FESTSCHRIFT SYMPOSIUM FOR

WALTER C. LABYS

Agricultural and Resource Economics
West Virginia University

May 7, 2007

PUBLIC INPUT IN RURAL LAND PRESERVATION: MODELING PREFERENCE ASYMMETRIES IN STATED PREFERENCE DATA

Robert J. Johnston and Kelly L. Giraud*

* Robert J. Johnston, PhD is the Associate Director of the Connecticut Sea Grant and an Assistant Professor in the Department of Agricultural and Resource Economics, University of Connecticut
* Kelly L. Giraud, PhD is an assistant professor and coordinator of the Community Development program in the Department of Resource Economics and Development, University of New Hampshire
*This research was funded by the USDA Fund for Rural America 97-36200-5219. Opinions belong solely to the author and do not imply endorsement by the funding agencies or the U.S. Government.
Address correspondence to the author at the Connecticut Sea Grant College Program, University of Connecticut at Avery Point, 1080 Shennecossett Road, Groton, CT 06340-6048 or rjohnston@canr.uconn.edu.

PUBLIC INPUT IN RURAL LAND PRESERVATION: MODELING PREFERENCE ASYMMETRIES IN STATED PREFERENCE DATA

Table of Contents

I. INTRODUCTION

Public preferences for land use or other public policies are often elicited using variants of the common Likert scale, such as a scale from 1 to 5, where 1 = strongly oppose and 5 = strongly support.[1,2,3,4,5] Such scales are designed to provide information regarding a respondent's strength of preference above and beyond a simple referendum/binary (e.g., yes or no) response. However, in return for the ability to model the increased information provided by Likert scales (LS), researchers often accept implicit assumptions not required when modeling binary responses. These include the assumption that respondents choose a cardinal (rather than a more basic ordinal) response on the continuum of the provided scale by reference to a single underlying preference function.

Despite the common use of simplifying assumptions when working with LS data, literature addressing other choice contexts suggests that responses to such preference scales may be somewhat more complex. For example, as Likert scales often allow respondents to express varying degrees of either support or opposition, there is the possibility that responses will

[1] Bateman, I.J., R.T. Carson, B. Day, M. Hanemann, N. Hanley, T. Hett, M. Jones-Leee, G. Loomes, S. Mourato, E. Ozdemiroglu, D.W. Pierce, R. Sugden, and J. Swanson. 2002. *Economic Valuation with Stated Preference Surveys*. Northampton, MA: Edward Elgar.

[2] Danielson, L., T.J. Hoban, G. Van Houtven, and J.C. Whitehead. 1995. Measuring the Benefits of Local Public Goods: Environmental Quality in Gaston County, North Carolina. *Applied Economics* 27(12): 1235-1243.

[3] Kline, Jeffrey D. and Denis Wichelns. 1998. Measuring Heterogeneous Preferences for Preserving Farmland and Open Space. *Ecological Economics* 26(2):211-224.

[4] Lynne, G.D., J.S. Shonkwiler and L.R. Rola. 1988. Attitudes and Farmer Conservation Behavior. *American Journal of Agricultural Economics* 70(1): 12-19.

[5] Variyam, J.N., J.L. Jorday, and J.E. Epperson. 1990. Preferences of Citizens for Agricultural Policies: Evidence from a National Survey. *American Journal of Agricultural Economics* 72(2): 257-267.

manifest preference or response asymmetries.[6,7] In other words, the statistical distribution of the responses may not have a symmetrical balance on both sides. Response asymmetries formally imply that different factor weightings determine the extent to which respondents support versus oppose otherwise identical statements, and might also cause the determinants of an initial binary choice (e.g., oppose versus support) to differ from determinants of preference intensity (e.g., how strongly do I oppose or support).

The only formal discussion of response asymmetries in the stated preference literature is provided by Johnston and Swallow, who show that asymmetries may occur in more complex, two-stage stated preference questions.[8] An example of a two-stage stated preference question would be one in which respondents are first asked whether they support or oppose a hypothetical policy, then asked for their strength of support or opposition. In this context, Johnston and Swallow demonstrate that different functions may govern the extent to which respondents support versus oppose hypothetical watershed management plans—an extension of prior experimental findings reported in the psychology literature.[6,7] However, while Johnston and Swallow demonstrate the existence of response asymmetries in two-stage questions, they fail to provide a practical modeling alternative that allows for such behavioral patterns. Hence, as admitted by the authors, the analytical and policy guidance provided by their empirical results is somewhat limited.

This paper assesses whether similar behavioral patterns manifest in (much more common) stated preference questions designed to be answered in a single stage; a classic example is the LS rating. Specifically, we assess implications of preference asymmetry for cases in which statistical models are used to assess differencesdifferences in stated preferences associated with demographic or other attributes of individual respondents. For example, one might wish to assess heterogeneity in support for particular land use policy tools associated with attributes such as age, income, and education. These models are typically estimated using ordered logit or probit, with the LS response as an independent variable.[9] A discovery of response asymmetries in such common choice frameworks would represent a significant and perhaps surprising finding, as it would imply that even simple ordered preference ratings along a single, continuous preference scale (e.g., a Likert scale) may involve more complex choice processes than are currently anticipated or modeled in the literature.

Simply put, when estimating ordered response models of LS data, one typically assumes that responses are symmetric. In empirical terms, ordered response models presume that the weight given to independent variables—as revealed by estimated coefficients—is approximately constant over the range of possible outcomes, subject to increasing or decreasing returns and/or interactions captured by the chosen functional form. A corollary to this assumption is that respondents choose a LS rating with a single-stage process. However, other choice mechanics are possible. For example, when presented with a LS question regarding support for a land use policy, respondents might (without prompting) first assess whether they support or oppose the

---

[6] Yamagishi, K., and J.M. Miyamoto. 1996. Asymmetries in Strength of Preference: A Focus Shift Model of Valence Effects in Difference Judgments. *Journal of Experimental Psychology* 22: 493-509.

[7] Shafir, E. 1993. Choosing Versus Rejecting: Why Some Options are Both Better and Worse Than Others. Memory and Cognition 21: 546-556.

[8] Johnston, R.J. and S.K. Swallow. 1999. Asymmetries in Ordered Strength of Preference Models: Implications of Focus Shift for Discrete Choice Preference Estimation, Land Economics 75(2): 295-310.

