting that the efficiency loss of using the randomized design plan to estimate the main effects is not pronounced.

Interaction Effects

The randomized design provides an opportunity to investigate the importance of interaction effects. For our application, there are 62 possible interactions in this model. When all of these interactions were run at once, none of the interactions were significant by themselves. A variety of models were then run to see if subsets of the variables mattered. Across all model runs, we observed that the main effect parameters are robust to interactions, both in term of sign, magnitude, and significance levels. Moreover, only four of the interaction effects were found to be significant at $p<0.1$ across a variety of models. Of these, two involve an interaction between Atype@ and Ahabitat.@ Since wetland Atype@ was not a significant variable by itself, these could be policy relevant interactions. Of course, without the more general designs, one could not test for such interactions.

Discussion

How practical is it to implement a fully randomized design? The answer depends on the mode for collecting the survey data. For internet surveys, which are increasingly popular, the added complexity and cost of the fully randomized design is trivial. The same is true for face-to-face interviews conducted using computer assisted interviewing software. Randomized designs are even feasible with simple paper instruments (An et al., 2002). Although we've shown it is feasible in the context of a mail survey, we judge the difficulty of using the randomized design to be the highest when a survey is implemented via the mail. The reason for this is that the randomized design requires individualized survey instruments for each person in the survey. We accomplished this task by using the merge feature of our wordprocessor, and then printing batches of the surveys on a high speed laser-printer. None the less, this approach is labor and time intensive, and can cost more than standard photocopying. We experienced paper and cartridge costs in the range of 10 cents a page. Our survey included several pictures of wetlands, and image quality from the laser printer was superior to standard photocopies. Factoring in the labor, the resulting production costs for the randomized design are somewhat higher than the costs of a high quality print-job for the 64 versions of the main-effects design.

In our results, as expected, the randomized design was strictly less efficient than the main effects plan for estimating a model with only main effects. However, our results also found a few significant interaction effects among the habitat quality variables. These interaction effects cannot be identified in the main-effects plan. Thus, while less efficient, the randomized designs might be preferred due to their to ability to detect such interaction effects B effects which would be difficult to guess at a priori. Moreover, the fully randomized design approach is particularly tractable and extremely simple to implement for internet and computer-based collection of stated choice data.

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Table 1: Stylized Binary Stated Choice Question

	Alternative A	Alternative B
Attribute X_1	X_1^A	X_1^B
Attribute X_2	X_2^A	X_2^B
	!	!
Attribute X_K	X_K^A	X_K^B
Which is Best?	ò	o

Table 2: Wetland Attributes and Levels

Variable	Levels	#
Baseline acres	5, 7, 9, 12, 15	5
Restored acres (multiple of baseline)	0.8, 1, 13, 12, 2	5
Public assess/trails	No, yes, yes with trails	3
Habitat: Frogs/turtles	poor, good, excellent	3
Habitat: Song birds	poor, good, excellent	3
Habitat: Wading birds	poor, good, excellent	3
Habitat: Wild flowers	poor, good, excellent	3

Table 3: Estimated Wetland Mitigation Preference Parameters from Random Effects Probit

Variable	Parameter	*p-value*
Constant	-0.199	0.0009
Acres	0.056	0.0000
Marsh	-0.059	0.3240
Wooded	-0.058	0.3277
Public	0.262	0.0000
Trails	0.096	0.0882
Low_1	-0.349	0.0000
Low_2	-0.327	0.0000
Low_3	-0.365	0.0000
Low_4	-0.190	0.0008
Hi_1	0.151	0.0112
Hi_2	-0.177	0.0025
Hi_3	0.180	0.0031
Hi_4	0.088	0.1129
Rho	0.475	0.0000

N = 532; Choices = 2,609;

Overall, 61% predicted correctly; 59% Ayes@ predicted correctly; 65% Ano@ predicted correctly.

Figure 1: Illustration of What is Meant by AStacking@ the X=s and Then Drawing a Main Effects Plan for $X = X^A * X^B$

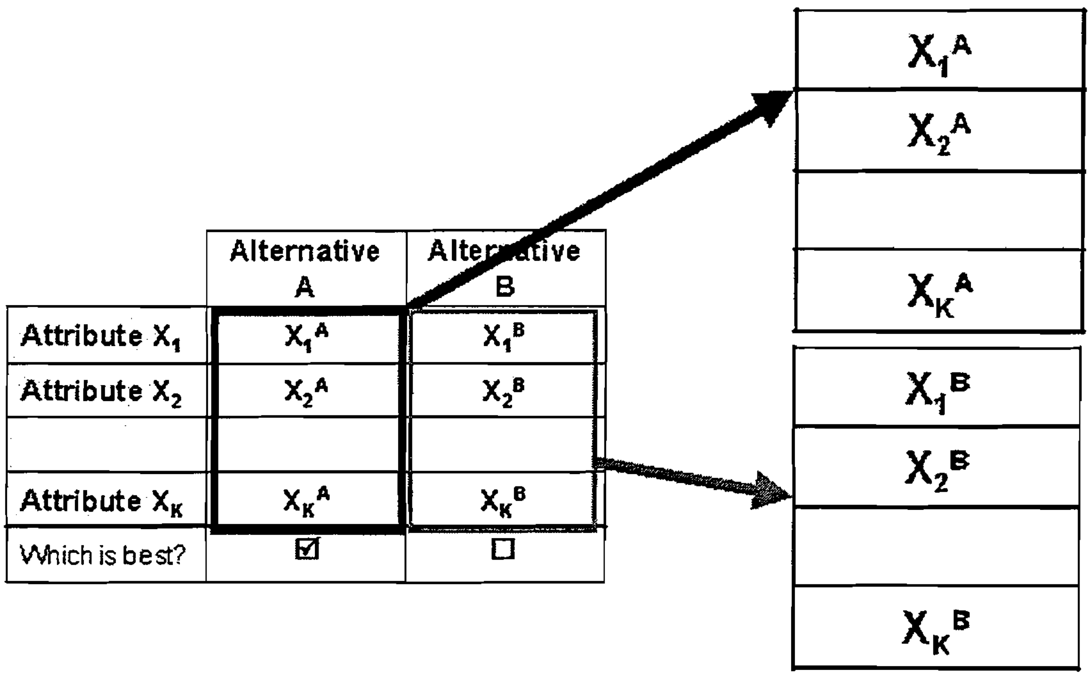
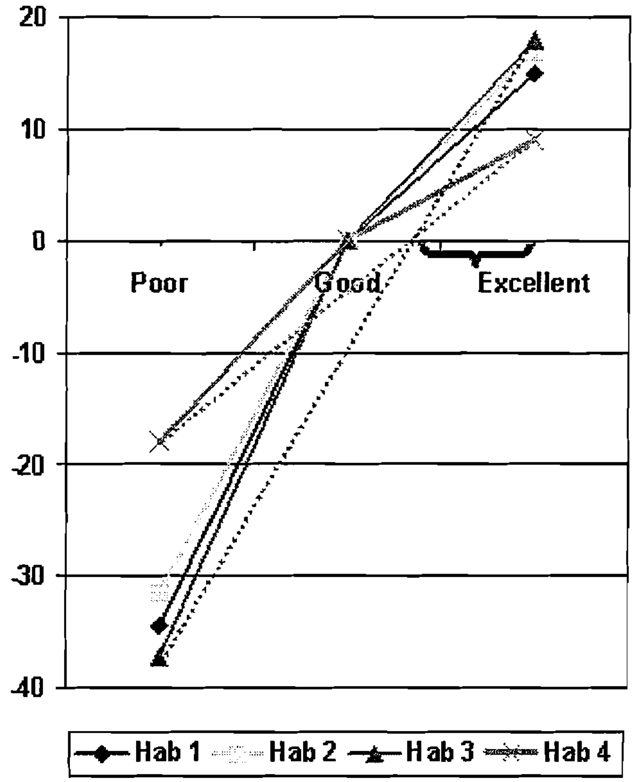


Figure 2: Non-Linear Habitat Variables



Combining Voluntary State Agricultural Support and Agricultural Land Preservation Programs: An Evaluation of Farmer Characteristics

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Abstract

Recently the goals of U.S. agricultural policy have shifted from providing sustainable sources of food and fibre, or market based outputs, toward correcting market-failures or positive externalities associated with the preservation of environmental amenities such as water quality and open space, particularly in areas of growing urban and sub-urban populations. The objective of this research is to investigate farmers who have chosen to voluntarily participate in an agricultural income support program, and their characteristics that significantly influence whether they also choose to participate in a farmland preservation program. In other words what influences farmland owners to fully participate in a joint objective agricultural program. It is found that the close ties to farming in terms of experience, and the percentage of total income from farming, are characteristics that will increase the probability of participation; and that overall higher income and grown children have a significant negative impact of the probability of participation. As such if income based incentives polices are to be used to preserve agricultural lands, it is important to distinguish the proportion of the land owners income which is earned from farming activities.

Key Words: Joint Objective Policy, Voluntary Farmland Preservation Programs, Probit Participation Model, Farmland Owner Characteristics

Introduction

There are many policy goals associated with the preservation of agricultural land in the United States. More recently these goals have shifted from providing sustainable sources of food and fibre, or market based outputs, toward correcting market-failures or positive externalities associated with the preservation of environmental amenities such as water quality and open space, particularly in areas of growing urban and sub-urban populations. The State of Maryland has used both State and county level voluntary programs to encourage farmland owners to relinquish their development rights via easement sales, since the late 1970s in an effort to preserve agricultural lands. Ideally such farmland preservation programs place easements on the property which specifically prevent the farmland from being developed for residential or commercial purposes, in perpetuity. The result being a more socially optimal level of agricultural lands or open space is maintained, given the presence of positive externalities.

Recognition of the external benefits provided by preserved farmland has lead to the use of non-market valuation techniques by environmental economists to value these benefits. Poe (1999) provides a summary of such studies. The contingent valuation method (CVM) has been used to estimate farmer willingness-to-accept compensation to participate in environmentally beneficial practices, and CVM studies have also been conducted to estimate general household WTP for benefits associated with preserving farmland (Halstead 1984, Bergstrom it al 1985, Beasly 1986, Waddington1990 and Ready 1993). Also Ready et. al. (1997) used a hedonic property value model to estimate the value of open-space amenities associate with agricultural lands. Nickerson and Lynch (2001) use a hedonic property model to investigate the impact of agricultural land preservation programs on farmland values incorporating spatial patterns along with benefits estimates.

Through the acknowledgment of, and associated valuation measurements of the benefits provided by preserved farmland, have in part, lead to a shift in U.S. agricultural policy whereby preservation of environmental amenities associated with land and water resources, is being included as a joint objective in agricultural policy development. One example of such a policy is a joint state agriculture support and land preservation policy in the state of Maryland known as the Tobacco Buyout (TB) program. Non-market valuation studies of preserved farmland have shown that society places significant value on the associated non-market benefits, and as such, the existence and expansion of land preservation justifies linking a agricultural transition and income support programs, to agricultural land preservation programs. Essentially, the Maryland TB program is a joint objective policy whereby farmers in southern Maryland who are eligible to transition their agricultural crop production away from tobacco to what the government describes as more "life sustaining" crops, are also given the option of also selling the development rights to their land. If they choose to participate fully in the joint objective program, by selling their land development rights, they become eligible to receive an easement bonus of 10% above the negotiated easement sale price under either the State or a similar county level agricultural land preservation program. In other words, the Maryland government chose to provide incentive payments to a specific group of farmers, to not only shift their crop production, but to agree to restrict their lands from ever being converted to non-agricultural uses. This TB joint objective program, from an altruistic, societal perspective, would have immense benefits. However, this program is consistent with the inherit conflict associated agricultural preservation programs, in that the non-market benefits accrue to society and presumably increase with urbanization or the numbers of people within society, yet the forgone develop opportunity costs accrue to the private land owners. Therefore if voluntary joint objective policies are to succeed policy makers should understand the landowner characteristics that significantly influence their participation decisions. This understanding of participant characteristics, is of particular importance for land preservation programs which must be voluntary in part, due to the private property rights issues associated with development rights purchase programs.

The need for these joint objective policies is likely to become even more apparent given an increasing urban society who's demand for the non-market environmental amenities associated with agricultural land preservation programs is correspondingly increasing. At the same time it should be recognized that preserving a viable farm sector would also help prevent farmland from being developed for residential or commercial purposes, thus the need for joint objective policies. The objective of this research is to investigate farmers who have chosen to voluntarily participate in an agricultural income support program, and their characteristics that significantly influence whether they also choose to participate in a farmland preservation program. In other words what influences farmland owners to fully participate in a joint objective agricultural program.

The following sections of this paper examine the regulatory setting that enabled a survey based data set to be constructed to study this objective; the utility based economic decision model; the data set components; the discrete choice participation model used to analyze the data; the empirical results; and conclusions.

Regulatory Background

In Maryland, the Maryland Agricultural Land Preservation Foundation (MALPF) program was established in 1977. The basic goal of the MALPF program is to preserve agricultural lands to help curb urban development thereby protecting agricultural and wood lands as open space. These preserved lands serve members of society in many ways. One major benefit of this program is the protection of wildlife habitat as well as the reduction of environmental degradation of the Chesapeake Bay and its tributaries, in terms of altered hydrology and urban runoff. The MALPF program is funded by agricultural land transfer taxes that are assessed on all agricultural lands when taken out of production. Under this State program land owners who have already established a land preservation district for their farmland can submit easement bid applications to the MALPF. The Foundation will then either accept the bid or make a counter offer to purchase the development rights. Once a price is agreed upon, the landowner goes to settlement and development easements are placed on the property technically into perpetuity, however a review is possible in 25 years.

In 1999, the State of Maryland was one of 46 states to receive settlement monies from lawsuits against tobacco companies. Known as the Master Settlement Agreement monies, the state of Maryland designated these funds to be used to promote public health through, for example, funding underage anti-smoking educational programs; and to encourage and assist tobacco farmers to transition out of tobacco production toward profitable life-sustaining crops and at the same time, preserve rural agriculture in southern Maryland where tobacco production has been a farmer mainstay for over 300 years.

The transition program as noted above, became know as the Tobacco Buyout (TB) Program. This is a voluntary program targeted toward eligible tobacco farmers in five southern Maryland counties. Designed to support and preserve agriculture, the TB program supports the income of enrolled farmers for 10 years if they agree to not grow tobacco on any lands they previously did for the remainder of their lives, and to agree to remain actively involved in farming for 10 years[1]. Essentially, the income support payments are intended to assist farmers

[1]Payments of $1.00 per pound of eligible tobacco are paid for 10 years. Eligible poundage is calculated based on a three-year sales average of 1997, 1998 and 1999.

as they transition toward the production of alternative crops. Tied to the TB program was a joint objective, designed to further preserve rural agriculture in southern Maryland. Essentially, the TB program also provides additional financial incentive to those farmers enrolled in the program, if they also voluntarily agree to place their land in the MALPF program. This additional financial incentive is equal to a 10% easement premium, to be paid out of the TB program funds. This research uses a sample of TB farmers to investigate the characteristics of these farmers who also chose to fully participate in this joint objective voluntary agricultural income support and land preservation program given a financial incentive or bonus.

