Policy Implications of Econometric Specifications: An Agro-environmental Choice Experiment Application

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Abstract:

We examine the stated preferences of corn and soybean farmers in the Maumee watershed using a discrete choice experiment regarding government-sponsored incentive programs to install edge-of-field filter strips. We compare a standard conditional logit model with Latent Class Analysis (LCA) and random parameters logit models, which allow for discrete and continuous farmer preference heterogeneity, respectively. In addition to comparing coefficient and marginal willingness-to-accept estimates for these models, we also conduct policy simulations and draw two conclusions. First, models that fail to account for preference heterogeneity tend to overstate the cost of policies that are relatively small in scope and understate the cost of policies that are large in scope. Second, models that do not account for and estimate farmer heterogeneity an unable to estimate the cost savings of using rent-reducing enrollment techniques like reverse auctions.

Researchers have utilized econometric methods of analyzing discrete choice data for decades. The most popular methods involve the multinomial logit and more general conditional logit models (McFadden 1973), both of which are built upon the assumptions of random utility theory (Thurstone 1927; McFadden 1973). These early models introduced important statistical rigor to discrete choice analysis, however they also carried with them important limiting assumptions due at least partially to the computational limitations of the time. Specifically, these econometric approaches do not model unobserved preference heterogeneity. All variation in preferences is assumed to be the result of the systematic and observable components of utility included in the model specification.

In recent decades, as computational limitations have gradually receded, researchers have developed models that relax the homogeneous preference assumptions baked into the conditional logit model. Specifically, two models that allow for preference heterogeneity are in widespread use today. One of these models, the random parameters logit (or mixed logit) model, assumes that individual preference parameters are draws from a continuous distribution of preferences. This model typically makes ex-ante assumptions about the nature of this preference distribution and estimates a mean preference value in the data as well as some measure of preference dispersion. The other method in common use today, known as latent class analysis or latent class models, assumes discrete preference heterogeneity between individuals. Specifically, these models allow for a discrete number of classes. All individuals within a class have the same preferences, while preferences can vary between classes.

There is a rich literature comparing these heterogeneous preference models with the conditional logit model as well as with each other. These comparisons span a variety of disciplines, from transportation research (Greene and Hensher 2003; Hess, et al. 2011; Shen, Sakata and Hashimoto 2006; Shen 2009) and health economics (Ammi and Peyton 2016; Behnood and Mannering 2016; Hole 2008) to marketing (Allenby and Rossi 1999) and environmental economics (Greiner 2016; Campbell, et al. 2014; Colombo, Hanley and Louviere 2009; De Valck, et al. 2014; Hynes, Hanley and Scarpa 2008; Provencher and Bishop 2006; Provencher and Moore 2006; Schwirplies, et al. 2016). While these studies vary in many respects, they share the finding that heterogeneous preference models provide improved model fit relative to the conditional logit (though there is no similar consensus regarding the relative merits of random parameter logit and latent class models). As one would expect, these papers also show that relaxing the homogeneous preference assumption leads to different model estimates, both of preference parameters and of willingness-to-pay (WTP) estimates and policy simulations that are derived from these estimates. This paper highlights how the differences found in the literature understate the true differences that exist between homogeneous and heterogeneous preference models.

One plausible reason for this is that model comparisons typically are made using measures that are common in the literature (marginal WTP/WTA estimates, for instance). These and other measures common to the discrete choice literature were likely established as standard practice precisely because they don't highlight the shortcomings of the conditional logit model. In addition to these standard measures, we produce policy simulations that vary the size of the program in question and examine the effect of price discrimination in policy implementation. We hypothesize that homogeneous preference models will yield markedly different results than their heterogeneous preference counterparts under these conditions.

The rest of the paper proceeds as follows. The next section details the discrete choice data used in our analysis. This if followed by a description of the econometric models and a section detailing the results of our estimation and policy simulation. The final section concludes.

Data

Data are from a 2012 mail survey of farmers in the Maumee watershed, located primarily in northwest Ohio. We received 790 responses from a total of 2000 surveyed corn and soybean farmers (39.5% response rate). Of these, 596 indicated that they operated a farm in 2011. Many of those who responded did not complete the entire survey, so our analysis is limited to 396 farmers for whom we have no missing variables of interest. Table 1 compares demographic information for the sample of 396 and the entire farmer population for counties in the Maumee watershed (USDA, 2009). Our sample is skewed toward large farms with high gross sales. To correct this, we generate a set of farmer weights to make our sample representative of the watershed, with weighted sample demographics also presented in Table 1. For all analyses that follow, we use our weighted sample. Addresses for the targeted sample were provided by a private vendor, and were pulled from lists of farmers receiving government payments and from farming magazine rolls. The survey was conducted using a variation of the tailored design method (Dillman 2007). The total set of mailings included an announcement letter, a survey packet, a reminder letter and a replacement packet for non-responders. Those who completed the survey were entered into a raffle for one free pair of tickets to an Ohio State Buckeyes home football game. Several months before the initial mailing of the survey a pilot test was conducted with farmers recruited by local extension professionals.