[9] Swallow, S.K., J.J. Opaluch and T.F. Weaver. 2001. Strength-of-Preference Indicators and an Ordered Response Model for Ordinarily Dichotomous, Discrete Choice Data. Journal of Environmental Economics and Management 41(1): 70-93.

policy, then assess the strength of their support or opposition. In such cases, LS responses may no longer be symmetric, and typical ordered response models may provide improper inferences regarding the impact of independent variables on policy support or opposition.

In cases where response asymmetries are evident, alternative choice models may reveal behavioral patterns obscured by traditional modeling approaches. To address such possibilities, this paper presents a model of LS responses that may be applied when preference asymmetries are suspected, and contrasts this alternative to a more traditional ordered response approach. This allows both formal hypothesis tests for the presence of preference asymmetries and assessments of policy implications.

II. A STANDARD STRENGTH OF PREFERENCE MODELS

Our application concerns estimation of the relationship between attributes of survey respondents and stated preferences for common land use policy tools. Preference for each tool is measured on a standard LS, in which respondents are asked to rate each policy tool on a five-point scale ranging from “strongly oppose” (1) to “strongly support” (5).

Standard random utility models assume that a respondent’s strength of preference for a given policy tool (or statement) is determined by the happiness, or *utility* that would result from the application of that tool, compared to the utility generated by the status quo, or lack of that tool. That is, for each management tool i, the difference in utility resulting from the application of that tool may be specified

$$dU_i = dv_i(\mathbf{D}) + \theta_i \qquad (1)$$

where $dv_i(\mathbf{D})$ is the deterministic or observable component of the change in utility, **D** is a vector of variables characterizing demographic and other characteristics of the individual or household hypothesized to influence management preferences, and θ_i is the random, unobservable element of the utility difference. Equation (1) models heterogeneity in preferences for specific policy tools, as a function of individual and household attributes.

Ordered response models represent a standard approach to such problems. This approach presumes that the individual assesses the utility difference dU_i associated with a particular policy tool, then indicates within which of a set of intervals this utility difference falls. Here, each interval corresponds to a specific LS response represented by a strength of preference indicator variable L_{ij}, where j = {1, 2, ..., 5}, such that

$$\begin{aligned} L_{ij} &= 1 \text{ if } \alpha_{i,j-1} < \mathrm{dU} \le \alpha_{i,j} \\ &= 0 \text{ otherwise.} \end{aligned} \qquad (2)$$

For example, if the respondent “strongly opposes” a management tool, then L_{i1} = 1, and L_{i2} =...= L_{i5} =0. The α_{ij} in (2) represent utility thresholds associated with particular values of L_{ij}. These thresholds are unobserved and treated as parameters by the ordered response model.[10]

Assumptions regarding the distribution of θ determine whether the model is estimated as an ordered probit or ordered logit model, with appropriate likelihood functions provided by Maddala, among others.[10] Here, we estimate the model using an ordered probit likelihood function. We emphasize the fact that such models estimate parameters defining a single preference function, dv_i, applicable to responses over the entire continuum represented by the Likert scale.

[10] Maddala, G.S. 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge, UK: Cambridge University Press.

III. A MODEL ALLOWING FOR PREFERENCE ASYMMETRIES

In contrast to the standard approach exemplified by (1), (22) above, models incorporating preference asymmetry would allow judgments of *how strongly do you support* to be determined by a different choice mechanism or component weighting than judgments of *how strongly do you oppose*, following a binary choice in which an option is either supported or opposed.[11,12] For example, when faced with the opportunity to rate a policy tool on a continuous LS, a respondent might first make an initial (binary) decision to support or oppose the tool in question. Simultaneously, the respondent would choose a level of support or opposition. These two choices, however, need not be governed by an identical choice or preference functions.

The model specifies one preference or choice function to govern the initial support versus oppose choice,

$$dU_{1i} = dv_{1i}(\mathbf{D}) + \theta_{1i} \qquad (3)$$

where the subscript '1' denotes the support versus oppose choice. The respondent's choice is represented by the indicator variable L_j which here takes on a value of 0 if the respondent opposes policy tool i and 1 if the respondent supports the tool. We denote this as the "first-stage" choice, although it may be made simultaneously to the "second-stage" choice revealing preference intensity.

The second-stage choice reveals a respondent's preference intensity, or strength of support or opposition. We consider that it is made simultaneously to the first-stage choice, although one might also consider it a subsequent choice. The preference intensity choice is assumed to be governed by the function

$$dU_{2i} = dv_{oi}(\mathbf{D}) + dv_{si}(\mathbf{D}) + \theta_{2i} \qquad (4)$$

where the subscripts o and s represent 'oppose' and 'support', $dv_{oi}(\mathbf{D}) = 0$ for $L_i = 1$, and $dv_{si}(\mathbf{D}) = 0$ for $L_i=0$. Simply put, for those whose first-stage choice indicates support for the policy tool in question, $dU_{2i} = dv_{si}(\mathbf{D}) + \theta_{2i}$. For those whose first-stage choice indicates opposition, $dU_{2i} = dv_{oi}(\mathbf{D}) + \theta_{2i}$.

We assume that strength of support or opposition is revealed through a binary choice, represented by the indicator variable S_i. Respondents who support tool i may choose to "moderately" (S_i=0) or "strongly" (S_i=1) support. Respondents who oppose tool i may choose to "strongly" (S_i=0) or "moderately" (S_i=1) oppose. Note that S_i is defined for support and oppose contexts such that the directional effect of utility difference on strength of preference is preserved.[13]

---

[11] Yamagishi, K. 1996. Strength of Preference and Effects of Valence in the Domains of Gains and Losses. Organizational Behavior and Decision Making Processes 66 (June): 290-306.

[12] Yamagishi, K., and J.M. Miyamoto. 1996. Asymmetries in Strength of Preference: A Focus Shift Model of Valence Effects in Difference Judgments. *Journal of Experimental Psychology* 22: 493-509.