Economic Model

The basic underlying economic theory of farmer participation studies is based on utility theory, such that the land owner will be willing to give up or sell the development rights associated with their property if the utility associated with selling the land for development is less than that from preserving it as farmland. The land owners utility function is thus modeled indirectly as a function of both the market (potential development and agricultural products) and non-market (environmental, altruistic and family heritage) attributes of the land. Lynch and Lovell (2003) use this utility based framework to investigate the factors that influence land owner participation in single objective agricultural land preservation programs. Where single objective implies that participating in the agricultural land preservation program is not dependent on participation in another agricultural stabilization program. Essentially the land owner decides to participate in the agricultural land preservation program at some point in time, 't', such that the utility they receive from participating exceeds that of non-participation. For each potential participant, 'i', their individual utility, V_i, is dependent on their individual characteristics 'A_i', and modeled as a function of the following: their farming income, including any income support payments, $F_i(A_i, t)$; their non-market value of the land including family heritage, $H_i(A_i, t)$; the value of converting the land to non-agricultural uses at a point in time 't_1', $D_i(A_i)$; the per acreage easement value $E_i(A_i)$; and the land owners annual off farm wage income $W_i(A_i, t)$. The land owner seeks to maximize their utility given their time preference 'ρ' at some discount rate 'r', and their participation decision which is denoted by 'τ', is set equal to one if the land owner participates in the preservation program, or else is set equal to zero. In other words at some point in time 't_1' if the land owner's utility from selling the development rights to their land and thereby placing an easement on the property's title, exceeds that of not selling these rights, the individual land owner will choose to participate in the land preservation program. The individual land owner's utility maximization decision is as follows:

$$V_i = \max(1-\tau)\left[\int_{t=0}^{t_1} U_i(F_i, H_i, W_i)e^{-\rho t}dt + \int_{t_1}^{\infty} U_i(W_i, rD_i)e^{-\rho t}dt\right] + \tau\left[\int_{t=0}^{\infty} U_i(F_i, W_i, rE_i, H_i)e^{-\rho t}dt\right]$$

Such that the participation decision occurs when τ=1, or that:

$$\left[\int_{t=0}^{t=1} U_i(F_i, W_i, H_i)e^{-\rho t}dt + \int_{t_1}^{\infty} U_i(W_i, rD_i)e^{-\rho t}dt\right] < \left[\int_{t=0}^{\infty} U_i(F_i, W_i, rE_i, H_i)e^{-\rho t}dt\right]$$

This utility based decision model lends itself to a discrete choice participation model that has been used to assess voluntary environmental programs. Alberini and Sergerson (2002) in their review of voluntary environmental programs note that participation in such programs may in part be motivated by environmental stewardship, which would be included in the above described model as value of non-market attributes associated with farm land ownership. This would explain in part, a why farmers may voluntarily agree to participate in land preservation programs. Cooper and Keim (1996) and Lohr and Park (1995) use a contingent valuation dichotomous choice framework to investigate farmer willingness to participate in conservation practices on environmentally sensitive lands in an ex-anti type framework. However, as noted by Alberini and Segerson, firms may not actively participate in voluntary environmental programs designed to address externalities in the absence of a profit motive, and thus government incentives such as cost-sharing or financial subsidies may be necessary. In the case of the joint objective agricultural policy or program considered in this research, the government uses a easement bonus incentive to encourage full participation in both the income support and land preservation components. The primary methodology used to assess firm characteristics of those who chose to participate in the voluntary environmental programs, is a discrete choice or probit/logit participation models (Arora and Carson 1996, DeCanio and Watkins 1998, Khanna and Damon 1999, Carraro and Devque 1999, and Videras and Alberini 2000). This study uses a similar empirical approach to investigate the utility based participation decision as described above.

Data Description

The southern region of Maryland consists of five counties between the Chesapeake Bay's western shore and the Potomac River. Tobacco production in this region dates back some 300 years. St. Mary's county, prior to the TB program, was the largest tobacco producing county in Maryland, accounting for approximately 30% of the eligible TB program acreage. We focus on the TB program participants in St. Mary's County for this research. As of December 2002, 202 or approximately one-third of St. Mary's County farmers had enrolled in the TB program. At the time of enrolling in the TB program, farmers were given the opportunity to voluntary agree to register their farmland for the 10% easement bonus through the MALPF program. In an effort to investigate the characteristics of the TB farmers who signed up for the agricultural land preservation program, survey questionnaires were sent to the 202 St. Mary's County farmers enrolled in the TB program, in January 2003. The names and addresses of the TB program participants in St. Mary's county were obtained via written request from the Tri-County Council of Southern Maryland's Agricultural Development Office, which administers the buyout program. The purpose of the survey was two-fold: 1) to assess potential alternative crops for the TB program participants; and 2) to investigate what characteristics of the TB program participants have a significant effect on the probability that they would also voluntarily sign up for the farmland preservation easement bonus. The number of returned questionnaires was 90 , for a response rate of approximately 46%, after subtracting for deaths, invalid addresses, and protest or returned incomplete questionnaires. Of the valid responses, 83 completed the participation in the easement bonus program question. Of these 25 or about 30%, indicated 'YES' they registered to participate in the easement bonus program. The survey data compiled for this analysis included specific farming characteristics of the survey respondents, along with basic demographic data. Table 1 defines the specific explanatory variables used in the discrete choice participation model. We use years of farming experience, education, and acres farmed as individual farmer characteristics. Family legacy and the adult children variables are included as prozies for the respondent's non-market value component of their utility function. We also include a variable indicating the percentage of their income that is earned from crop production, and total household income, which presumably well be earned regardless of their land preservation program decision. Table 2 reports the summary statistics for the variables, complied separately for the participants and non-participants in the voluntary agricultural lands preservation easement bonus program. The variable means between participants and non-participants were statistically different for the years of farming experience, percentage of income from crop production, and the household incomes variables. The means for the other explanatory variable were not statistically different at the 99% level.

Discrete Choice Participation Model

The discrete choice participation model (Maddala 1983 and Greene 2003) assumes that the underlying, unobservable, response variable, y_i*, is defined by the following regression equation:

$$Y_i^* = \beta' x_i + u_i \tag{1}$$

In practice, because the response variable y_i* is unobservable we define an indicator or index variable '***y***' as follows:

$$\begin{aligned} y &= 1 \qquad && \textit{if } y_i^* > 0 \\ y &= 0 && \textit{otherwise} \end{aligned}$$

As such, given a farmer agrees to voluntarily participate in the MALPF easement bonus program '***y***' takes on a value of one, and correspondingly if the farmer does not choose to participate, '***y***' takes on a value of zero. The associated probabilities regarding participation are then defines as:

$$\begin{aligned} &\text{Prob } (y = 1) = F(\beta' x) \\ &\text{Prob } (y = 0) = 1 - F(\beta' x) \end{aligned} \tag{2}$$

Where '***β***' is a vector of parameters to be estimated, that reflect changes in the corresponding vector of farmer characteristics as defined by the variable vector '***x***', on the probability of farmer participation in the MALPF easement bonus program. Also '***F***' is defined as the cumulative distribution function which depends on the continuous probability distributional assumption made regarding the random regression component 'u_i'. Typically either the normal or logistic distributions are assumed, yielding the probit and logit models, respectively. The probit model is applied in this agricultural land preservation participation analysis, yielding the following model:

$$Prob(y = 1) = \int_{\infty}^{\beta' x} \phi(t)\,dt = \Phi(\beta' x) \tag{3}$$

Where $\Phi(\square)$ denotes the standard normal distribution function. The probit model is estimated by LIMDEP software, using the maximum likelihood method. In general, the likelihood function, which specifically depends on the functional form of $F(\square)$ and is based on the observed values of 'y_i', along with the associated probabilities that vary per observation depending on 'x_i', is defined as follows:

$$L = \prod_i [F(\beta x_i)]^{y_i} [1 - F(\beta x_i)]^{1-y_i} \tag{4}$$

The log-likelihood function from which maximum likelihood parameter estimates of 'β' are derived, is written as follows:

$$\ln L = \sum_i \{ [y_i \ln F(\beta x_i)] + (1 - y_i) \ln[1 - F(\beta x_i)] \} \tag{5}$$

Consistent with any nonlinear regression model, the marginal effects of changes in the explanatory variables 'x_i', on the probability of participation do not correspond directly to the maximum likelihood parameter estimates. In general, these marginal effects are calculated as the derivatives for the probabilities as:

$$\begin{aligned} \frac{\partial E[y|x]}{\partial x} &= \left\{ \frac{dF(\beta' x)}{d(\beta' x)} \right\} \beta \\ &= f(\beta' x)\beta \end{aligned} \tag{6}$$

where $f(\square)$ is the density function which corresponds to the cumulative distribution function $F(\square)$. For the probit model the marginal effects are derived as:

$$\frac{\partial E(y|x)}{\partial x} = \phi(\beta' x)\beta \tag{7}$$

where $\varphi(\square)$ is the standard normal density. It is typical to compute these marginal effects at the sample means of the data.

The discrete choice pobit participation model is used to investigate the characteristics of farmers enrolled in the TB program in terms of whether they chose to register for the easement bonus when they place their land in the MALPF program. For those farmers who voluntarily registered for the easement bonus under the TB program, we assume that their land possesses some positive easement value, above the strictly agricultural land-use value. In other words, if the easement value were zero or negative, potential or future development value would not exist.

Typical land preservation easement programs do not pay 100% of the easement value and as such, it is plausible to assume that those farmers who chose to participate in these programs base their decision in part, on an environmental stewardship or land ethic criteria.

The following probit model results help to explain which farmer characteristics amongst the sample of St. Mary's County TB farmers, play a role in identifying those farmers more likely to fully participate in a joint objective agricultural program, as indicated by their willingness to participate in the MALPF easement bonus program.

Probit Model Results

The probit regression results are presented in Table 3. As might be expected with cross sectional survey data, heteroskedasticity was present within the model. As such White's consistent standard errors are reported in Table 3. The farmer characteristics as model by the explanatory variables, that had a positive and significant influence on the probability of voluntarily registering for the 10% easement bonus under the MALPF program include: years of farming experience, acreage farmed, percent of income from crop production and a high school education. The intuition underlying these positive effects is consistent with our expectations, and is consistent with the findings of Lynch and Lovell in their single objective agricultural land preservation participation model. Thus respondents with more farming experience could be seen as having a stronger land ethic regarding farmland preservation. Also the positive coefficient sign for the number of acres farmed is expected in part because a minimum of 50 contiguous acres are required to apply for the MALPF easement program in St. Mary's county. We assume that the greater the percentage of the respondent farmer's income from crop production to be a indicator of the extent that they are full-time farmers, and thus are less likely to supplement their income from off-farm sources. As such the positive coefficient for this variable, indicates that the greater the percentage of income from farming, the greater the probability the respondent is concerned with preserving the land and thus, more likely to participate. With respect to the education variables, we would expect that with greater levels of education, comes more knowledge regarding the preservation of farmland as open apace and correspondingly slowing suburban sprawl. The coefficients on the education variables, as expected are positive, although only the coefficient estimate for the high school variable was significantly different from zero.

With respect to the coefficient estimates that have a negative and significant influence on the probability that a farmer registered for the 10% easement bonus land preservation program, the intuitive reasoning may no be as straight forward. In St. Mary's county many of the farmers can date their farming ancestors back hundreds of years. The negative coefficient sign on the generational farming history may be indicative of the respondents strong conservative roots, and the associated resistance to participating in a government program which may be perceived as restricting their rights to use they property in perpetuity. Although they did agree to participate in the ten year TB program. Following this reasoning, one could argue that the farmers with adult children would be less likely to place easements on their farmland because they have strong feelings toward this property rights restriction, which may indeed limit potential future land development income to their children.

Farmers in our sample with higher incomes were less likely to participate in the voluntary land preservation program even when offered a 10% easement bonus. This indicates that in general, monetary incentives may not be the recommended policy instrument to encourage private farmland owners to participate in land preservation easement programs, unless a high percent of the farmer's income is earned from direct farming activities.

Conclusions

The increasing use of joint objective agricultural policy is an important instrument when dealing with external societal benefits that accrue from preserving privately held farmland. Yet given the importance of protecting private property rights in the U.S., if such joint objective voluntary agricultural policies are to succeed in providing optimal levels of environmental and other non-market amenities to society, a strong understanding of what motivates the farmland owners to voluntarily participate in land preservation programs is imperative. This study uses a discrete choice probit participation model to investigate which characteristics of a sample of farmers who were eligible to participant fully in a joint objective farmland preservation easement bonus program.

It is found that the close ties to farming in terms of experience, and the percentage of total income from farming, are characteristics that will increase the probability of participation; and that overall higher income and grown children have a significant negative impact of the probability of participation. As such income based incentives may not be appropriate public polices to preserve agricultural lands, without being able to distinguish the proportion of the land owners income which is earned from farming activities. This may also help to explain why in more urban, higher income counties or regions, participation in agricultural land preservation programs may be lower.

Our results show that farmland owner characteristics can significantly contribute to participation in an agricultural land preservation program which is provided in conjunction with a transitional crop income support program, and supplemented with a financial bonus for those who voluntarily choose to participate. Policies that combine agricultural production policies with environmental programs designed to correct for positive externalities associated with open space and land preservation, must take into consideration the characteristics that motivate farmers to participate.

Table 1: Farmer Characteristics Explanatory Variables

FARM_YR	The number of years of farming experience (continuous).
FAMIL_YR	The number of years past generations of the survey respondent's family have been farming in St. Mary's County (continuous).
ACRES	The number acres typically farmed (continuous)
PERC_INC	The percent of the respondent's 2002 household income from agricultural crop production (continuous).
ADULT_CH	A dummy variable equal to one if respondent has adult children, equal to zero otherwise.
HIGHSCH	A dummy variable equal to one if highest level of completed education was high school, equal to zero otherwise.
COLLEGE	A dummy variable equal to one if highest level of education was some attendance at a 2 or 4 year college, equal to zero otherwise.
INCOME	The survey respondent's 2002 household income before taxes (continuous).

Table 2: Characteristics Explanatory Variable Summary Statistics

Variable Name	*Participants Mean (s.d.)*	*Non-Participants Mean (s.d.)*	*t-Statistic* [a]
FARM_YR	47.08 (19.68) n=25	33.47 (15.93) n=57	3.0475***
FAMIL_YR	121.43 (79.81) n=23	142.83 (79.69) n=54	0.1712
ACRES	231.32 (315.75) n=25	148.86 (303.66) n=57	1.1014
PERC_INC	0.46 (0.34) n=23	0.2373 (0.25) n=51	5.3266***
ADULT_CH	0.52 (0.51) n=25	0.54 (0.50) n=56	0.1640
HIGHSCH	0.60 (0.50) n=25	0.67 (0.47) n=55	0.5329
COLLEGE	0.04 (0.20) n=25	0.1091 (0.31) n=55	0.9011
INCOME	35,000 (25,669) n=22	53,971 (28,867) n=51	2.7884***

a. To test the null hypothesis of equal means between program participants and non-participants.