[13] That is, for both oppose and support contexts Sij = 1 corresponds to a higher level of utility or preference dU2i within each category. One may also envision this intuitively as splitting the data (observations) into support (S) and oppose (O) responses, creating two independent datasets of binary strength of preference responses. The support (S) data include all "support" and "strongly support" responses (LS responses 4, 5); the oppose (O) data include all "strongly oppose" and "oppose" responses (LS responses 1,2). The resulting support and oppose datasets are then vertically "stacked", or pooled into a single binary dataset, such that the directional effect of the utility difference on strength of preference is preserved. The result is a pooled dataset incorporating both the oppose and support data vertically stacked. For examples of similar data transformations, see Mazzotta, M.J., and J.J. Opaluch. 1995. Decision Making When Choices Are Complex: A Test of Heiner's Hypothesis. Land Economics 71(4): 500-515. and Johnston, R.J. and S.K. Swallow. 1999. Asymmetries in Ordered Strength of Preference Models: Implications of Focus Shift for Discrete Choice Preference Estimation, Land Economics 75(2): 295-310.

The special case, implied by the standard ordered response model (1)-(2), is that $dv_{1i}(\mathbf{D}) = dv_{oi}(\mathbf{D}) = dv_{si}(\mathbf{D})$—allowing the two-component decision governed by (3) and (4) to be collapsed into a single-component decision governed by (1). However, while it is certainly possible that the same underlying preference or utility function determines support or opposition, strength of support (for supported tools), and strength of opposition (for opposed tools), a preference asymmetry model considers this an hypothesis subject to testing. That is, it would also allow for the case in which $dv_{1i}(\mathbf{D}) \neq dv_{oi}(\mathbf{D}) \neq dv_{si}(\mathbf{D})$, as suggested by (3)-(4) above.

As a result of the additional flexibility characterized by (3) above, models incorporating preference asymmetries allow for possibilities not often considered by the stated preference literature. For example, standard ordered response models assume that each demographic indicator (e.g., age) has a fixed marginal effect on utility difference function, and that this single function determines the LS rating of the entire continuum. Implicit in this approach is the assumption that both the magnitude and directional impact (i.e., sign) of each indicator is fixed.

Such behavioral assumptions notwithstanding, there are a variety of other systematic mechanisms through which demographic and other indicators may systematically influence stated preferences. Perhaps the most obvious is that certain demographic attributes may be associated with stronger (or more moderate) preferences for any given policy choice, regardless of whether that policy choice is supported or opposed. For example, older respondents may tend to have more extreme opinions than younger residents—stating stronger opposition to disliked policies and stronger support for favored policies, *ceteris paribus*.

Were such patterns to hold, the marginal directional effect of age on strength of preference (i.e., the sign of the coefficient) would change as one moved from the "oppose" to "support" segment of the LS continuum. Because standard ordered response models of LS data do not allow for this possibility, misspecification of respondents' choice behavior is possible. A typical symptom of such misspecification would be that the model would fail to identify a systematic effect of a particular attribute (e.g., age) on strength of preference, when in fact a systematic and significant effect exists.

A. The Statistical Model

While estimation of ordered response models for LS data is well established, appropriate modeling of preference asymmetries in such data has (to the authors' knowledge) little precedent in the literature.[14]

Moreover, the model characterized by (3) above lends itself to a variety of existing estimation methods, depending on the behavioral assumptions and data manipulations that one is prepared to accept.[15]

Here, we model the choices implicit in (3) and (4) as simultaneous bivariate decisions with correlated disturbances, in the tradition of seemingly unrelated regressions, where correlation is

---

[14] Johnston and Swallow (1999) present hypothesis tests that establish the presence of preference asymmetries in two-stage stated preference questions, yet fail to provide a consistent approach that would allow one to model respondents' choices in the presence of such asymmetries.

[15] Perhaps the most straightforward approach to this issue would be to apply generalized ordered logit, an approach which relaxes the proportional odds assumption implicit in traditional ordered logit models (US EPA. 2002. CatReg Software Documentation. Washington DC: United States Environmental Protection Agency, Office of Research and Development. EPA/600/R-03/002). We eschew this model in favor of an alternative specification (bivariate probit) which formalizes the hypothesized two-stage decisions implicit in a preference asymmetry model. We thank Scott Shonkwiler for suggesting this alternative approach.

incorporated by ρ=Cov[θ_{1i}, θ_{2i} | **D**].[16] The first bivariate choice, corresponding to (3), indicates a respondent's opposition ($L_i=0$) or support ($L_j=1$) for a specific management tool i. The second bivariate choice, corresponding to (4), indicates a respondent's strength of preference (S_i={0,1}), where statistical determinants of this choice may differ between those opposing and supporting tool i as noted above.

Non-independence between the two choices may be incorporated by assuming a bivariate normal distribution of equation errors, leading to estimation using a bivariate probit likelihood function.[17] Given parameters are estimated using a readily estimable bivariate probit model; the likelihood function for this model is provided by Greene and Poe, among others.[16,17]

Model estimation allows for readily accessible hypothesis tests of various aspects of potential preference asymmetry. For example, the test of null hypothesis H_0: the statistical determinants of strength of opposition to tool i are significantly not different from those of strength of support, and H_A: the statistical determinants are statistically different. Moreover, comparisons of the overall fit and performance of the ordered response and bivariate probit models allow appraisals of each model's ability to appropriately characterize respondents' choice behavior.

B. Treatment of Neutral Responses

Although the bivariate probit approach provides significant flexibility in allowing for preference asymmetries, it does so at a cost. Specifically, as the model is specified as a combination of two bivariate decisions, it cannot incorporate neutral responses, described in the survey as "neither oppose nor support". Recall, the data of interest is comprised of LS ratings on a five point scale, where the median scoree represents a neutral response to tool i. The ordered response model (1), (22) is able to incorporate such data points within model estimation, as part of the continuum of LS responses. However, the bivariate probit model models a binary "oppose versus support" choice jointly with a binary strength of preference choice; it does not incorporate neutral responses, which are dropped from the data prior to estimation. Hence, certain information (data) is lost in estimating the bivariate probit model.[18] This is not unique to this approach to preference asymmetries; Johnston and Swallow also drop neutral responses in hypothesis tests of preference asymmetries in two-stage stated preference questions.[19] Nonetheless, it is important to view the performance of the bivariate probit model in light of the smaller dataset from which it is estimated. In theory, the additional information incorporated in the ordered response models should afford additional efficiency and robustness. However, such advantages may be offset if such models misspecify respondents' behavior.

In a formal referendum, voters are allowed to vote "yes", "no" or leave the ballot blank. In this case, we treat neutrals as blank ballots. We do not, however ignore the neutral responses and shall investigate them separately.

IV. THE DATA

Data are drawn from the *Rhode Island Rural Land Use* survey, an instrument designed to

---

[16] Greene, W.H. Econometric Analysis, 5th ed. Upper Saddle River, NJ: Prentice Hall.
[17] Poe, G.L., M.P. Welsh, and P.A. Champ. 1997. Measuring the Difference in Mean Willingness to Pay When Dichotomous Choice Contingent Valuation Responses Are Not Independent. Land Economics 73(2): 255-267.
[18] As a practical matter, neutral responses make up a very small proportion of the Likert scale data in question. However, some data is nonetheless discarded in estimating the bivariate probit model.
[19] Johnston, R.J., S.K. Swallow, D. Marie Bauer, and C.M. Anderson. 2003. Preferences for Residential Development Attributes and Support for the Policy Process: Implications for Management and Conservation of Rural Landscapes. Agricultural and Resource Economics Review. 32(1): 65-82.

assess rural residents' tradeoffs among attributes of residential development and conservation. Survey development required over eighteen months, including background research; interviews with policy makers and residents; and focus groups.[20] Surveys were mailed to 4000 randomly selected residents of four Rhode Island rural communities following the total survey design method.[21] Of 3702 deliverable surveys, 2157 were returned, for a response rate of 58.2%. Further details of the survey and its administration are provided by survey researchers.[22,23]

Survey respondents were asked to indicate their degree of opposition to, or support for twenty-one different land use management policy options, on a five-point LS ranging from 'strongly oppose' (1) to 'strongly support' (5). Policy options included zoning changes, fee-based land preservation techniques, tax policies, housing caps, impact fees, and other land use policy tools common in Rhode Island rural communities. Based on the results of focus groups, all policies were described in simple, non-technical terms. Table 1 lists the policy options rated by respondents, and the mean support ratings associated with each option. Mean scores above 3.0 indicate that the average respondent supports the policy option, with higher scores indicating greater mean support. Mean scores below 3.0 indicate that the average respondent opposes the policy option, with lower scores indicating greater mean opposition. Diversity in average responses across similar management tools suggests that respondents considered each policy in detail when providing LS responses, rather than providing identical ratings of broadly similar policies (e.g., tools 1 and 2; tools 7-9).

V. EMPIRICAL RESULTS

Empirical models compare performance of the ordered probit (traditional) and bivariate probit (preference asymmetry) approaches, applied to the same LS data. For both models, responses are modeled as a function of an identical set of independent variables. Independent variables include length of residency in the rural community, standard demographic descriptors characterizing age, income, and education, and other indicators such as membership in environmental or business organizations or ownership of a local home (table 2).

Distinct ordered and bivariate probit models are estimated for each of the 21 management tools considered by respondents, resulting in a total of 42 estimated models. Table 3 summarizes overall model statistics including the likelihood ratio χ^2 for each model, McFadden's pseudo-R^2 for both models, and the likelihood ratio χ^2 for the null hypothesis H_0: the statistical determinants of strength of support are identical to those for strength of opposition, in the bivariate probit model.[24,25]

All models are statistically significant at better than $p<0.01$, as indicated by likelihood ratio tests (table 3).). Model fit statistics provide support for the bivariate probit model.

---

[20] Johnston, R.J., S.K. Swallow and D.M. Bauer. 2002. Spatial Factors and Stated Preference Values for Public Goods: Considerations for Rural Land Development. Land Economics 78(4): 481-500.

[21] Dillman. D.A. 2000. Mail and Internet Surveys: The Tailored Design Method. New York: John Wiley and Sons.

[22] Johnston, R.J., S.K. Swallow and D.M. Bauer. 2002. Spatial Factors and Stated Preference Values for Public Goods: Considerations for Rural Land Development. Land Economics 78(4): 481-500.
Johnston, R.J., S.K. Swallow, D. Marie Bauer, and C.M. Anderson. 2003.

[23] Johnston, R.J., S.K. Swallow, D. Marie Bauer, and C.M. Anderson. 2003. Preferences for Residential Development Attributes and Support for the Policy Process: Implications for Management and Conservation of Rural Landscapes. Agricultural and Resource Economics Review. 32(1): 65-82.

[24] McFadden, D. 1974. The Measurement of Urban Travel Demand. Journal of Public Economics 3: 303-328.

[25] The $\chi 2$ statistic is calculated as -2[LRR - LRU], where LRR is the log likelihood function of the restricted model in which $\gamma oi = \gamma si$, and LRU is the log likelihood function of the unrestricted model (7).

Bivariate probit results also show strong evidence of preference asymmetry in strength of preference responses. The null hypothesis H_0: is rejected at p<0.01 in all cases (table 3), showing strong evidence that determinants of strength of preference for opposed tools differs from analogous determinants for supported tools—violating one of the primary assumptions upon which traditional ordered response modeling relies. The presence of such asymmetries may help explain the relatively poorer statistical performance of ordered probit relative to the bivariate probit in this context. Hence, while direct specification tests are infeasible, and despite the larger dataset from which the ordered response model is estimated, the general fit of the bivariate probit model of LS responses appears to improve over that of the traditional (i.e., ordered response) approach.

A. Implications for Heterogeneity in Policy Preferences

Additional insight regarding the policy relevance of such results may be gained by reviewing model results for specific management tools. Given the impracticality of illustrating full estimation results for each of the 42 estimated models, we focus discussion on a subset of cases. Although we emphasize cases in which evidence of preference asymmetry is relatively clear, similar evidence may be found in most estimated models. This evidence suggests that asymmetric responses may have considerable and meaningful impacts on the results of standard ordered preference models.

For example, table 4 illustrates results for tool 1 and tool 6, including both bivariate probit and ordered probit models. As noted in table 4, tool 1 is described as "attract new commercial development to your town by offering tax incentives." BasedB on likelihood ratio tests, both the bivariate and ordered models are statistically significant at better than p<0.001 for tool 1 (table 4). The ordered probit model model suggests that the following four attributes influence strength of preference at p<0.10: length of residency (positive influence); age (positive); membership in an environmental organization (negative); and membership in a business group (positive).