*** indicates statistically significant at the 99% level.

Table 3: Probit Participation Regression Results

Variable Name	*Coefficient Estimate*	*Standard Error (a)*	*P-Value*	*Marginal Effects*
CONSTANT	-0.7713	0.7559	0.3076	-0.2574
FARM_YR	0.0540***	0.0155	0.0005	0.0129
FAMIL_YR	-0.0120***	0.0043	0.0058	-0.0036
ACRES	0.0018**	0.0008	0.0245	0.0005
PERC_INC	1.9227**	0.8157	0.0184	0.5994
ADULT_CH	-1.2983***	0.4783	0.0066	-0.2708
HIGHSCH	0.7978*	0.4898	0.1033	0.2814
COLLEGE	0.5348	0.6768	0.4294	0.3290
INCOME	-0.000026***	0.000008	0.0007	-0.000007

Log-Likelihood -25.4235
McFadden R-Square 0.3952
Number of Observations 68
(a) White's consistent standard errors.
*, **, *** indicate significance at .10, .05 and .01, respectively.

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Incomplete Demand Systems, Corner Solutions, and Welfare Measurement

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Abstract

This paper demonstrates how corner solutions raise difficulties for the specification, estimation, and use of incomplete demand systems for welfare measurement with disaggregate consumption data as is common in the outdoor recreation literature. A simple Kuhn-Tucker model of consumer behavior is used to elucidate the potential biases for welfare measurement arising from modeling the demand for M goods as a function of $M + N$ prices ($N > 1$) and income when consumers do not consume all goods in strictly positive quantities. Results from a Monte Carlo experiment suggest that these biases can be substantial for policy scenarios involving relatively large price changes if prices are highly correlated.

Introduction

Applied researchers are often interested in developing empirical demand models for a subset of goods entering an individual's preference ordering. A practical issue arising in these situations is the treatment of the remaining goods whose demands are not explicitly modeled. The dominant strategies for resolving this issue in applied microeconomic analysis involve either separability or Hicksian composite commodity assumptions. Both of these approaches imply restrictions on preferences or prices that may not hold empirically. When they do not, Epstein [1982] has proposed an incomplete demand system strategy where the analyst models the demand for the goods of interest as functions of their own prices, the remaining goods prices, and income. LaFrance and Hanemann [1989] prove that if the incomplete demand system satisfies a set of regularity conditions analogous to the classical integrability conditions for complete demand systems, it is consistent with a rational preference ordering and can be used to generate Hicksian welfare measures for changes in the prices of the goods whose demands are explicitly modeled.

To illustrate the potential usefulness of the incomplete demand system framework, consider a common empirical problem in the outdoor recreation literature.[1] Analysts are often interested in valuing the access to a single recreation site that is located in a larger geographic region containing several substitute or complement sites. The varying proximity of individuals to these sites as well as differences in each individual's opportunity cost of time suggest that the sites' implicit prices (i.e., travel costs) vary across the target population. Data limitations often imply that the analyst only has trip data for the site of interest. The combination of these preference linkages, price variations, and data limitations suggest that employing separability assumptions or the Hicksian composite commodity theorem in a demand model for the relevant site would be inappropriate. However, the insights of Epstein and LaFrance and Hanemann suggest that the incomplete demand system approach in principle can be used to derive a consistent demand specification and Hicksian welfare measures for the site of interest. In fact, several authors (e.g., Gum and Martin [1975], Hof and King [1982], Caulkins, Bishop, and Bouwes [1985],

[1] See, e.g., Herriges and Kling [1999] for an overview of this literature.

Rosenthal [1987], Kling [1989], Smith [1993], Ozuna and Gomez [1994], Gurmu and Trivedi [1996]) have suggested and/or empirically implemented demand specifications that fall under the rubric of incomplete demand system approaches.[2]

This paper raises difficulties with the specification, estimation, and use of the incomplete demand system framework for welfare measurement with disaggregate consumption data. An empirical regularity with many individual or household level data sets is that consumer demand for the goods of interest and their related substitutes and/or complements are a mixture of interior (i.e., strictly positive valued) and corner (zero) solutions. When the individual chooses not to consume a subset of these goods, their market prices are not behaviorally relevant for the remaining goods.[3] Rather, economic theory suggests that their Marshallian virtual prices (Neary and Roberts [1980]), i.e., the prices that would drive their demands to zero, influence choice. These virtual prices are bounded from above by their corresponding market prices and are functions of the structural parameters of the individual's utility function as well as the prices of the goods consumed in strictly positive quantities. Frequently in applied situations, the individual's demands for the related goods are unknown to the analyst *a priori*. As a result, whether the observed market prices or the unobserved virtual prices are behaviorally relevant cannot be determined.

The misuse of observed prices when virtual prices are appropriate can influence policy inference in at least two ways. In terms of estimation, employing observed prices in place of behaviorally relevant virtual prices results in biased and inconsistent estimates of the structural parameters of the individual's demand functions. The direction and magnitude of these biases cannot be ascertained in general because the analyst in essence is employing the wrong prices for the non-consumed goods. For the calculation of

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[2] Boardman et al. [2001] have summarized this line of research as follows:

> "Estimating the demand for a particular recreation site… is conceptually straightforward. First, select a random sample of households within the market area of the recreation site. Second, survey these household to determine their number of visits to the site over some period of time, all of their costs from visiting the site, their costs of visiting substitute sites, their incomes, and other of their characteristics that may affect demand. Third, specify a functional form for the demand schedule and estimate it using the survey data." [p 345]

[3] Pudney [1989] and Phaenuf, Kling, and Herriges [1998] raise similar points in the context of complete demand systems. Neither, however, use Monte Carlo techniques to explore the empirical implications of using market prices in place of virtual prices.

welfare measures, the improper use of observed prices does not capture how changes in market prices for the goods of interest influence the related goods' virtual prices. Failure to account for these feedback effects on virtual prices further confounds welfare measurement.

A Monte Carlo experiment is used to illustrate how these sources of bias can impact welfare measurement. A five-good complete demand system is developed and calibrated using parameter estimates, descriptive statistics, and empirical results reported in Phaneuf [1999]. 500 simulated data sets are generated from the model and used to estimate an incomplete demand model for a single good that employs observed market prices in place of the behaviorally relevant virtual prices for the remaining goods. A comparison of welfare estimates from the incomplete demand system specification with estimates generated from the true model for two alternative policy scenarios suggests that the bias introduced by using market prices in place of virtual prices is relatively small (less than 4 percent) for small price changes regardless of the correlation structure among the good's own price and substitute prices. However, for scenarios involving large price changes such as the elimination of a good, the bias can be as large as 35 percent if the good's own price is strongly correlated with substitute prices.

The remainder of the paper is structured as follows. Section II develops a theoretical model of consumer demand to illustrate the linkages among incomplete demand systems, corner solutions, and welfare measurement. Section III describes the Monte Carlo experiment that is used to demonstrate how using market prices in place of behaviorally relevant virtual prices can result in substantially biased welfare estimates. Section IV concludes by proposing some alternatively strategies for consistently accounting for corner solutions within the incomplete demand system framework.

Conceptual Framework

This section develops a simple model of consumer choice that is used to clarify the difficulties arising from the improper use of market prices when corner solutions are present. A maintained assumption throughout the section is that consumer preferences for a set of $M + N$ ($N > 1$) goods can be represented by a smooth, continuously differentiable, strictly increasing, and strictly quasi-concave utility function:

$$U(x,z), \tag{7}$$

where x and z are $M \times 1$ and $N \times 1$ vectors of goods. The partitioning of goods into x and z subgroups reflects the analyst's interest in the welfare implications of price or access changes for the goods in x alone. To allow for corner solutions, it is assumed that all goods in x and z are nonessential. The individual behaves as if she maximizes (1) with respect to her budget constraint,

$$p^{\mathsf{T}}x + q^{\mathsf{T}}z \leq y, \tag{8}$$

where $\boldsymbol{p}$ and $\boldsymbol{q}$ are $M \times 1$ and $N \times 1$ vectors of exogenous and strictly positive prices and y is income. The following consumption inequalities complete the characterization of the consumer's choice problem:

$$x \geq 0, z \geq 0. \tag{9}$$

The optimal consumer demand functions can be solved for by maximizing the following Lagrangian:

$$L = U(x,z) + \lambda(y - p^{\mathsf{T}}x - q^{\mathsf{T}}z) + \delta^{\mathsf{T}}x + \mu^{\mathsf{T}}z, \tag{10}$$

where λ, δ, and μ are a scalar, $M \times 1$ vector, and $N \times 1$ vector of Lagrange multipliers, respectively. Because a strictly increasing utility function implies budget exhaustion, the implied Kuhn-Tucker conditions can be written:

$$\frac{\partial U(x,z)/\partial x_i}{\lambda} = p_i - \delta_i/\lambda,\ i = 1,\ldots,M, \tag{11}$$

$$\frac{\partial U(x,z)/\partial z_j}{\lambda} = q_j - \mu_j/\lambda, j = 1,\ldots,N, \tag{12}$$

$$\delta^{\mathsf{T}}x = 0, \mu^{\mathsf{T}}z = 0, \tag{13}$$

in addition to equations (2) and (3) above.

Equations (5), (6), and (7) implicitly define the optimal consumption bundle, $x^*(p,q,y)$ and $z^*(p,q,y)$, as well as the optimal Lagrange multipliers, $\lambda^*(\cdot) > 0$, $\delta^*(\cdot) \geq 0$, and $\mu^*(\cdot) \geq 0$. Inserting these optimal values into (5) and (6) allows one to define the Marshallian "virtual" prices (Neary and Roberts [1980]) for each of the $M + N$ goods:

$$\xi_{x_i}^*(p,q,y) = \frac{\partial U(x^*,z^*)/\partial x_i}{\lambda^*} = p_i - \delta_i^*/\lambda^*, i = 1,\ldots,M, \tag{14}$$

$$\xi_{z_j}^*(p,q,y) = \frac{\partial U(x^*,z^*)/\partial z_j}{\lambda^*} = q_j - \mu_j^*/\lambda^*, j = 1,\ldots,N. \tag{15}$$

Equations (8) and (9) suggest that each $\xi_{x_i}^*(\cdot)$, i = 1,…, M, and $\xi_{z_j}^*(\cdot)$, j = 1,…, N, equals its corresponding market price only if δ_i^*= 0 or μ_j^*= 0, respectively. Given the complementaryslackness conditions in (7), this occurs only if the demand for the good is strictly greater than zero, i.e., $x_i^* > 0$ or $z_j^* > 0$. When the non-negativity constraint binds, δ_i^* or μ_j^* is strictly greater than zero, reflecting the fact that the individual's utility would increase if the constraint could (hypothetically) be relaxed.

Alternatively, one can derive the same optimal solutions by maximizing (1) with respect to the following notional budget constraint:

$$\xi_x^*(\boldsymbol{p},\boldsymbol{q},y)^{\mathrm{T}}\boldsymbol{x}+\xi_z^*(\boldsymbol{p},\boldsymbol{q},y)^{\mathrm{T}}\boldsymbol{z}=y, \tag{16}$$

where $\xi_x^*(\cdot)$ and $\xi_z^*(\cdot)$ are $M\times1$ and $N\times1$ vectors of quasi-fixed virtual prices implied by (8) and (9), respectively. Approaching the constrained optimization problem in this way suggests that the optimal demand functions can be written as functions of all virtual prices, and income, i.e.:

$$\boldsymbol{x}^*=\boldsymbol{x}(\xi_x^*(\boldsymbol{p},\boldsymbol{q},y),\xi_z^*(\boldsymbol{p},\boldsymbol{q},y),y), \tag{17}$$

$$\boldsymbol{z}^*=\boldsymbol{z}(\xi_x^*(\boldsymbol{p},\boldsymbol{q},y),\xi_z^*(\boldsymbol{p},\boldsymbol{q},y),y). \tag{18}$$

To highlight the difficulties with measuring the welfare implications for changes in $\boldsymbol{p}$ within an incomplete demand system framework, it is instructive to compare equation (11) with the incomplete demand system specifications that have been suggested and/or used in the applied literature (e.g., Gum and Martin [1975], Hof and King [1982], Caulkins, Bishop, and Bouwes [1985], Rosenthal [1987], Kling [1989], Smith [1993], Ozuna and Gomez [1994], Gurmu and Trivedi [1996]). Except for Ozuna and Gomez,[4] these authors model the demand for a single good (i.e., $M = 1$) as a function of its own price, substitute goods' prices, and income using a linear-in-parameters structure of the general form:

$$f(x_1^*)=\begin{cases}\alpha_1+\beta_{11}g(p_1/q_N)+\sum_{i=1}^{N-1}\phi_{1i}h_i(q_i/q_N)+\mu_1 l(y/q_N)+\varepsilon_1 & \text{if } x_1^*>0\\ 0 \text{ otherwise}\end{cases}, \tag{19}$$

where $\alpha_1, \beta_{11}, \phi_{1i}$, and μ_1 are estimable structural parameters, $f(\cdot)$ is a strictly increasing function defined over the nonnegative orthant, and $g(\cdot)$, $h_i(\cdot)$, and $l(\cdot)$ are strictly increasing functions defined over the strictly positive orthant, and ε_1 captures unobserved determinants of choice that are

[4] Ozuna and Gomez specify a two good incomplete demand system model.

known to the individual but unknown and random from the analyst's perspective. In general, equation (13) is not a consistent demand specification in the presence of corner solutions. As suggested by the structure of equations (8) and (11), it is consistent only if $\delta^* = 0$ and $\mu^* = 0$, i.e., there are no corner solutions. Therefore, the parameter values arising from the estimation of (13) are biased and inconsistent estimates of the true structural parameters when individuals in the sample choose not to consume all goods. *A priori*, one cannot determine the direction and/or magnitude of bias because the analyst is in essence employing the wrong prices. A correctly specified version of (13) should instead take the form:

$$f(x_1^*) = \begin{cases} \alpha_1 + \beta_{11} g(p_1 / \xi_{z_N}^*) + \sum_{i=1}^{N-1} \phi_{1i} h_i(\xi_{z_i}^* / \xi_{z_N}^*) + \mu_1 l(y / \xi_{z_N}^*) + \varepsilon_1 & \text{if } x_1^* > 0 \\ 0 \text{ otherwise} \end{cases}. \tag{20}$$

In addition to biased parameter estimates, using (13) to construct Hicksian welfare measures for price changes will generate invalid policy inference because it fails to incorporate the feedback effects of a change in the price of p_1 on the other goods' virtual prices. To illustrate this point concisely, (14) is restricted such that $\mu_1 = 0$. If x_1^* is strictly positive, (14) becomes:

$$x_1^* = f^{-1}\left[\alpha_1 + \beta_{11} g_1(p_1 / \xi_{z_N}^*) + \sum_{i=1}^{N-1} \phi_{1i} h_i(\xi_{z_i}^* / \xi_{z_N}^*) + \varepsilon_1\right] \tag{21}$$

Because income effects are absent, (15) is both a Hicksian and Marshallian demand function whose integral evaluated over the relevant price range generates consistent Hicksian welfare measures (LaFrance and Hanemann [1989]). Consider a policy involving a price change from p_1' to p_1'' and recall that the virtual prices for the remaining goods whose demands are not modeled are in general functions of p_1. Therefore, as p_1 changes from p_1' to p_1'', the virtual prices in (15) may also change. If the analyst uses a demand specification identical to (15) above except for market prices replacing virtual prices, she would fail to account for these links.