In contrast, the bivariate probit model allows attribute influence to differ depending on the choice being made. For the support versus oppose choice, the bivariate model finds statistically significant influence associated with six attributes, including: length of residency (positive); age (positive); gender (female respondents associated with more negative responses); home ownership (positive); membership in an environmental organization (negative); and membership in a business group (positive).

The results of both models are intuitive. For example, members of environmental organizations might be expected to state greater opposition to tax incentives designed to attract commercial development, while members of business groups might be expected to express greater support. However, the bivariate model is able to discern statistically significant effects (at least in the support versus oppose model) for two additional attributes: gender (p<0.01) and home ownership (p<0.05). Based on bivariate probit results, these attributes influence the probability of supporting commercial tax incentives. While the ordered probit p-values for these attributes are close to the generally accepted p=0.10 threshold for statistical significance, we nonetheless cannot reject the individual null hypotheses of zero influence on LS responses (table 4).

Policy implications of such results are not difficult to envision. For example, if a policymaker were to request information on support for commercial tax incentives among local homeowners, the traditional approach to LS data (ordered response modeling) would indicate no statistically significant influence—a result of potential importance when seeking to identify constituencies for particular policy options. However, the bivariate strength of preference model suggests that this conclusion may be misleading. Based on bivariate probit results, one would conclude that homeowners are more likely to support such tax incentives (at $p<0.05$).

The potential rationale for this discrepancy is straightforward. The bivariate model indicates that home ownership influences both the probability of supporting commercial tax incentives (*own_home*, table 4), as well as strength of opposition for those respondents who oppose such policies ($own\_home \times oppose$; $p<0.05$). However, home ownership cannot be shown to influence the strength of support among those who support such policies ($own\_home \times support$; $p=0.21$). The lack of a statistically significant effect over a *portion* of the LS continuum likely contributes to the failure of the ordered probit model to identify a statistically significant effect of home ownership over the entire response continuum.[26]

Aside from an improved ability to identify statistically significant attribute effects, the bivariate model also reveals differences in preference determinants among those who oppose and those who support tool 1 (table 4). For example, significant effects on strength of opposition ($dv_{oi}(\mathbf{D})$) are associated with residence duration (positive or *weaker* opposition), female respondents (negative or *stronger* opposition), age (negative), home owners (positive), and members of environmental groups (negative). In contrast, strength of support ($dv_{si}(\mathbf{D})$) is associated with age (positive or *stronger* support), female respondents (negative or *weaker* support), members of environmental groups (negative), and members of business organizations (positive). Hence, as suggested by the joint hypothesis test in table 3, the bivariate probit model for tool 1 indicates that determinants of strength of support and strength of opposition differ.

Bivariate strength of preference results for tool 1 also reveal a characteristic incidence of preference asymmetry associated with the variable *age*. As noted above, older residents who oppose tool 1 reveal stronger opposition at $p<0.01$ ($age \times oppose<0$; table 4). However, older residents who support tool 1 reveal stronger support at $p<0.03$ ($age \times support>0$). Combining these results leads to the conclusion that increasing age is associated with stronger preferences for commercial tax incentives—both in support and opposition—a classic representation of response asymmetry associated with a demographic attribute.

Similar results are evident for tool 6 (table 4). To streamline discussion of these results, table 5 provides a simplified illustration of statistically significant effects identified by each model, with ‘plus’ and ‘minus’ signs indicating positive and negative statistically significant impacts. As shown by table 5, the signs of statistically significant effects in the bivariate support/oppose model are identical to those found in the ordered probit model—a sign that both models are identifying similar patterns in LS responses. However, among various symptoms of response asymmetry manifest in the bivariate strength of preference model for tool 6, table 5 provides another archetypal illustration of preference asymmetry and its potential implications.

The identified preference asymmetry is associated with the attribute *house_size* (the number of people in the household). Household size cannot be shown to influence the probability of supporting the “revitalization of town centers using public funds” (tool 6). However, for those respondents who support tool 6, larger household sizes are associated with stronger support at $p<0.01$ (tables 4,5). In contrast, for those respondents who oppose tool 6, larger household sizes are associated with stronger opposition at $p<0.08$. Such patterns cannot be captured by standard ordered response specifications—despite the statistically significant patterns identified by the bivariate model, the ordered probit model shows *house_size* to have an insignificant effect on LS responses.

[26] Recall, the ordered probit model estimates only one parameter estimate per attribute, which applies over the entire continuum of Likert scale responses.

Here again, we find a pattern of potential relevance obscured by the ordered response framework: members of larger household tend to express stronger preferences regarding revitalization of town centers. If one opposes such policies he/she will oppose more strongly; if one supports he/she will support more strongly. Aside from indicating patterns of heterogeneity in policy support, these results also have potential implications for the implicit weight given to respondents from larger households in analysis of LS responses. That is, the tendency of such respondents to provide more extreme (or outlier) responses may provide them with a greater-than-average influence on statistical results.

A final illustration of response asymmetries is provided for tool 8, described in the survey as "purchase and preserve undeveloped land with public funds." A summary of statistically significant effects is provided by table 6. Again, for simplicity we emphasize only the direction (sign) of statistically significant effects.[27] Here, the ordered probit model identifies preference heterogeneity associated with only three out of nine attributes: *age*, *hi_educate*, and *envi_group*. In contrast, the bivariate probit model—including both the support/oppose and strength of preference models—identifies statistically significant impacts with six out of nine attributes: *age*, *female*, *house_size*, *hi_educate*, *envi_group*, and *bus_group*. Here, the ability to distinguish attribute effects on the support/oppose choice versus the strength of preference choice allows the identification of additional sources of response heterogeneity, in this case associated with household size, gender, and membership in business organizations. For example, results indicate an negative effect of household size on the probability of supporting the purchase and preservation of undeveloped land ($p<0.05$); the statistical significance of this effect is not apparent in the ordered response model. For policymakers or researchers interested in forecasting referendum support for proposed policies among different demographic groups, such patterns may be of considerable relevance.

Similar patterns are found (to varying degrees) in models addressing LS responses for all 21 management tools considered. Results strongly support the hypothesis that response asymmetries occur, thereby refuting a primary assumption upon which standard ordered response models rely. However, perhaps more importantly, results show that alternative choice models—here a bivariate probit specification—are able to identify behavioral patterns obscured by traditional ordered response models of LS data. These findings illuminate aspects of preference heterogeneity that—while of questionable policy relevance in some cases—may be of considerable importance in particular policy or analysis contexts.

B. Investigation of Neutral Responses

As mentioned earlier, neutral responses create an issue in many models, and in many policy decision situations. Referendums generally allow voters to vote "yes", "no", or leave the measure blank. While blanks are often simply ignored in our political process, it is useful to see how the socioeconomic attributes help to describe those who are more likely to have a neutral response. In order to get a broad representation of the land use policies, three tools are examined in Table 7: Tool 1, which is pro new commercial development, Tool 6 is pro revitalization of existing retail development, and Tool 8 is pro land preservation.

Identifying attributes of residents who are likely to have neutral responses (or choose not to vote) can be a useful tool if planners wish to target education programs and increase non-neutral responses. Using a basic probit model to estimate the relationship of the attributes and the presence of a neutral vs. stated preference results in a few interesting results. Table 7 shows the parameters

[27] Full results for all models are available from the authors upon request.

and tests for goodness of fit. The models perform relatively well for cross-sectional data, with significant likelihood ratio statistics and Psuedo R^2s from 0.1723 to 0.42. In this model, we look at the how the variables relate to the probability that a respondent would choose a neutral stance on an issue. In Table 7, variable with significant positive coefficients denote a tendency to be neutral on that issue as that variable increases. Variables that were positive and significant for $p < 0.05$ for at least one tool include, gender, belonging to an environmental group and a pattern of voting neutral on other policy tools. If a variable is negative and significant, there is an indication that there is less of a tendency to have neutral feelings for a policy tool as the variable increases. Variables that are negative and significant include age, number of years residing in the town, and home ownership

It follows logically that people who tend to have neutral preferences for other policy tools would be more likely to feel neutral for tools 1, 6 and 8. These variables are positive and significant in all three models. It is also logical that the longer one lives in a town, the less likely they are to be neutral on a land use tool. Resid_years is significantly negative for tools 1 and 6, which both deal with development – either encouraging new commercial development, or revitalizing current town or village centers. This variable was insignificant for tool 8 (preserving undeveloped land). Age was significant and negative in tool 1, showing that older respondents were likely to have a definite preference for commercial development. Female respondents were more likely to be neutral for encouraging commercial development. Home ownership was significant and negative only for downtown revitalization. Homeowners are more likely to want to see their downtowns revitalized.

Interestingly, members of environmental groups were more likely to have neutral preferences for commercial development. As expected, they are not likely to have neutral votes for open space preservation. Preceding models also show that having membership in an environmental organization is strongly correlated with strong preferences in support of conservation policies. Finally, members of business groups were more likely to indeed have a stated preference for commercial development and for town center revitalization.

The only characteristic that were consistent across neutral respondents were that the more neutral responses people had on other policy tools, the more likely they were to be neutral in the three tools.

VI. CONCLUSION

If one is solely interested in calculating mean policy support over a sample of respondents, then findings of preference asymmetry in LS responses may be of little relevance. However, if one wishes to characterize heterogeneity in support for management tools or assess statistical determinants of LS responses, then the potential for such patterns may be of critical importance. Here, we show that the assumption of response symmetry implied by common ordered response models may prevent detection of potentially significant influences on strength of support or opposition, as revealed by LS data. Model results support the potentially surprising conclusion that statistically significant response asymmetries are both common and policy relevant, even in relatively straightforward LS ratings applied over a single ordered preference scale.

Aside from establishing the general existence of response asymmetries in our LS data, findings here indicate that preferences for land use tools are potentially more complex than is typically assumed. For example, bivariate probit specifications of our LS data frequently reveal differences among those variables influencing the decision to support or oppose particular land use policies and those variables influencing strength of preferences for supported or opposed policies.

Moreover, while certain universal and intuitive patterns are apparent (e.g., environmental group membership is almost universally associated with stronger support for pro-environment policies and stronger opposition to pro-development policies), the effect of other attributes varies considerably. Such patterns suggest caution in making general statements concerning heterogeneity in preferences for particular types of land use policies.

Although the present analysis provides evidence that response asymmetries occur in simple LS questions (i.e., questions designed to be answered in a single stage, on a five-point continuum) and discusses potential policy implications of such patterns, there is much left for future research. For example, researchers often use principal component factor analysis of the response correlation matrix to estimate latent factors that capture a high degree of variation in LS responses. Resulting factor scores are then used as either independent or dependent variables in statistical models (e.g., Variyam et al. 1990). Implications of response asymmetry (in the raw LS data) on derived factor scores—and on statistical models incorporating these scores—has yet to be explored.

Additional areas of future research include alternative approaches to data incorporating response asymmetries. Bivariate probit models represent only one potential means to model response asymmetries of the type identified here. Other potential approaches might be drawn from variants of Heckman-type sample selection models or nested choice models (e.g., nested logit).[28] While exploration of these and other potential approaches to LS data is beyond the scope of this paper, we emphasize that the bivariate model estimated here is only one potential approach. Other, as-yet-undeveloped approaches might (or might not) provide superior means to model LS response asymmetries of the type identified here (e.g., alternative approaches might allow preference asymmetries to be modeled while allowing retention of neutral responses). The potential performance of potential alternative approaches notwithstanding, results here suggest that models allowing for response asymmetries in LS data may provide considerable insight over and above that provided by traditional ordered response models.

[28] Greene, W.H. Econometric Analysis, 5th ed. Upper Saddle River, NJ: Prentice Hall.