There is an additional difficulty with using market prices in (15) when estimating the total Hicksian value of x_1^* or a relatively large price change that drives the demand for x_1^* to zero. In this case, the Hicksian consumer surplus is defined as the integral from the current market price to the Hicksian "choke" price, $p_1^c(\cdot)$, i.e., the price that drives Hicksian demand for the good to zero. Because p_1 can enter all virtual price functions, $p_1^c(\cdot)$ derived from (15) may be substantially different from a similarly structured demand function where market prices replace virtual prices. As a result, the bounds of the integral that define the Hicksian consumer surplus are not properly specified and welfare estimates may be further biased.

In general, the combined effect of these biases is uncertain. It is possible, albeit unlikely, that they do not substantially influence derived welfare measures. In the next section, a Monte Carlo experiment is used to illustrate that the net bias may in fact be substantial for large price changes when own and substitute good prices are highly correlated. This finding is of course conditional on the assumed structure of consumer preferences, the judgements made in calibrating the simulation experiment, and the policy scenarios considered. Nevertheless, it illustrates the critical role of virtual prices in the construction of welfare measures from incomplete demand systems.

Monte Carlo Experiment

The Monte Carlo experiment employs the following quasilinear complete demand system specification developed by Bockstael, Hanemann, and Strand [1986]:

$$x_i^* = \alpha_i + \sum_{k=1}^{M} \beta_{ik}\xi_{x_k}^* / q_N + \sum_{l=1}^{N-1} \phi_{il}\xi_{z_l}^* / q_N + \varepsilon_i, i = 1,\ldots,M \tag{22}$$

$$z_j^* = \widetilde{\alpha}_j + \sum_{k=1}^{M} \widetilde{\beta}_{jk}\xi_{x_k}^* / q_N + \sum_{l=1}^{N-1} \widetilde{\phi}_{jl}\xi_{z_l}^* / q_N + \widetilde{\varepsilon}_j, i = 1,\ldots,N-1 \tag{23}$$

$$z_N^* = \frac{1}{q_N}\left[y - \sum_{i=1}^{M} p_i x_i^* - \sum_{j=1}^{N-1} q_j z_j^* \right] \tag{24}$$

Note that a maintained assumption with the above specification is that z_N^* is consumed in strictly positive quantities and, by implication, q_N is its behaviorally relevant price. The corresponding indirect utility function can be written compactly using vector notation as:

$$V(\cdot) = y / q_N - (\alpha + \varepsilon)^{\mathrm{T}}(\xi^* / q_N) - \tfrac{1}{2}(\xi^* / q_N)^{\mathrm{T}}\Phi(\xi^* / q_N) \tag{25}$$

where α and Φ are a (N+M-1)×1vector and a (N+M-1)×(N+M-1) matrix of constant terms and (Hicksian) own and cross price effects, respectively, ε is the (N+M-1)×1 vector of unobserved determinants of choice, and ξ^* is the (N+M-1)×1 vector of virtual prices. The above specification is homogenous of degree zero in prices and income and satisfies the adding-up condition given $z_N^* > 0$.

To insure economic consistency, Φ must be symmetric (i.e., $\Phi = \Phi^{T}$) and negative semi-definite (the eigenvalues of Φ must be non-positive).

To calibrate (16), (17), and (18), the Monte Carlo experiment employs parameter estimates, descriptive statistics, and empirical results reported in Phaneuf [1999]. Table 1 documents the assumptions and procedures used to fit Phaneuf's homothetic Indirect Translog model for four Wisconsin outdoor recreation sites to the above framework. These four goods and a Hicksian composite are partitioned into disjoint sets such that only the demand for a single good is explicitly modeled (and, by implication, $N = 1$ and $M = 4$). A potentially significant piece of information for this application not reported in Phaneuf is the correlation structure among implicit prices (i.e., travel costs) for the four sites. To evaluate the sensitivity of derived welfare measures to alternative correlation structures, five alternative correlation specifications are developed. Because all prices are assumed to be log-normally distributed, the five specifications assume that the correlation coefficient between $\ln p_1$ and $\ln q_j$ equals r for $j = 1,2,3$, and that the correlation coefficient between $\ln q_i$ and $\ln q_j$ equals zero for $\forall i, j = 1,2,3; i \neq j$. Across the five specifications, r ranges from -.5 to +.5 in .25 increments.

Table 2 includes descriptive statistics from the calibrated model. They suggest that the simulated sample's average prices and participation rates match the observed behavior in the Wisconsin data set reasonably well. Table 2 also suggests that the induced correlations between (p_1, q_j), $j = 1,2,3$, resulting from the assumed correlations between $(\ln p_1, \ln q_j)$, $j = 1,2,3$, range from roughly -.30 to +.40 across the five specifications.

These five calibrated models were then used to generate estimates of the sample's unconditional expected Hicksian consumer surplus arising from a \$20 price increase for x_1 as well as the loss of x_1. These estimates were generated by a simulation algorithm with 500 replications and are used to benchmark the subsequent analysis. Table 3 outlines the main components of this algorithm.[5]

To evaluate the welfare implications of incomplete demand systems specified as functions of market prices when corner solutions are present, a second simulation algorithm was developed. As

[5] All components of the Monte Carlo experiment were coded in *Stata 6.0*. A copy of the source code can be obtained from the author upon request.

Table 4 describes, the demands for all goods were first simulated using the correctly specified structural model. The simulated demand for x_1 was then modeled as a linear function of the four goods' normalized prices and a constant term (i.e., the same structure as (16) except for market prices replacing virtual prices). The structure of the virtual price functions in equation (9) suggests that the difficulty with this specification is that the terms, $-\tilde{\phi}_{1j}\mu_j^* / \lambda^*, j = 1,2,3$, are excluded from the regression. Since these terms are in general functions of the prices of goods consumed in strictly positive quantities, their exclusion will likely generate biased and inconsistent estimates of the structural parameters as a result.[6] To account for the empirical regularity that some individuals in the simulated sample do not consume x_1, a censored regression model with a normal distribution for the unobserved determinants of choice was employed. The parameter estimates from the censored regression model were then used to construct welfare estimates for the three policies. These procedures were replicated 500 times and the results are reported in Table 5.

Table 5 suggests that using market prices in place of virtual prices can result in substantially biased estimates of the structural parameters as expected. In particular, the mean estimates of the own price effect, $\hat{\beta}_{11}$, are biased towards zero for all specifications except (1) (when $r = -.5$), while all estimates of cross price effects are consistently biased towards zero. Except for the specification (1), the estimates of the intercept term, $\hat{\alpha}$, are significantly biased downwards, and all standard error estimates ($\hat{\sigma}$) are consistently and significantly biased upwards.

Turning to the welfare estimates reported in Table 6, one finds that the mean percentage biases arising from using market prices in place of virtual prices are negligible for the \$20 price increase scenario. For all five correlation specifications, the percentage bias is less than 4 percent in absolute value. For the loss of x_1 scenario, however, the percentage biases vary substantially across the five specifications and are as large as 35.2 percent in absolute value. In general, the biases are smallest when prices are orthogonal and largest when prices are strongly correlated. These findings suggest that when corner solutions are prevalent, prices are highly correlated, and the analyst is attempting to evaluate the welfare implications of relatively large price changes, using market prices in place of behaviorally relevant virtual prices can result in substantially biased policy inference.

[6] Of course, small bias in the parameter estimates should be expected due to the fact that maximum likelihood estimates are only consistent when the model is correctly specified.

Discussion

This paper has used both a theoretical model of consumer behavior and a Monte Carlo experiment to illustrate how virtual prices link incomplete demand systems, corner solutions, and welfare measurement. The theoretical section described the potential biases arising from the misuse of market prices in place of behaviorally relevant virtual prices. These biases arise both in the estimation of the structural parameters and with the calculation of Hicksian welfare measures. For relatively small price changes, the results from the Monte Carlo experiment suggest that these biases may not significantly compromise the integrity of the derived welfare measures. However, when the analyst considers scenarios involving large price changes, these biases may be substantial.

What should the analyst do in these situations? Short of relying on restrictive separability and/or aggregation assumptions, two strategies can be pursued. The first involves jointly estimating the consumption of all goods that influence the demands for the goods of interest and are not consumed in strictly positive quantities by all members in the target population. In the Monte Carlo experiment, this would involve estimating the demand for the four goods and the Hicksian composite simultaneously. Two practical limitations with this strategy deserve mention. It of course requires additional consumption data that may not be available in practice. Moreover, estimating flexible demand system models that consistently account for both interior and corner solutions can be computationally burdensome when the number of goods is large (e.g., Wales and Woodland [1983], Lee and Pitt [1986], Phaneuf, Herriges and Kling [2000], von Haefen, Phaneuf, and Parsons [2003]). Both of these limitations are significant, but with continued advancement in data collection and computational power, these constraints will become less binding in the future.

A second, conceptually distinct approach involves viewing the difficulties arising from corner solutions from a purely statistical perspective. That is, instead of modeling an individual's demand for a set of commodities entering the incomplete demand system, one can model the individual's *expected* demand for these goods. Assuming that the expected demands of all goods whose prices enter the incomplete system are strictly positive, one can argue that the market prices should be included in the estimated equations. Although corner solutions in this framework are essentially ignored in the demand specification, they can be accounted for statistically through the specification of a distribution (such as a count distribution) that places a significant probability mass on zero outcomes. As von Haefen and Phaneuf [2003] argue, derived welfare measures from these models should be given a representative consumer interpretation and may not be substantially different from estimates derived from comparable models that consistently account for interior and corner solutions. Notably, this statistical approach to accounting for corner solutions is implicitly embraced by existing count data incomplete demand system applications (Ozuna and Gomez [1994], Gurmu and Trivedi [1996]).

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Mixed Poisson Regression Models with Individual Panel Data from an On-site Sample[1]

by

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Introduction

Cost considerations often drive analysts to rely upon intercept (or on-site) surveys to collect information about recreation demand at a site (or sites) of interest. This guarantees that survey respondents will include users of the resource in question. Unfortunately, the sampling procedure also comes at a cost of both truncation (excluding non-users) and endogenous stratification (over sampling those individuals who are more frequent users of the site). As a result, the sample is no longer representative of the broader population. Failure to correct for on-site sampling will result in biased estimates of recreation demand and any corresponding welfare estimates.

There have been a number of papers in the literature focused on controlling for intercept sampling in recreation demand analysis. Shaw (1988) develops a correction for both the truncation and endogenous stratification problems in the case of a single site Poisson count data model. Englin and Shonkwiler (1995) subsequently extended Shaw's correction to the case of the Negative Binomial (NB) count data model. The advantage of the NB model is that it allows for overdispersion (i.e., the situation in which the conditional mean number of trips is less than the conditional variance of trips), a common characteristic of recreation demand data. The limitation of both of these efforts is that they are focused on a single demand equation.

The purpose of this paper is to consider the problem of controlling for on-site sampling in the context of a system (or panel) of demand equations.[1] Specifically, we are concerned with the situation in which survey respondents are asked to provide information not only about the actual trips to a specific site (observed behavior), but also their anticipated trips (either under current conditions or given price and quality changes). The latter trip data, typically known as contingent behavior data, has been used to study the impact of changing environmental conditions (See, e.g., Rosenberger and Loomis, 1999; Whitehead *et al.*, 2000; and Grijalva, *et al.* 2002). Unfortunately, if the observed and contingent behavior data are collected through an on-site survey, the sampling problems become more complex. The observed behavior data are, as before, subject to truncation and endogenous stratification. While the contingent behavior data

[1] The literature has already shown a need for this research as evidenced by Englin et al. (2001), who acknowledge their inability to estimate population values since their panel data was collected on-site.

are not directly impacted, they are *incidentally* truncated and endogenously stratified. That is, while the sampling does not exclude individuals who anticipate zero trips in the future, they are less likely because the sampling procedure has excluded individuals who took zero trips in the past and oversampled individuals who, at least in the past, frequently took trips. As a result, it is important to model the observed and contingent behavior data in a panel data framework, controlling for correlation between these data sources and the sampling mechanism used.

In this paper, two random effects mixed Poisson regression models are used to jointly model the observed and contingent behavior data and to correct for on-site sampling. The first is the standard panel data count model, the multivariate Poisson-gamma (MPG) model, which is more commonly known as the random effects Poisson model (Hausman *et al.*, 1984). The second is the multivariate Poisson-log normal (MPLN) model. Aitchison and Ho (1989) first suggested the MPLN model but did not include regressors in their analysis. Munkin and Trivedi (1999) estimate a bivariate PLN model. The advantage of the MPLN specification is the fact that, as Shonkwiler (1995) notes, "...only the multivariate Poisson-lognormal distribution can both reproduce an arbitrary correlation structure and account for overdispersion." We modify both models to control for on-site sampling.

The resulting models are used to analyze survey data collected on-site at Clear Lake in north central Iowa. Specifically, the survey data included observed trips for 2000 and contingent behavior trips for 2001 under both current prices and two sets of price increases. We find a substantial bias results if the sampling procedures are ignored, overstating both the average number of trips to the site (by a factor of six) and the welfares associated with the recreational opportunities at Clear Lake.

Correcting for On-Site Sampling

It has long been recognized that, while on-site (or intercept) surveys provide a convenient mechanism for insuring that a sample includes site users, the resulting sample is no longer representative of the population as a whole. This section provides an overview of the corrections developed for the single-site setting. These corrections are then extended for the multivariate scenario.

The Univariate Model

Shaw (1988) was the first to recognize the complex set of problems that characterize on-site samples in recreation demand analysis. In addition to the count nature of the data (i.e., non-negative integers), he notes that on-site surveys exclude those who do not visit the site (truncation) and over sample those who frequent the site regularly (endogenous stratification).[2] His correction for these problems, based on the Poisson regression model, is both intuitive and easy to implement.[3]

Shaw (1988) begins by assuming that population trips to the single site of interest follow a univariate Poisson distribution. That is,

$$f(y_i \mid x_i) = \frac{\exp(-\lambda_i)(\lambda_i)^{y_i}}{y_i!}, \quad y_i = 0,1,2,\ldots \tag{1}$$

where y_i denotes the number of trips taken by individual i,

$$\begin{aligned} \lambda_i &= E(y_i \mid x_i) \\ &= \exp(\beta' x_i) \end{aligned} \tag{2}$$

denotes the expected number of trips for an individual with characteristics vector x_i, and β denotes the unknown parameters of the distribution to be estimated.

In correcting for the on-site sampling, Shaw assumes that visitors taking y_i trips are y_i times more likely to be sampled than someone who takes only one trip. He demonstrates that the on-site sample's distribution is then the product of the population distribution and odds (relative to an average individual) of being included in the sample; i.e.,

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[2] As Shaw (1988) notes, a number of authors recognized earlier the truncation issue associated with on-site surveys, including Smith and Desvousges (1985). The issue of truncation in recreation demand was further discussed by Creel and Loomis (1990) and Grogger and Carson (1991).

[3] Shaw (1988) actually provides two solutions to the on-site sampling, one based on the Poisson regression model and a second based on a continuous regression model of trip data. We focus our attention here on the count data model, though the corrections could be adapted for the continuous setting.

$$
\begin{aligned}
f_{OS}(y_i \mid x_i) &= \frac{y_i}{E(y_i \mid x_i)} f(y_i \mid x_i) \\
&= \frac{y_i}{\lambda_i} \frac{\exp(-\lambda_i)(\lambda_i)^{y_i}}{y_i!} \\
&= \frac{\exp(-\lambda_i)(\lambda_i)^{y_i-1}}{(y_i-1)!}, \quad y_i = 1,2,\ldots
\end{aligned} \tag{3}
$$

The form of the on-site sample's distribution is convenient since it can be estimated using standard statistical packages designed to estimate a Poisson regression model. The only change required for on-site sampling is to replace y_i with $y_i - 1$ as the dependent variable.

One limitation of Shaw's model is, like all Poisson models, it imposes the assumption of equidispersion; i.e.,

$$\lambda_i = E(y \mid x_i) = Var(y_i \mid x_i). \tag{4}$$

In practice, however, recreation demand data typically exhibit overdispersion with the conditional trip variance exceeding the conditional trip mean. Following the logic of Shaw, Englin and Shonkwiler (1995) extend the on-site corrections to the negative binomial model. Specifically, if population trips are characterized by the negative binomial distribution

$$f(y_i \mid x_i) = \frac{\Gamma(y_i + \alpha_i^{-1})\alpha_i^{y_i}\lambda_i^{y_i}(1+\alpha_i\lambda_i)^{-(y_i+\alpha_i^{-1})}}{\Gamma(y_i+1)\Gamma(\alpha_i^{-1})}, \tag{5}$$

then the on-site sample will be characterized by the distribution

$$f_{OS}(y_i \mid x_i) = \frac{y_i\Gamma(y_i + \alpha_i^{-1})\alpha_i^{y_i}\lambda_i^{y_i-1}(1+\alpha_i\lambda_i)^{-(y_i+\alpha_i^{-1})}}{\Gamma(y_i+1)\Gamma(\alpha_i^{-1})}. \tag{6}$$

In this case the mean and variance for the on-site sample are

$$E(y_i \mid x_i) = \lambda_i + 1 + \alpha_i\lambda_i \tag{7}$$

and

$$Var\left(y_i \mid x_i\right)=\lambda_i\left(1+\alpha_i+\alpha_i\lambda_i+\alpha_i^2\lambda_i\right), \tag{8}$$

allowing for overdispersion and reducing to Shaw's Poisson model when $\alpha_i \to 0$.

The Multivariate Setting

The results of the previous section apply only to the univariate setting. However, there are many examples in practice where a system of counts must be modeled. This is the case, for example, if intercept surveys are conducted at several sites simultaneously or if trip data are gathered at a single site for a series of years or under a series of hypothetical or actual scenarios. Laitila (1999) has addressed the former problem using independent Poisson distributions for each site and conditioning on the total number of trips taken. In this paper, we focus our attention on the latter problem. As noted above, the latter scenario has arisen in recent years, as recreation demand surveys frequently ask not only for information on past trips (observed behavior), but also inquire as to changes in trip behavior in future years and under hypothetical changes to the recreation site of interest (contingent behavior). We begin this section by reviewing the multivariate count data models and then develop corrections to those models for on-site samples.

Multivariate Count Data Models

The simplest extension of the univariate Poisson count data model to the multivariate setting is to assume that trip data follow independent Poisson distributions. Specifically, if y_{ij} denotes the number of trips that individual *i* would take (or has taken) under scenario *j*, then the joint conditional distribution for the vector of trips $y_{i\square}=\left(y_{i1},\ldots,y_{iJ}\right)'$ is given by

$$f\left(y_{i\square} \mid x_{i\square}\right)=\prod_{j=1}^{J}\frac{\exp\left(-\lambda_{ij}\right)\left(\lambda_{ij}\right)^{y_{ij}}}{y_{ij}\,!},\quad y_{ij}=0,1,2,\ldots \tag{9}$$

where

$$\begin{aligned}\lambda_{ij}&=E\left(y_{ij} \mid x_{ij}\right)\\&=\exp\left(\beta_j' x_{ij}\right)\end{aligned} \tag{10}$$

and $x_{i\square}=\left(x_{i1},\ldots,x_{iJ}\right)'$.

The problem with the model in (9) is that the assumption of independence is unlikely to hold in practice. Individuals who have taken a large number of trips in the past (say y_{i1}) are also likely to take a large number of trips in the future or under proposed changes to the site being studied (i.e., $y_{i2},\ldots,y_{iJ}$). There have been a number of multivariate count data models developed in the literature to allow for correlation across counts for the same individual. Most of these are mixed Poisson models that allow for a common shared source of unobserved heterogeneity in the counts for a given individual. Mixed Poisson models begin by assuming that there is an unobserved factor, $v_{ij}=\exp\left(\varepsilon_{ij}\right)$, associated with trips taken by individual i under scenario j. If v_{ij} were known, then the corresponding trips would follow a standard Poisson process, with

$$f\left(y_{ij}\mid x_{ij},v_{ij}\right)=\frac{\exp\left(-\tilde{\lambda}_{ij}\right)\left(\tilde{\lambda}_{ij}\right)^{y_{ij}}}{y_{ij}!},\quad y_{ij}=0,1,2,\ldots \tag{11}$$

and

$$\begin{aligned} E\left(y_{ij}\mid x_{ij},v_{ij}\right)&=\tilde{\lambda}_{ij}\\ &=\lambda_{ij}v_{ij}\\ &=\exp\left(\beta_j' x_{ij}+\varepsilon_{ij}\right), \end{aligned} \tag{12}$$

With the v_{ij} (or equivalently ε_{ij}) being unobserved, the relevant distribution for $y_{i\cdot}$ becomes

$$f\left(y_{i\cdot}\mid x_{i\cdot}\right)=\int\cdots\int\prod_{j=1}^{J}\frac{\exp\left(-\lambda_{ij}\exp\left(\varepsilon_{ij}\right)\right)\left(\lambda_{ij}\exp\left(\varepsilon_{ij}\right)\right)^{y_{ij}}}{y_{ij}!}g\left(\varepsilon_{i\cdot}\right)d\varepsilon_{i1}\cdots d\varepsilon_{iJ},\quad y_{ij}=0,1,2,\ldots \tag{13}$$

where $g\left(\varepsilon_{i\cdot}\right)$ denotes the pdf for $\varepsilon_{i\cdot}$. Thus, the distribution of the trip vector, $y_{i\cdot}$, becomes a mixture of Poisson distributions. There are two consequences of this mixing process. First, the equidispersion assumption in equation (4) will no longer apply to the individual trip data (i.e., the y_{ij}'s). Second, allowing for correlation among the ε_{ij}'s across scenarios (j) for a given individual (i) will induce correlation among the corresponding y_{ij}'s for that individual.

In this paper, we will focus our attention on two specific mixed Multivariate Poisson models, the Multivariate Poisson-Lognormal distribution (MPLN) and the Multivariate Poisson-Gamma Model (MPG).[4] The MPLN model was introduced by Aitchison and Ho (1989) and gets its name from the fact that the vector $\nu_{i\cdot}$ is assumed to follow a multivariate lognormal distribution, or equivalently that $\varepsilon_{i\cdot}$ follows a multivariate normal distribution; i.e.,

$$\varepsilon_{i\cdot} \sim N(0,\Omega). \tag{14}$$

Substituting this distributional assumption into (13), we then have that

$$f(y_{i\cdot} \mid x_{i\cdot}) = \int \cdots \int \prod_{j=1}^{J} \frac{\exp(-\tilde{\lambda}_{ij})(\tilde{\lambda}_{ij})^{y_{ij}}}{y_{ij}!} \frac{\exp\left[-\frac{1}{2}\varepsilon_{i\cdot}'\Omega^{-1}\varepsilon_{i\cdot}\right]}{(2\pi)^{J/2}|\Omega|^{1/2}} d\varepsilon_{i\cdot}, \quad y_{ij} = 0,1,2,\ldots \tag{15}$$

The conditional trip means and variances become

$$E\left[y_{ij} \mid x_{ij}\right] = \lambda_{ij}\exp\left(\tfrac{1}{2}\sigma_j^2\right) \equiv \delta_{ij} \tag{16}$$

and

$$Var\left[y_{ij} \mid x_{ij}\right] = \delta_{ij} + \left[\exp\left(\sigma_j^2\right) - 1\right]\delta_{ij}^2, \tag{17}$$

where $\sigma_j^2 = Var\left(\varepsilon_{ij} \mid x_{ij}\right)$. Thus, equidispersion results only if $\sigma_j \to 0$. Correlation among the trips emerges because

$$Cov\left[y_{ij}, y_{ik}\right] = \delta_{ij}\left[\exp\left(\sigma_{jk}\right) - 1\right]\delta_{ik}, \; j \neq k. \tag{18}$$

where σ_{jk} denotes the $(j,k)^{\text{th}}$ element of Ω. One of the attractive features of the MPLN specification is that it does not restrict the sign of this correlation. The correlation between trips for two distinct scenarios j and k can be positive, negative, or zero and depends directly upon the

[4] Both the MPLN and MPG models can be viewed as incorporating random individual effects. An alternative approach would be to allow for individual fixed effects. Hausman, Hall and Griliches (1984) develop a fixed effects model in the context of patents and R&D expenditures. Englin and Cameron (1996) apply their model in the recreation demand context.

sign of the corresponding σ_{jk}. The downside of the MPLN specification is that, at the estimation stage, the pdf in (15) requires integration over a *J*-dimensional integral. However, either standard numerical procedures or simulation techniques can be used to address this problem as long as the number of scenarios, *J*, remains relatively small; i.e., less than eight.

An alternative to the MPLN model is the Multivariate Poisson Gamma specification.[5] In this case, it is assumed that there is a single unobserved factor, u_i, shared by all trip scenarios for the same individual; i.e.,

$$v_{ij} = u_i \ \forall j \tag{19}$$

and that u_i follows a $gamma(\alpha,\alpha)$ distribution with a mean of 1 and a variance of α^{-1}. Substituting this assumption into (13) yields[6]

$$f(y_{i\cdot} \mid x_{i\cdot}) = \frac{\Gamma\left(\sum_{j=1}^{J} y_{ij} + \alpha\right)\alpha^{\alpha}\left(\sum_{j=1}^{J}\lambda_{ij} + \alpha\right)^{-\left(\sum_{j=1}^{J} y_{ij}+\alpha\right)}}{\Gamma(\alpha)} \prod_{j=1}^{J} \frac{\lambda_{ij}^{y_{ij}}}{y_{ij}!}, \quad y_{ij} = 0,1,2,\ldots \tag{20}$$

The corresponding conditional means and variances are given by

$$E\left[y_{ij} \mid x_{ij}\right] = \lambda_{ij} \tag{21}$$

and

$$V\left(y_{ij} \mid x_{ij}\right) = \lambda_{ij} + \alpha^{-1}\left(\lambda_{ij}\right)^2. \tag{22}$$

Thus, the degree of overdispersion is a decreasing function of α. The covariance between trip responses for a given individual becomes

$$Cov\left[y_{ij}, y_{ik}\right] = \alpha^{-1}\lambda_{ij}\lambda_{ik}. \tag{23}$$

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[5] The MPG specification was introduced by Arbous and Kerrich (1951) in a bivariate context and subsequently extended by Bates and Neyman (1952) and Nelson (1985). In the economics literature, Hausman, Hall and Griliches (1984) use the MPG model as a random effects model to capture correlation between patents and R&D expenditures.

[6] See Winkelmann (2000, p. 196).

Unlike the MPLN, the MPG imposes considerable structure on this correlation, requiring it to always be positive. However, the closed form nature of the pdf makes estimation straightforward.

Controlling for On-Site Sampling

The problem of on-site sampling emerges for the application we are considering because the first of the trip scenarios, j=1, corresponds to current trips to the site in question. Thus, y_{i1} is truncated, excluding observations in the population with $y_{i1}=0$, and endogenously stratified, with the sample over representing individuals that frequently visit the site. If we were only interested in observed trip behavior, then the univariate Poisson, Negative Binomial (both described in the previous section), or the univariate PLN model could be applied. However, individuals visiting the site are asked not only about their actual trip taking behavior to the site, but also about how often they plan to visit the site in future years and under a variety of possible changes to the site, generating a vector of trip counts $y_{i\square}=(y_{i1},y_{i2},\ldots,y_{iJ})'$. The contingent behavior trips $y_{i,-1}\equiv(y_{i2},\ldots,y_{iJ})'$, while not directly truncated or endogenously stratified, are impacted by the on-site nature of the survey through the correlation between y_{i1} and $y_{i,-1}$. Specifically, following the same logic as Shaw (1988) used in the univariate case,

$$f_{OS1}(y_{i\square}\,|\,x_{i\square})=\frac{y_{i1}}{E(y_{i1}\,|\,x_{i\square})}f(y_{i\square}\,|\,x_{i\square}),\quad y_i=1,2,\ldots \tag{24}$$

where the subscript *OS1* is used to denote the fact that the on-site sampling *directly* impacts the trips for scenario j=1.