Table 1. Likert Scale Strength-of-Support Ratings for Land Use Policy Options[a]

Option	Description (survey text)	Mean Rating (Std. Dev.)
1	Attract new commercial development to your town by offering tax incentives	2.49 (1.26)
2	Attract new residential development to your town by offering tax incentives	1.85 (0.94)
3	Encourage preservation by reducing property taxes on undeveloped land	4.11 (0.89)
4	Encourage new development by expending public water and sewer services	2.31 (1.11)
5	Discourage people from moving into your town by increasing the tax rate	1.94 (0.89)
6	Revitalize town or village centers using new public funds	3.36 (1.03)
7	Purchase and preserve undeveloped land with private funds (e.g., land trust donations)	4.08 (0.81)
8	Purchase and preserve undeveloped land with public funds (e.g., public bond issues)	3.58 (1.05)
9	Purchase and preserve undeveloped land through a new real estate sales tax	2.68 (1.16)
10	Collect fees from developers to offset costs of additional public services for new developments	4.16 (0.86)
11	Collect fees from developers to offset additional environmental damages from new developments	4.28 (0.83)
12	Encourage residential development by decreasing zoning restrictions	1.79 (0.92)
13	Encourage commercial development by decreasing zoning restrictions	1.95 (1.04)
14	Require new developments to preserve some undeveloped land	4.21 (0.76)
15	Require trees and shrubs between new houses and roads	4.11 (0.82)
16	Further protect water resources by increasing zoning restrictions	4.08 (0.83)
17	Further protect wildlife resources by increasing zoning restrictions	4.04 (0.87)
18	Require new commercial development to occur along major roadways	3.75 (1.01)
19	Require new commercial development to occur within town or village centers	3.00 (1.09)
20	Institute a cap on the total number of new homes allowed to be built each year	4.09 (0.93)
21	Tighten enforcement of existing zoning and subdivision regulations	4.02 (0.86)

[a] Measured on a five-point Likert-scale in which 1 = “strongly oppose” and 5 = “strongly support.” Numbers in parentheses are standard deviations.

Table 2. Variables Included in the Strength of Preference Models

Variable Name	Description	Units and Measurement	Mean (Std. Dev.)
Resid_year	Length of residency in the community in which a respondent currently resides.	Number of Years	16.59 (15.55)
Age	Reported age of survey respondent.	Number of Years	47.28 (12.44)
Female	Dummy variable distinguishing male and female respondents.	Binary (0,1), 1 = female; 0 = male.	0.33 (0.47)
House_size	Size of household, including children.	Number of individuals.	2.93 (1.30)
Own_home	Dummy variable identifying those who indicate that they own their principle residence (versus renting).	Binary (0,1), 1 = home owner.	0.91 (0.28)
Hi_educate	Dummy variable identifying those respondents with at least a four-year college education.	Binary (0,1), 1 = four-year college or greater education.	0.34 (0.47)
Hi_income	Dummy variable identifying those respondents with reported household income above $39,999 per year.	Binary (0,1), 1 = income > $39,999.	0.53 (0.49)
Envi_group	Dummy variable identifying those indicating membership in environmental groups (Audubon Society, land trusts, etc.).	Binary (0,1), 1 = environmental group member.	0.19 (0.39)
Bus_ group	Dummy variable identifying those indicating membership in business organizations (chambers of commerce, etc.).	Binary (0,1), 1 = business group member.	0.20 (0.40)
Neutrals	Number of times respondent expressed neutral preferences toward one of the policy tools	Number of neutral votes	3.59 (3.28)
ToolOppose	Dummy variable indicating a preference in opposition of a policy tool	Binary (0,1), 1 = opposed policy tool	Tool1: 2.50 (1.24) Tool6: 3.34 (1.02) Tool8: 3.56 (1.04)

Table 3. Model Statistics: Ordered Probit and Bivariate Probit Estimation Results

Model (Policy Tool)	Ordered Probit LR χ^2 (df=9)[a]	Ordered Probit Pseudo-R^2	Bivariate Probit LR χ^2 (df=28)[a,b]	Bivariate Probit Pseudo-R^2	LR χ^2 for H_0: $\gamma_{oi} = \gamma_{si}$ (p-value)
1	93.64	0.017	192.48	0.047	76.00 (0.01)
2	96.00	0.021	111.96	0.035	38.58 (0.01)
3	63.65	0.014	163.30	0.048	103.71 (0.01)
4	101.70	0.019	162.96	0.045	70.96 (0.01)
5	26.06	0.006	79.00	0.027	43.00 (0.01)
6	48.77	0.009	173.99	0.054	118.26 (0.01)
7	97.79	0.023	172.10	0.055	100.92 (0.01)
8	100.20	0.019	219.37	0.062	117.45 (0.01)
9	94.13	0.016	206.82	0.055	89.95 (0.01)
10	39.93	0.009	119.96	0.037	61.83 (0.01)
11	43.41	0.011	115.92	0.035	54.21 (0.01)
12	111.55	0.025	110.16	0.034	29.18 (0.01)
13	115.73	0.024	153.25	0.043	28.82 (0.01)
14	55.87	0.014	135.56	0.043	63.04 (0.01)
15	69.84	0.016	150.39	0.051	88.80 (0.01)
16	44.85	0.010	140.67	0.046	93.87 (0.01)
17	75.30	0.016	153.47	0.049	92.21 (0.01)
18	48.92	0.010	135.45	0.040	74.79 (0.01)
19	51.67	0.009	169.25	0.047	96.63 (0.01)
20	37.82	0.008	115.89	0.034	67.27 (0.01)
21	57.71	0.013	146.52	0.049	92.67 (0.01)

[a] All models are statistically significant at $p<0.01$.

[b] Statistics are for the full bivariate probit model including both equations.

Table 4. Ordered and Bivariate Probit Results: Tools #1 and #6[a]