If the trips are independently distributed and each follow a Poisson process, then

$$f_{OS1}(y_{i\square}\,|\,x_{i\square})=\frac{\exp(-\lambda_{i1})(\lambda_{i1})^{y_{i1}-1}}{(y_{i1}-1)!}\prod_{j=2}^{J}\frac{\exp(-\lambda_{ij})(\lambda_{ij})^{y_{ij}}}{y_{ij}!},\quad y_{ij}=1,2,\ldots \tag{25}$$

If the MPLN specification applies, however, then

$$f_{OS1}(y_{i\square} \mid x_{i\square}) = \int \cdots \int \frac{y_{i1}}{\delta_{i1}} \prod_{j=1}^{J} \frac{\exp(-\tilde{\lambda}_{ij})(\tilde{\lambda}_{ij})^{y_{ij}}}{y_{ij}!} \frac{\exp\left[-\frac{1}{2}\varepsilon'_{i\square}\Omega^{-1}\varepsilon_{i\square}\right]}{(2\pi)^{J/2}|\Omega|^{1/2}} d\varepsilon_{i\square}, \quad y_{ij} = 1,2,\ldots \quad (26)$$

Similarly, if the MPG specification applies, then

$$f_{OS1}(y_{i\square} \mid x_{i\square}) = \frac{y_{i1}\Gamma\left(\sum_{j=1}^{J} y_{ij} + \alpha\right)\alpha^{\alpha}\left(\sum_{j=1}^{J}\lambda_{ij} + \alpha\right)^{-\left(\sum_{j=1}^{J} y_{ij}+\alpha\right)}}{\lambda_{i1}\Gamma(\alpha)} \prod_{j=1}^{J} \frac{\lambda_{ij}^{y_{ij}}}{y_{ij}!}, \quad y_{ij} = 1,2,\ldots \quad (27)$$

Data and Model Specification

The data used in our empirical application are drawn from an intercept survey of visitors to Clear Lake located in north central Iowa. Visitors' names and addresses were collected on-site in the summer of 2000. These individuals were then mailed a survey in October, 2000. The survey asked respondents to provide four trip totals:

- Observed Behavior (OB): Their total number of trips to Clear Lake between November 1999 and October 2000.
- Contingent Behavior (CB_0): Their anticipated number of trips in 2001, given current travel costs.
- Contingent Behavior (CB_1): Their anticipated number of trips in 2001, given an increase in the total cost per trip of \$*B*. Specifically, individuals were asked: "Suppose that the price of visiting Clear Lake increases by \$*B* per trip (due for example to gas prices, user fees, or equipment costs). How many times would you visit next year?" The value of *B* was randomly assigned to each survey respondent and varied across individuals in the sample from \$3 to \$15, with a mean of \$7.26.
- Contingent Behavior (CB_2): Their anticipated number of trips in 2001, given a price increase of \$*C* per trip, where *C*>*B*. Again, the value of *C* was randomly assigned to each survey respondent and varied across individuals in the sample from \$7 to \$30, with a mean of \$16.88.

In addition to gathering trip data, the survey also asked a series of contingent valuation questions, inquired as to the respondents' attitudes towards water quality improvements, and gathered socio-demographic information.

Of the 1,024 individuals intercepted at Clear Lake, 626 (or 62.7% of the deliverable surveys) returned a completed mail survey. In the analysis below, individuals were excluded from the final sample if they reported seasonal trips in excess of 52, allowing one trip per weekend. This resulted in 36 individuals being excluded from the sample. We also excluded households whose travel time was greater than five hours one way. Clear Lake is a unique natural lake in Iowa and does draw travelers from around the state. However, it is a regional attraction and the assumption is that anyone traveling from farther than five hours likely made the journey primarily for reasons other than to visit the lake. This excluded 19 additional households. Finally, for simplicity, a balanced panel was obtained by excluding visitors who did not answer all of the trip questions. The final sample size used in the analysis was N=543.

In the models estimated below, the average number of trips under scenario j (λ_{ij})is assumed to be a function of the travel cost to Clear Lake, household income, and socio-demographic characteristics of the household. Specifically,

$$\lambda_{ij} = \exp\left(\beta_{0j} + \beta_{Pj}P_{ij} + \beta_{Ij}I_i + \delta_j' z_i\right), \tag{28}$$

where P_{ij} denotes the roundtrip travel costs from individual i's home to Clear Lake and back, I_i denotes individual i's annual income, and z_i is a vector of socio-demographic characteristics of the household, including:

- *Male* =1 if the survey respondent is male, =0 otherwise;
- *Age* = the age of the survey respondent;
- *Age^2;*
- *School* = 1 if the survey respondent has attended or completed some level of post-high school education; and
- *Household* = the total number of household members.

For observed trips (OB) and forecasted trips for 2001 (CB_0), travel costs were computed as \$0.25 times the round-trip travel distance, computed using *PCMiler*, plus one third the respondent's wage rate times their round-trip travel time. P_{ij} for CB_1 and CB_2 are computed in the same fashion, except that \$B and \$C are added to the travel costs, respectively.

Table 1 provides a summary of the data used in the analysis. There are a number of attributes of the raw trip data that are worth noting. First, for all four trip variables, the unconditional mean number of trips in the sample is roughly the same order of magnitude as the corresponding unconditional standard deviation, indicating that the unconditional variance will be eight to twelve times the unconditional mean. This suggests that overdispersion is likely to be a problem for all four trip variables and that a simple Poisson model for each trip variable will be inappropriate. Second, the observed number of trips (OB) is large, with households in the sample averaging over a dozen trips per year. This should not, however, be interpreted as indicative of the population as a whole, but rather a reflection of the on-site sampling process. Households who frequent Clear Lake are more likely to be included in the sample precisely because they were more likely to be there when the intercepts occurred, hence inflating the sample average number of trips relative to the population's average. Third, the observed trips (OB) are slightly higher (12.32) than the number of trips anticipated by the survey respondents for 2001, suggesting relatively stable demand for visits to Clear Lake between 2000 and 2001. Fourth, and finally, the anticipated number of trips for 2001 decrease, as expected, with the total cost per trip, from an average number of trips just under 12 per year under current conditions (CB_0) to approximately 7.5 trips per year given an average cost increase of \$17 per trip (CB_2). Thus, households appear to be responding to the hypothetical price increase at least in the direction expected.

Both the percentage of males (62%), average household income, and level of education are higher than in the Iowa population as a whole. This, in part, is also a consequence of the on-site nature of the survey process, as frequent recreationists are more likely to be included in the sample and these, in turn, are more likely to be males with a higher level of income and education.

In estimating the MPLN and MPG models using the Clear Lake data, several restrictions were imposed on the form of the λ_{ij}'s. First, we assume that the β's in equation (28) are the same across the three contingent behavior trips, with expected trips changing only due to changes in the corresponding price levels. Second, we assume that the socio-demographic factors (other than income) impact the expected number of trips in the same way for both observed trips and the three contingent trips.[7] The resulting functional forms for the λ_{ij}'s are given by:

$$\lambda_{ij} = \begin{cases} \exp\left(\beta_{0,OB} + \beta_{P,OB} P_{i1} + \beta_{I,OB} I_i + \delta' z_i\right) & j = 1 \\ \exp\left(\beta_{0,CB} + \beta_{P,CP} P_{ij} + \beta_{I,CB} I_i + \delta' z_i\right) & j = 2,3,4. \end{cases} \tag{29}$$

Finally, we also impose a restriction on the structure of the variance-covariance matrix for the MPLN model. Specifically, we assume that Ω in equation (14) is given by

$$\begin{aligned} \Omega &= \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ & \sigma_2^2 & \sigma_{23} & \sigma_{24} \\ & & \sigma_3^2 & \sigma_{34} \\ & & & \sigma_4^2 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_O^2 & \rho_{OC}\sigma_O\sigma_C & \rho_{OC}\sigma_O\sigma_C & \rho_{OC}\sigma_O\sigma_C \\ & \sigma_C^2 & \rho_{CC}\sigma_C^2 & \rho_{CC}\sigma_C^2 \\ & & \sigma_C^2 & \rho_{CC}\sigma_C^2 \\ & & & \sigma_C^2 \end{bmatrix}. \end{aligned} \tag{30}$$

This implies that the unobserved error component for the three contingent trips (CB_0, CB_1, and CB_2) have the same covariances with each other and with the observed trip data.

Results

Table 2 provides the estimates of the MPLN and MPG models.[8] For each model, we present estimates both with and without the correction for on-site sampling. Several patterns emerge in the results. First, in all four models, the price and income coefficients have the expected signs and are statistically significant at a one percent level for both observed and contingent behavior trips. All else equal, an increase in travel cost decreases the expected

[7] A more general specification allowing the demographic effects to differ between observed trips and contingent trips was estimated, but the differences between the OB and CB parameters were not statistically different as a group based on a likelihood ratio test.
[8] The MPLN model was estimated using maximum simulated likelihood following Munkin and Trivedi (1999), with antithetic acceleration and 1000 draws employed in the simulation. Standard maximum likelihood techniques were employed in estimating the MPG models.

number of trips, whereas trips increase with income. Second, these coefficients (i.e., the $\beta's$) do not differ substantially between the observed and contingent trips. However, the price responsiveness is lower among the contingent trips than for the observed trips, whereas contingent trips are more sensitive to income than observed trips. Third, the price and income coefficients do not change substantially with the correction for on-site sampling, though they are generally smaller in size.

Turning to the socio-demographic characteristics, the results are less consistent across the four models. For the MPLN specification corrected for on-site sampling, all of the socio-demographic characteristics (except the number of household members) are statistically significant and have the expected signs. Men are found to take significantly more recreational trips to Clear Lake than women and the relationship between age and trips is quadratic, with the young and old taking more trips than middle aged individuals. Having attended college decreases recreational trips. For the other model specifications, the socio-demographic coefficients are generally insignificant. In particular, failure to correct for the on-site sampling leads to the erroneous conclusion that the socio-demographic characteristics do not generally influence trip behavior.

Finally, it is worth noting the parameters associated with the mixing distributions. For the MPLN model, we clearly reject both equidispersion and independence of the observed and contingent trip data. The correlation among the trips is high, with both ρ_{OC} and ρ_{CC} estimated to be positive and close to one. Both σ_O and σ_C are significantly different from zero, indicating overdispersion in the data. For the MPG specification, the gamma distribution's coefficient is tightly measured and also consistent with the overdispersion property.

The parameter estimates in Table 2 can be used to illustrate implications of the models in terms of trip behavior and the implied welfare gains associated with each trip. Table 3a provides estimates of the consumer surplus per trip calculated as $CS_j = \beta_{P,j}^{-1}$ for both observed trips (*j*=1) and predicted trips for 2001 (*j*=2). Both models (MPLN and MPG) predict roughly the same consumer surplus per trip, ranging from \$69 to \$98. As one would expect given the estimated price coefficients, the surplus per trip is generally larger for the contingent behavior trips (CS_O)

than for the observed trips (CS_1). Moreover, correcting for the on-site sampling consistently leads to a larger surplus measure, with an increase of between 13 and 39%.

The big impact, however, from correcting for on-site sampling comes in the form of the predicted number of trips. Table 3b provides estimates of the population average trips. For the MPLN model this corresponds to δ_{ij} in equation (16), whereas for the MPG model it corresponds to λ_{ij} in equation(21). As expected, there is a substantial difference between the average numbers of trips when the model is corrected for on-site sampling versus when it is not. Without this correction, average trips range from 12.50 to 15.5. This is consistent with the sample averages reported in Table 1. However, correcting for the on-site sampling, we see a substantial drop in the estimated average number of trips in the population. For the MPLN model the average is reduced by two-thirds to only five trips per household, while the average is reduced by four-fifths for the MPG specification to fewer than three trips per household. The estimates in Table 3b are based upon the average household characteristics (i.e., age, income, education, etc.) found in the survey sample. However, these too are biased by the on-site sampling process. Table 3c recalculates the estimated average number of trips using population averages for the explanatory variables drawn from a separate random sample of Iowa households. The average number of trips per household drops further as a result to about two trips per household for the MPLN specification to just over one trip for the MPG model.

Finally, there are a number of hypothesis tests of interest. Rather than conducting these tests for both specifications, we focus our attention on the MPLN model as it dominates the MPG specification based on the Akaike information criterion. The first of the hypothesis tests we consider constrains the parameters of the observed and contingent behavior trip functions to be the same; i.e., $\beta_{k,O} = \beta_{k,C}$, $k = 0, P, I$. The results, reported in column three of Table 4. In general, the resulting parameters are a compromise between the observed and contingent behavior parameters, but the hypothesis itself is clearly rejected with a p-value of less than 0.001.

The second hypothesis we consider replaces the multivariate lognormal mixing distribution with a single lognormal variable (i.e., $\varepsilon_{ij} = \varepsilon_i \sim N\left(0, \sigma^2\right) \forall j$). Essentially, we are restricting $\sigma_O = \sigma_C$ and $\rho_{OC} = \rho_{CC} = 1$. This mimics the structure of the MPG distribution, but uses a lognormal mixing distribution rather than a gamma one. Again, this restriction on the unconstrained model is rejected based on a likelihood ratio test with a p-value of less than 0.001. Interestingly, the results from this test suggest that the unrestricted MPLN specification dominates the MPG for two reasons. First, the lognormal mixing distribution fits the current data better than the MPG distribution when a single mixing distribution is used (with log-likelihoods of -6145 for the restricted MPLN in Table 4 versus -6403 for the MPG in Table 2). Second, the unrestricted MPLN model in Table 2 allows for a richer correlation structure, with different variances and correlations for the observed and contingent behavior data.

Conclusions

On-site samples are frequently used in recreation demand analysis to insure that users of the site in question are represented in the sample. It has long been recognized that this results in a sample that is both truncated and endogenously stratified with respect to the respondents' reported trips to the site. The correction procedures that have been previously developed focused on observed trip data alone (e.g., Shaw, 1988, and Englin and Shonkwiler, 1995). However, researchers are frequently incorporating contingent behavior questions into their recreation demand surveys as well, asking households to indicate their future trip plans and how their trips might change given price or quality change to the site in question (See, e.g., Rosenberger and Loomis, 1999; Azevedo, Herriges, and Kling, 2003; and Grijalva, *et al.* 2002). While the contingent behavior trip responses are not directly truncated or endogenously stratified, they are impacted indirectly through their correlation with observed trips. The contingent behavior data, like its observed counterpart, will not be representative of the population as a whole. In this paper, we have presented an extension of Shaw's (1988) correction to a multivariate setting using two multivariate mixed-Poisson models, the MPLN and the MPG.

The empirical analysis, using data from an intercept survey at Clear Lake in northcentral Iowa, indicates that the failure to correct for on-site sampling procedures results in substantial bias in the estimated average number of trips to the site, both observed and contingent, overstating population trip levels by a factor of three to five depending upon the model specification. The impact on the estimated consumer surplus per trip is somewhat small. In general we find the MPLN model fits the data better, providing for a more flexible correlation structure between observed and contingent trips. We also reject the hypothesis that the observed and contingent trips follow exactly the same demand structure, but the differences, while statistically significant, appear to be minor.