Variable Name	Parameter Estimate	Std. Error	p>|z|	Parameter Estimate	Std. Error	p>|z|
Bivariate Probit: Support/Oppose						
	Tool #1			Tool #6		
Resid_year	0.012	0.003	0.001	0.005	0.003	0.045
Age	0.005	0.003	0.067	-0.012	0.003	0.001
Female	-0.189	0.072	0.008	0.272	0.079	0.001
House_size	-0.023	0.026	0.387	0.010	0.030	0.742
Own_home	0.266	0.130	0.041	-0.316	0.140	0.024
Hi_educate	-0.067	0.074	0.364	-0.078	0.079	0.330
Hi_income	0.001	0.073	0.992	-0.001	0.080	0.990
Envi_group	-0.260	0.091	0.004	0.139	0.098	0.156
Bus_group	0.228	0.082	0.005	0.158	0.093	0.088
Intercept	-0.763	0.186	0.001	0.874	0.218	0.001
Bivariate Probit: Strength of Preference[b]						
Resid_year × Oppose	0.009	0.002	0.001	0.009	0.004	0.015
Age × Oppose	-0.008	-0.002	0.001	-0.017	0.005	0.001
Female × Oppose	-0.137	0.068	0.045	0.178	0.117	0.129
House_size × Oppose	-0.016	0.021	0.448	-0.074	0.042	0.076
Own_home × Oppose	0.242	0.121	0.045	-0.322	0.222	0.148
Hi_educate × Oppose	-0.087	0.072	0.225	-0.138	0.108	0.203
Hi_income × Oppose	-0.091	0.071	0.196	-0.018	0.113	0.873
Envi_group × Oppose	-0.249	0.085	0.004	0.158	0.138	0.254
Bus_group × Oppose	0.093	0.082	0.259	0.023	0.125	0.855
Intercept × Oppose	0.853	0.110	0.001	2.157	0.306	0.001
Resid_year × Support	0.003	0.003	0.422	0.005	0.003	0.076
Age × Support	0.011	0.005	0.023	-0.005	0.004	0.267
Female × Support	-0.215	0.120	0.074	0.105	0.092	0.252
House_size × Support	-0.004	0.047	0.933	0.097	0.034	0.005
Own_home × Support	0.293	0.233	0.209	-0.303	0.147	0.040
Hi_educate × Support	-0.009	0.114	0.940	0.056	0.096	0.558
Hi_income × Support	0.011	0.120	0.929	0.067	0.097	0.489
Envi_group						

× Support	-0.404	0.166	0.015	0.081	0.113	0.476
Bus_group						
× Support	0.333	0.119	0.005	0.178	0.105	0.091
Intercept						
× Support	-2.108	0.345	0.001	-1.456	0.267	0.001
ρ	0.999	0.001	0.001	0.998	0.332	0.004
N	1648			1401		
-2 LnL χ^2 (df=28)	192.48		0.001	173.99		0.001
			Ordered Probit			
Resid_year	0.009	0.002	0.001	0.006	0.002	0.001
Age	0.007	0.002	0.003	-0.007	0.002	0.003
Female	-0.083	0.053	0.119	0.193	0.053	0.001
House_size	0.024	0.021	0.243	0.026	0.020	0.207
Own_home	0.142	0.092	0.123	-0.249	0.091	0.006
Hi_educate	-0.065	0.056	0.246	-0.007	0.055	0.894
Hi_income	-0.005	0.055	0.928	0.014	0.055	0.794
Envi_group	-0.224	0.066	0.001	0.049	0.064	0.446
Bus_group	0.163	0.064	0.011	0.127	0.064	0.047
Estimated Cut-Points						
α_1	-0.112			-1.602		
α_2	0.640			-0.904		
α_3	1.085			-0.076		
α_4	2.175			1.281		
N	1886			1899		
-2 LnL χ^2 (df=9)	93.64		0.001	48.77		0.001

[a] The text describing tool #1 is: "attract new commercial development to your town by offering tax incentives." Tool #6 is described as "revitalize town or village centers using new public funds."

[b] For bivariate probit strength of preference model oppose responses, 0=strongly oppose and 1=moderately oppose. For support responses, 0=moderately support and 1=strongly support (see text for additional information)

Table 5. Summary of Statistical Results: Tool 6[a]

	Bivariate Probit			Ordered Probit
Variable Name	Support / Oppose	Strength of Preference Support	Strength of Preference Oppose	
Resid_year	+	+	+	+
Age	-		-	-
Female	+			+
House_size		+	-	
Own_home	-	-		-
Hi_educate				
Hi_income				
Envi_group				
Bus_group	+	+		+

[a] A '+' indicates a statistically significant positive effect. A '-' indicates a statistically significant negative effect.

Table 6. Summary of Statistical Results: Tool 8[a]

	Bivariate Probit			Ordered Probit
Variable Name	Support / Oppose	Strength of Preference Support	Strength of Preference Oppose	
Resid_year				
Age	-		-	-
Female		+		
House_size	-			
Own_home				
Hi_educate	+	+		+
Hi_income				
Envi_group	+	+	+	+
Bus_group			-	

[a] Tool 8 described as "purchase and preserve undeveloped land with public funds (e.g., public bond issues)." A '+' indicates a statistically significant positive effect. A '-' indicates a statistically significant negative effect.

Table 7. Nuetral Response Probit Results: Tools #1, #6, and #8

Variable Name	Tool 1 Parameter Estimate	Tool 1 Std. Error	Tool 1 p>|z|	Tool 6 Parameter Estimate	Tool 6 Std. Error	Tool 6 p>|z|	Tool 8 Parameter Estimate	Tool 8 Std. Error	Tool 8 p>|z|
Nuetrals	0.103	0.013	0.000	0.084	0.010	0.000	0.155	0.012	0.000
Res_year	-0.008	0.003	0.008	-0.010	0.002	0.000	-0.002	0.003	0.564
Age	-0.011	0.004	0.011	0.006	0.003	0.069	-0.005	0.003	0.117
Female	0.227	0.097	0.020	-0.087	0.070	0.216	0.127	0.075	0.091
House_size	-0.026	0.039	0.504	-0.011	0.028	0.683	0.003	0.030	0.917
Own	0.271	0.172	0.115	-0.286	0.124	0.021	0.117	0.125	0.348
Hi_educate	-0.051	0.105	0.629	-0.087	0.075	0.246	0.016	0.080	0.847
Hi_income	-0.069	0.102	0.496	0.017	0.073	0.813	0.017	0.079	0.827
Envi_group	0.428	0.124	0.001	0.138	0.087	0.112	-0.546	0.105	0.000
Bus_group	-0.449	0.122	0.000	-0.215	0.088	0.014	-0.160	0.096	0.097
ToolOppose	-9.425	8145906	1.000	-7.879	270290	1.000	-8.884	580160	1.000
Intercept	0.041	0.286	0.886	-0.602	0.204	0.003	-0.869	0.222	0.000
N	1948			1948			1948		
-2 LnL χ^2 (df =11)		802.54	0.001		413.11	0.001		448.48	0.001
Pseudo R^2		0.429			0.172			0.213	

Table 6. Summary of Statistical Results: Neutral Responses

Variable Name	Probit: Neutral/Preference Tool 1	Tool 6	Tool 8
Neutrals	+	+	+
Resid_year	-	-	
Age	-		
Female	+		
House_size			
Own_home		-	
Hi_educate			
Hi_income			
Envi_group	+		-
Bus_group	-	-	
ToolOppose			