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
OB trips (y_{i1})	12.32	11.86	1	52
CB_0 trips (y_{i2})	11.73	11.74	1	50
CB_1 trips (y_{i3})	10.34	10.82	1	50
CB_2 trips (y_{i4})	7.51	8.99	1	50
Travel Cost ($P_{i1} = P_{i2}$)	\$57.06	\$56.85	\$5.38	\$512.50
Travel Cost + \$*B* (P_{i3})	\$64.32	\$57.76	\$8.38	\$522.50
Travel Cost + \$C (P_{i4})	\$73.93	\$59.12	\$12.38	\$537.50
Household Income (I_i)	\$59,519	\$37,726	\$7,500	\$200,000
Male	0.62	0.49	0	1
Age	43.56	13.71	12	82
Education	0.74	0.44	0	1
Number of Household Members	3.05	1.40	1	9

Table 2. Multivariate Poisson Mixture Models
(Standard Errors in Parentheses)[a]

Parameter	Corrected for On-Site Sampling MPLN	Corrected for On-Site Sampling MPG	Not Corrected for On-Site Sampling MPLN	Not Corrected for On-Site Sampling MPG
$\beta_{0,OB}$	2.38**	1.60**	2.54**	3.16**
	(0.18)	(0.20)	(0.21)	(0.37)
$\beta_{0,CB}$	2.27**	1.40**	2.22**	2.91**
	(0.17)	(0.18)	(0.20)	(0.37)
$\beta_{P,OB}$	-1.26**	-1.19**	-1.43**	-1.44**
	(0.06)	(0.06)	(0.07)	(0.08)
$\beta_{P,CB}$	-1.04**	-1.03**	-1.46**	-1.36**
	(0.04)	(0.05)	(0.07)	(0.07)
$\beta_{I,OB}$	0.84**	0.90**	0.87**	1.22**
	(0.09)	(0.09)	(0.10)	(0.15)
$\beta_{I,CB}$	0.90**	1.00**	1.12**	1.38**
	(0.08)	(0.08)	(0.12)	(0.14)
Male	39.84**	-0.81	-0.23	1.68
	(3.58)	(4.97)	(3.34)	(8.89)
Age	-6.41**	-2.07*	-0.30*	-2.55
	(0.83)	(0.86)	(0.83)	(1.55)
Age^2	5.82**	2.09*	-0.05	2.45
	(0.90)	(0.95)	(0.88)	(1.71)
School	-13.55**	8.12	4.05*	10.68
	(4.48)	(5.82)	(6.51)	(10.49)
Household	1.23	-3.32	-2.49**	-3.24
	(1.41)	(1.95)	(2.18)	(3.52)
α		3.07**		1.03**
		(0.13)		(0.06)
σ_O	1.16**		1.01**	
	(0.04)		(0.03)	
σ_C	1.13**		1.10**	
	(0.03)		(0.03)	
ρ_{OC}	0.95**		0.94**	
	(0.005)		(0.007)	
ρ_{CC}	0.99**		0.99**	
	(0.003)		(0.004)	
LogLik	-6,140.72	-6,520.83	-6,059.85	-6,741.70

*Significant at 5% level; **significant at 1% level.

[a]All of the parameters are scaled by 100, except the constants (which are unscaled), the age-squared coefficient (which is scaled by 10000), and the income coefficient (which is scaled by 100,000).

Table 3. Fitted Trips and Consumer Surplus Measures

	Corrected for On-Site Sampling		Not Corrected for On-Site Sampling	
	MPLN	MPG	MPLN	MPG
	a. Consumer Surplus Per Trip			
CS_1	79.32**	84.14**	70.20**	69.67**
	(3.85)	(4.04)	(3.47)	(3.74)
CS_2	96.23**	97.74**	69.02**	73.66**
	(3.45)	(2.25)	(3.27)	(3.76)
	b. Fitted Population Trips			
$E[y_{i1} \mid x_{i1}]$	5.10	2.92	15.49	14.03
	(10.42)	(2.51)	(23.24)	(16.47)
$E[y_{i2} \mid x_{i2}]$	4.99	2.75	14.33	12.50
	(9.78)	(2.39)	(25.50)	(15.05)
	c. Fitted Population Trips (corrected for population characteristics)			
$E[y_{i1} \mid x_{i1}^P]$	1.89	1.18	NA	NA
	(3.46)	(1.28)		
$E[y_{i2} \mid x_{i2}^P]$	2.11	1.21	NA	NA
	(3.71)	(1.30)		

Table 4. Hypothesis Tests Using Multivariate Poisson-Lognormal Model
(Standard Errors in Parentheses)[a]

Parameter	Unrestricted	Consistency $\beta_{k,O}=\beta_{k,C},\ k=0,P,I$	Restricted Correlation
$\beta_{0,OB}$	2.38**		2.49**
	(0.18)	2.32**	(0.19)
$\beta_{0,CB}$	2.27**	(0.20)	2.30**
	(0.17)		(0.19)
$\beta_{P,OB}$	-1.26**		-1.29**
	(0.06)	-1.09**	(0.06)
$\beta_{P,CB}$	-1.04**	(0.05)	-1.12**
	(0.04)		(0.05)
$\beta_{I,OB}$	0.84**		0.92**
	(0.09)	0.78**	(0.08)
$\beta_{I,CB}$	0.90**	(0.08)	1.02**
	(0.08)		(0.08)
Male	39.84**	41.30**	24.58**
	(3.58)	(3.84)	(4.62)
Age	-6.41**	-6.67**	-6.97**
	(0.83)	(0.95)	(0.82)
Age^2	5.82**	6.35**	6.25**
	(0.90)	(0.98)	(0.88)
School	-13.55**	-10.58	1.54
	(4.48)	(5.63)	(5.12)
Household	1.23	1.05	0.14
	(1.41)	(1.51)	(1.37)
σ_O	1.16**	1.15**	
	(0.04)	(0.03)	1.16**
σ_C	1.13**	1.14**	(0.03)
	(0.03)	(0.03)	
ρ_{OC}	0.95**	0.95**	
	(0.005)	(0.005)	
ρ_{CC}	0.99**	0.99**	
	(0.003)	(0.005)	
LogLik	-6,140.72	-6,156.10	-6,265.11
$\chi^2_{df=3}$		30.76	248.78

*Significant at 5% level; **significant at 1% level.
[a]All of the parameters are scaled by 100, except the constants (which are unscaled), the age-squared coefficient (which is scaled by 10000), and the income coefficient (which is scaled by 100,000).

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Alternative Systems of Semi-logarithmic Incomplete Demand Equations: Modeling Recreational Off-Highway Vehicle Site Demand

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Alternative Systems of Semi-logarithmic Incomplete Demand Equations:

Modeling Recreational Off-Highway Vehicle Site Demand

Abstract

This study provides an empirical application of LaFrance's (1990) and von Haefen's (2002) approach to estimating a utility theoretic incomplete demand system. Two sets of utility theoretic restrictions are imposed on parameter sets estimated using Poisson and negative binomial II distributions. Data are provided by a survey conducted at four recreational off-highway vehicle (OHV) sites in western North Carolina. Results obtained under the two sets of restrictions are compared using a two-part likelihood ratio non-nested testing procedure, and welfare measures are calculated for the ordinary and compensated demands. In the analyses reported here, welfare estimates varied dramatically dependent on the specification of the set of parameter restrictions. The implication of this analysis is that researchers should not naively apply parameter restrictions when estimating systems of semi-logarithmic incomplete demand equations, but should test alternative sets of utility theoretic restrictions to determine which set best conforms to the data.

I. INTRODUCTION

Demand systems are becoming increasingly popular for estimating recreational site demand because demand systems address the idea that multiple recreation sites could be substitutes and therefore should estimated together (Burt and Brewer1971; Englin et al. 1998). Complete, partial, and incomplete demand systems are three frameworks for estimating systems of demand equations. Incomplete demand systems estimate demand as a function of income and the prices of concerned goods without regard to the allocation of remaining income. Incomplete demand systems are favored for modeling consumer choice based on a subset of total goods, because, unlike complete or partial demand systems, incomplete demand systems avoid the restrictive assumptions of aggregation and/or separability.

However, estimation of an incomplete demand system requires implementation of cross-equation parameter restrictions to maintain theoretical consistency between model estimations and underlying utility theory. Estimation of incomplete demand systems has become possible through the extensive work of LaFrance (1990), LaFrance and Hanemann (1984, 1989), and von Haefen (2002) identifying the necessary restrictions for maintaining integrability of the Slutsky symmetry matrix. LaFrance and LaFrance and Hanemann identified the integrability restrictions necessary for eight specifications of linear, log-linear, and semi-logarithmic demand systems. von Haefen extended the use of incomplete demand systems by adding 16 functional forms including linear, log-linear, and semi-logarithmic forms of expenditure and expenditure share systems.

In this study, two different cross-equation restriction specifications for a semi-logarithmic system of demand equations are estimated for visitation data to four recreational off-highway vehicle (OHV) sites in western North Carolina. The systems are estimated as travel cost models, and count data for OHV site visits are modeled using the Poisson and the negative binomial II distributions. Results from the two different cross-equation restriction specifications are compared using a two-part likelihood ratio non-nested testing procedure (Vuong 1989), and welfare measures are calculated for the ordinary and compensated demands.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical properties of incomplete demand systems and presents the semi-logarithmic demand equations used in this study. Data are described in section 3. Section 4 describes model estimation procedures and presents the likelihood ratio non-nested testing procedure that is used to compare the two different restriction specifications. Section 5 presents the results of model estimations, the non-nested testing procedure, and the welfare estimates. Finally, Section 6 is a discussion of results and conclusions.

II. BACKGROUND

There are numerous feasible functional forms for modeling incomplete demand systems. The semi-logarithmic functional form is appealing for demand analysis because it restricts demand to be non-negative. Therefore, this paper considers one form of a semi-logarithmic demand system for which LaFrance has derived appropriate econometric cross-equation restrictions. The model is:

$$x_i = \alpha_i(q)\exp\left(\sum_{j=1}^{n}\beta_{ij}\rho_j + \gamma_i y\right) \tag{1}$$

where x_i is the quantity of visits to site i demanded, $\alpha_i(q)$ is a demand shifter that accounts for influences of a vector (q) of non-income shift variables, β_{ij} is a price coefficient that captures the influence of ρ_j (the cost of visiting site j) on demand for good i, γ_i is the income coefficient, and y is income. Two sets of parameter restrictions satisfy the integrability requirements that are consistent with the Slutsky symmetry condition. The derivation of these restrictions are described in LaFrance (1990) and von Haefen (2002).

Restriction Set I

The first set of restrictions requires that (i) the demand shifter $\alpha_i(q)$ is positive, (ii) the income parameter is the same across sites, (iii) the cross-price effects are zero, and (iv) own-price coefficients are negative.

$$\alpha_i(q) > 0,\ \forall i \tag{2}$$

$$\gamma_i = \gamma_j \tag{3}$$

$$\beta_{ij} = 0,\ \forall i \neq j \tag{4}$$

$$\beta_{ii} < 0 \tag{5}$$

It is important to realize that, although equation (4) restricts the cross price effects to be zero in the system of ordinary demand functions, the compensated cross price effects might be non-zero. The expression for the compensated cross price effect between site j and k is:

$$S_{njk} = \gamma x_{nj} x_{nk}$$

where n represents the individual (Englin et al. 1998). If the parameter estimate representing the income effect (γ) is positive and significantly different than zero, and if individual n visits both sites j and k, then S_{njk} will be positive (i.e. the sites are substitutes). If individual n visits either site j or site k, but not both, then the compensated cross price effect for individual n is (naturally) zero (i.e. the sites are independent). If none of the recreationists sampled visit both site j and k, then the average value of S_{jk} for the sample will be zero. Of course, equation (6) indicates that the compensated cross price effects are symmetric.

Restriction Set II

The second set of restrictions that satisfy the integrability requirements is more restrictive because only one site's intercept (demand shifting parameter) is estimated, and other site intercepts are calculated as functions of the first site intercept and own-price coefficients (Equation 7). As in the first set of restrictions, the income effect is equal across sites. However, the cross-price effects of site k on all other sites are the same and are equal to the own-price coefficient of site k. Because the own price effect is negative (i.e. an increase in price is associated with a decrease in trips to that site), the cross price effect maintains that recreation sites are complements (an increase in price at one site is associated with a decrease in the number of trips to other sites in the system).

$$\alpha_i = (\beta_{ii} / \beta_{jj})\alpha_j > 0 \qquad (7)$$

$$\gamma_i = \gamma_j \qquad (8)$$

$$\beta_{ik} = \beta_{jk} = \beta_{kk} \forall k \qquad (9)$$

The empirical fit of these two restriction specifications is compared using recreational site demand data for off-highway vehicle users.

III. Data

Data for these analyses are from a survey of off-highway vehicle (OHV) users that was conducted at four U.S. Forest Service managed OHV recreational sites in western North Carolina (Figure 1). Data were collected by volunteers during the months of July-October 2000 at Badin Lake, Brown Mountain, Upper Tellico, and Wayehutta OHV recreation areas, as users exited the sites. A total of 357 surveys were collected: 97 at Badin Lake, 101 at Brown Mountain, 118 at Upper Tellico and 41 at Wayehutta. The data include numbers of visits to each of the four OHV areas in 1997, 1998, and 1999; site user fees; and demographic characteristics including sex, age, education, income, skill, and zip code.

For these analyses data were limited to surveys completed by individuals 18 years of age and older for which data were complete for at least one of the three focal years. This resulted in a total of 672 observations across the years 1997 to 1999.

A travel cost variable, two year variables, and four demographic variables (income, skill, education, and sex) were included in these analyses. COST was calculated as the sum of transit cost, opportunity cost of time, and site fee. Transit cost was calculated as the distance to and from a site (based on the residential zip codes of survey respondents) multiplied by the cost per mile ($0.25/mile). Opportunity cost was calculated as one third of the individual's wage rate (annual income divided by hours worked each year) multiplied by travel time assuming an average speed of 60 mph (Cesario 1976). Dummy variables were included for 1997 and 1998 to account for annual differences in visitation rates from 1997 to 1999. INCOME was reported in the survey and scaled as $1000's for model estimations. SKILL level was reported by survey respondents as beginner, intermediate, and advanced, and was coded as 1, 2, and 3 respectively for these analyses. EDUCATION is the number of years of school completed by the survey respondent, and FEMALE is a dummy variable for females.

IV. Model Estimation

Model estimation was conducted in GAUSS, and visits to each OHV site (Badin Lake, Brown Mountains, Upper Tellico, and Wayehutta) were estimated as functions of cost (ρ_i), income (y), year, skill-level, education, and sex. The number of visits to each site was estimated as (i) a Poisson distribution and (ii) a negative binomial II (NB2) distribution with site specific dispersion parameters (Cameron and Trivedi 1998). The Poisson distribution is commonly used when estimating recreation demand models because it is a non-negative, discrete distribution that allows for zero trips and provides unbiased parameter estimates regardless of the true underlying data generating distribution (Gourieroux et al 1984). The Poisson log likelihood function for a single site can be expressed as:

$$l_i = -\lambda + x_i \ln(\lambda) - \ln(x_i!) \tag{10}$$

where λ is the predicted/estimated number of visits for an individual to a site, and x_i is the observed number of visits for an individual to the site. One property of the Poisson distribution is that the variance equals the mean (λ).

Like the Poisson distribution, the negative binomial II (NB2) distribution assumes non-negative integer values. However, NB2 allows the variance to differ from the mean by including a dispersion parameter, thus allowing for the possibility for over-dispersion in the number of OHV trips. The NB2 log likelihood for a single observation at a site can be expressed as:

$$l_i = -d^{-1} \ln(1 + d\lambda) + \ln\left(\frac{\Gamma(x_i + d^{-1})}{\Gamma(x_i + 1)\Gamma(d^{-1})}\right) + x_i \ln\left(\frac{d\lambda}{1 + d\lambda}\right) \tag{11}$$

$$d \geq 0; \; x_i \geq 0$$

where ***d*** is the site specific dispersion parameter, λ is the predicted/estimated number of visits for an individual at the site, x_i is the observed number of visits of an individual to the site, and Γ is the gamma function.

One limitation of the NB2 distribution is that estimated parameters are not robust to distributional misspecification unless the dispersion parameter ***d*** is known with certainty, which it is not (i.e. it must be estimated). To account for potential distributional misspecification, White's (1980) method is employed to correct the variance-covariance matrix and to calculate White's corrected standard errors for both the Poisson and NB2 distributions. White's method provides a robust approach for hypothesis testing.

One other aspect of the distributional specification must be addressed. Parameters of the Poisson and NB2 distributions are *not* corrected for endogenous stratification which might result from over sampling people who often recreate at these sites. The full (rather than truncated) Poisson and NB2 distributions are used because zero trips to a particular site in the system are allowed (i.e. people intercepted at a particular site were asked about their visits to other sites). Finally, it is assumed that visits over consecutive years are independent.

In the log-likelihood functions shown above (Equations 10 and 11), λ is calculated using the semi-logarithmic demand equation shown in Equation 1. However, Equation 1 is modified as follows to include demographic variables and year:

$$\lambda_{im} = \alpha_i \exp\left(\sum_{j=1}^{n} \beta_{ij} \rho_{jm} + \xi z_m + \gamma y_m \right) \tag{12}$$

where λ_{im} is the estimated number of visits to site $\boldsymbol{i}$ by individual $\boldsymbol{m}$, ξ is a vector of parameter coefficients for the vector z of demographic variables and year, and all other parameters are the same as described above for Equation 1.

Four versions of this system of incomplete semi-log demand equations are estimated. These include estimation of both sets of parameter restriction specifications (Equations 2-5 and 7-9) using the Poisson and NB2 distributions. Robust standard errors are calculated using White's method and are used for calculating t-values.

Two step non-nested test of parameter restrictions:

The two sets of parameter restrictions are compared using a two step non-nested likelihood ratio testing procedure (Vuong 1989). This test was run using a Gauss based program written by von Haefen (2003). The first step of Vuong's test determines whether the non-nested models can be distinguished. This is done based on pair-wise comparisons of log-likelihood values for each model specification across individuals. If it is determined that the models can be distinguished, the second step of the Vuong test is implemented to determine which model, if either, is preferred. A detailed description of Vuong's non-nested test are provided in Vuong (1989) and in Englin and Lambert (1995).

V. RESULTS

Table 1 presents the maximum likelihood estimates for the four models estimated in this study. The site specific negative binomial dispersion parameters ***d*** are significantly different from zero ($p<0.05$) for both restriction specifications, supporting that the NB2 models are preferred to the Poisson specifications; this is confirmed by comparing the log-likelihood values between the Poisson and NB2 specifications for each set of restrictions. The results of Vuong's two step non-nested likelihood ratio testing procedure show that (i) the NB2 models are distinguishable (test statistic = 390.4; $p<0.001$) and (ii) the first set of restrictions is the preferred model (test statistic = 8.27; $p<0.001$). Thus, the best-fit model is the NB2 specification of the semi-log incomplete demand system with the first set of restriction specifications.

Both sets of restrictions and distribution specifications provide same-signed coefficient estimates and similar sets of significant parameters. Travel cost parameters for all sites are negative and significant ($p<0.05$) in the preferred model and negative and at least marginally significant ($p<0.10$) in all models. The magnitude of the own price parameter estimates suggest that demand is more elastic under the second set of restrictions. Income effects are positive and significant ($p<0.05$) across all models. Individuals made significantly fewer visits to sites in 1997 and 1998 than in 1999 across all models, and the skill of riders had a significant positive effect on site demand in all models except for the Poisson estimation of the first set of restrictions. The coefficient on education was only significant in the preferred model (the NB2 specification of the first set of restrictions) and suggested that individuals with more years of education have a higher demand for the OHV sites. The coefficient on female was positive and significant across all models except the preferred model in which it was only marginally significant ($p<0.10$).

Welfare measures associated with the Poisson and negative binomial models are calculated using the travel cost parameters, such that the per trip consumer surplus for an individual who takes a trip to site ***i*** is $1/\beta_i$. Based on the preferred model, consumer surplus for an OHV trip is \$27.32, \$29.59, \$131.58, and \$37.17 for Badin Lake, Brown Mountain, Upper Tellico, and Wayehutta, respectively. Estimated per trip consumer surpluses are slightly different for the Poisson specification of the first set of integrability restrictions, with values of \$41.84,

$31.15, $101.01,and $25.51 for Badin Lake, Brown Mountain, Upper Tellico, and Wayehutta, respectively. Interestingly, the ordering of sites by consumer surplus measures is different across the two distributions for the first set of parameter restrictions, but in both cases Upper Tellico OHV area provides the highest level of consumer surplus.

Consumer surplus estimations based on the second set of parameter restrictions are very different and much higher than for the first set of restriction specifications. Per trip consumer surpluses for the Poisson and NB2 specifications, respectively, were of $454.55 and $714.29 for Badin Lake, $476.19 and $1000.00 for Brown Mountain, $370.37 and $588.24 for Upper Tellico, and $625.00 and $909.09 for Wayehutta. The ordering of sites based consumer surplus and the second restriction set is both different across distributions and different than for the first restriction set.

Compensated variation (CV) can be calculated using a method presented by Englin and Shonkwiler (1995). The formula is:

$$CV = \frac{1}{\gamma}\ln\left(1 + \lambda\frac{\gamma}{\beta_i}\right) \tag{13}$$

where γ is the income coefficient and β_i is the cost coefficient for site i. The variance of the compensated variation estimates can be calculated as described in Englin and Shonkwiler (1995):

$$Var(CV) = \frac{\partial CV}{\partial \beta}\Psi\frac{\partial CV}{\partial \beta'} \tag{14}$$

where β is the vector of all model parameters and Ψ is the variance-covariance matrix for β. Compensated variations based on the preferred model are $43.79, $28.49, $238.92, and $33.12 for Badin Lake, Brown Mountain, Upper Tellico, and Wayehutta, respectively (Table 2). Calculated compensated variations based on estimates from the NB2 specification of the second restriction set do not vary across sites and are equal to $1029.99 which is much larger than for the first restriction set. Equality of compensated variations across sites under the second restriction set results from the site intercept restriction (Equation 7).

VI. CONCLUSIONS

In this study, two sets of integrability restrictions are independently imposed on parameter estimates for a semi-logarithmic incomplete demand system. A non-nested likelihood ratio test revealed that the first set of parameter restrictions (the less restrictive model) fit the empirical data significantly better than the second restriction set ($p < 0.001$). Likewise, model parameters indicated that data are over-dispersed and the negative binomial II (NB2) distribution fit the data better than the Poisson. However, because the NB2 is less robust to distribution misspecification, it remains unclear which distribution should provide more accurate welfare estimates.

One of the primary goals of demand system estimations is the derivation of welfare measures for different goods or characteristics. In the analyses reported here, welfare estimates varied dramatically dependent on the specification of the parameter restrictions. The implication of this analysis is that researchers should not naively apply parameter restrictions when estimating systems of semi-logarithmic incomplete demand equations, but should test alternative sets of utility theoretic restrictions to determine which set best conforms to the data.

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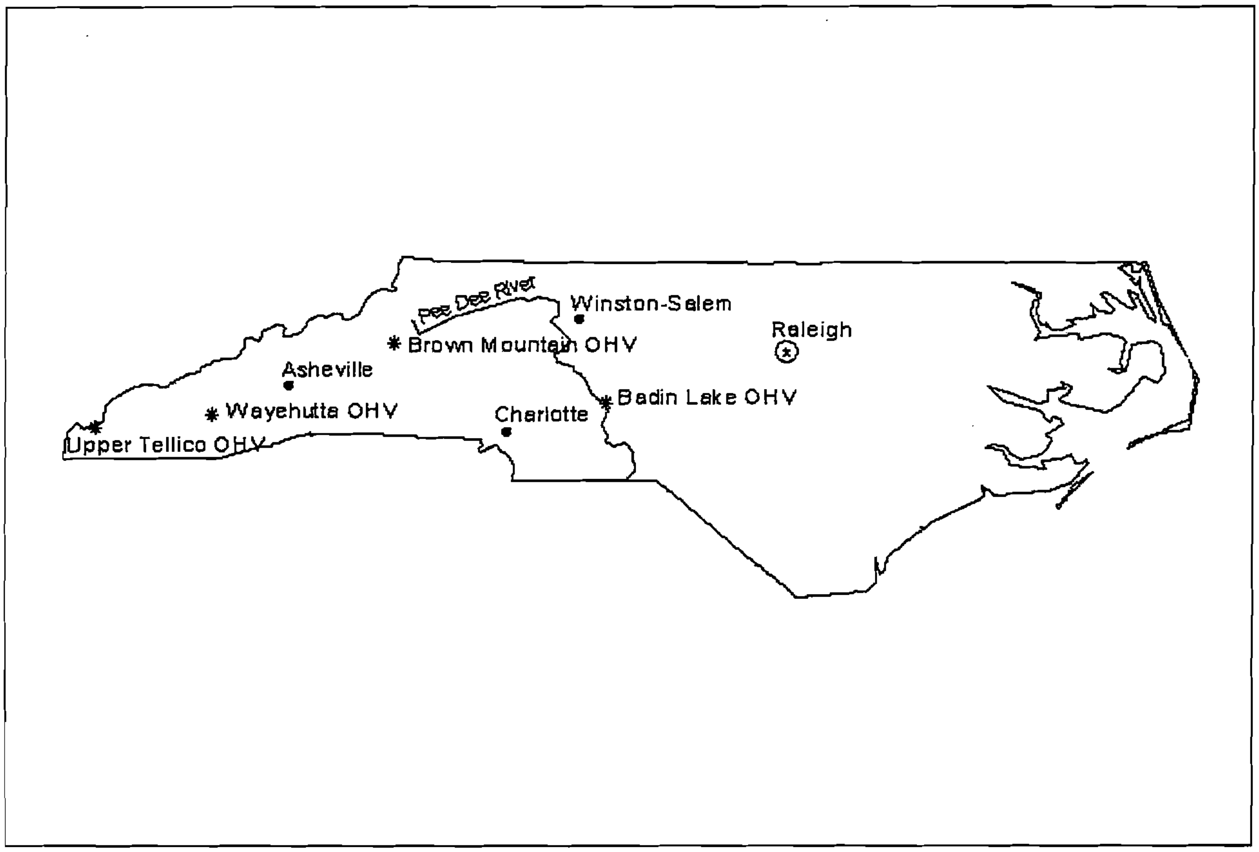

Figure 1. Location of the four United States Forest Service Off Highway Vehicle sites

Table 1. Parameter Estimates

	Restriction Set 1		Restriction Set 2	
	POISSON	NB2	POISSON	NB2
Badin Lake				
Intercept	0.4610	0.2052**	0.6513	0.1861**
	(1.4734)	(0.0915)	(0.8745)	(0.0751)
Travel Cost	-0.0239**	-0.0366**	-0.0022**	-0.0014*
	(0.0023)	(0.0032)	(0.0004)	(0.0008)
d		1.7943**		2.6539**
		(0.1726)		(0.1317)
Brown Mountain				
Intercept	0.7599	0.1359**	0.5977	0.1227
	(6.9731)	(0.0462)		
Travel Cost	-0.0321**	-0.0338**	-0.0021**	-0.0010**
	(0.0030)	(0.0061)	(0.0006)	(0.0005)
d		1.8428**		2.5091**
		(0.1429)		(0.1337)
Upper Tellico				
Intercept	0.2871	0.0463**	0.7926	0.2233
	(0.5833)	(0.0105)		
Travel Cost	-0.0099**	-0.0076**	-0.0027**	-0.0017*
	(0.0013)	(0.0019)	(0.0006)	(0.0009)
d		1.2591**		1.4531**
		(0.1086)		(0.0978)
Wayehutta				
Intercept	0.8200	0.0864**	0.4710	0.1382
	(10.7845)	(0.0240)		
Travel Cost	-0.0392**	-0.0269**	-0.0016**	-0.0011**
	(0.0082)	(0.0069)	(0.0005)	(0.0005)
d		3.1137**		3.5382**
		(0.1878)		(0.1588)
Demographic Variables				
Income ($1000's)	0.0127**	0.0137**	0.0089**	0.0073**
	(0.0018)	(0.0025)	(0.0021)	(0.0034)
1998	-0.5131**	-0.6744**	-0.5107**	-0.5914**
	(0.1579)	(0.1499)	(0.1435)	(0.1297)
1997	-0.8004**	-0.9268**	-0.7987**	-0.9552**
	(0.2342)	(0.1872)	(0.2113)	(0.1660)
skill	0.5803	0.8439**	0.5087**	0.8459**
	(0.3672)	(0.1445)	(0.1126)	(0.1218)
education	0.0629	0.1316**	0.0125	0.0296
	(0.1116)	(0.0369)	(0.0313)	(0.0405)
female	0.6028**	0.3563*	0.5105**	0.5193**
	(0.2040)	(0.2055)	(0.1966)	(0.2143)
Log likelihood	-5704.44	-2517.06	-7441.74	-2680.46

Table 2. Compensated Variation Estimates.

	Restriction Set 1		Restriction Set 2	
	Poisson	NB2	Poisson	NB2
Badin Lake	51.59	43.79	588.91	1029.99
	(2.89)	(5.92)	(37.73)	(291.14)
Brown Mountain	37.29	28.49	588.91	1029.99
	(1.99)	(3.70)	(37.73)	(291.14)
Upper Tellico	171.22	238.92	588.91	1029.99
	(10.65)	(37.86)	(37.73)	(291.14)
Wayehutta	24.75	33.12	588.91	1029.99
	(1.32)	(7.08)	(37.73)	(291.14)