The survey contained a section in which respondents were asked to "Consider one of your fields where runoff is a potential problem and where no filter strip exists." The survey then asked a series of questions regarding basic field attributes, including the field's distance from the nearest surface water, slope, soil type, and whether the field had working drainage tile. Following this section, the survey read,

> "Consider a situation where there is a voluntary program to establish *filter strips*. Sufficient state and federal funds are available to ensure that all applicants will be enrolled. Two options are available. Both options feature *100% reimbursement of the costs* for establishing the entire filter strip plus an annual rental payment detailed below."

The survey then detailed two filter strip programs and asked respondents to rank these two programs and their current program (i.e., a status quo option, which featured no filter strip program) as "best," "middle," and "worst." All filter strip programs allowed for mowing and specified that inspections will be annual and announced. The programs differed, however, in filter strip width (25 or 75 feet), paperwork burden (two, five or ten hours per year), annual rental payment (125, 175, 200 or 250 dollars per acre), and program length (five or ten years). Given the mail-survey format allowed for limited survey length, each respondent was presented two choice sets, each featuring two filter strip programs along with the status quo option. Each choice set featured one program with a 25-foot filter strip and one with a 75-foot filter strip with the order of appearance (first or second program presented) randomized. Program length was identical for the two programs within each choice set, but each respondent saw one pair of choices where both featured a 10 year length and one pair of choices where both featured a 5 year length with the order of appearance (first or second set) randomized. Finally, paperwork burden and annual rental payment levels were chosen such that each program within a choice set featured levels different from one another. We employ a full factorial experimental design, after applying the previously mentioned restrictions.[1] The survey also collected basic demographic information as well as less common farmer- and farm-level attributes, including risk tolerance and enrollment in current government-sponsored conservation or BMP programs.

Econometric Model

We adopt the random utility model, specifically that utility obtained from individual *n* choosing alternative *j* is comprised of a systematic element, denoted *V*, and a random error term ε, so the following equation holds:

$$U_{ni} = V_{nj} + \varepsilon_{nj} \tag{4}$$

We begin by describing the conditional logit model. This model assumes preference homogeneity, meaning it assumes there is a single preferences parameter shared by the population for each estimable variable in the model. Assuming the error terms are i.i.d. with a type 1 extreme value distribution and homogeneity of preferences, the probability that a farmer will choose policy alternative *j* as the best (or highest ranked) from a set of policy alternatives $\{1,\ldots, J\}$ is given by

[1] The full factorial experimental design should allow us to accurately estimate all main effects and interaction effects (Louviere *et al*. 2000). However, because we do not receive responses from every farmer solicited, we most likely do not have data on the full factorial. This would likely lead to inefficient experimental design, and could potentially bias estimates. However, given the random nature of choice set assignment to each potential respondent, the gaps in our full factorial design should also be random. This will possibly lead to an inefficient design, but is not likely to systematically bias our estimates in any particular direction.

$$Pr_n(j) = \frac{exp(\beta' X_{nj})}{\sum_{k=1}^{J} exp(\beta' X_{nk})}, \tag{5}$$

where X_{nj} is a vector of attributes associated with program j for farmer n and β is the vector of estimated coefficients associated with these attributes. Farmer responses in our survey gave a ranking, but for the purposes of this model we convert this ranking to an indicator variable equal to one if the program is considered the best and zero otherwise.

The assumption of farmer homogeneity has been repeatedly shown to be impractical (CITE). We next consider two models, the latent class model (Bhat 1997; Birol *et al*. 2006; Columbo, Hanley and Louviere 2009) and the random parameters or mixed logit model (Train 1998, 2009; McFadden and Train 2000), which allow for discrete and continuous preference heterogeneity, respectively. With both heterogeneous preference models, it is standard practice to assume that an individual decision maker's preferences stay constant over the full set of choices they make. Heterogeneity is only modelled through preference variation between decision-makers.

The latent class model estimates preference parameters for a discrete number of classes. Preferences within a specific class are homogeneous, but preferences are allowed to vary across classes. Under these assumptions, the probability that a farmer n will choose policy alternative j, conditional on the farmer belonging to class s, is given by

$$Pr_n(j \mid s) =, \frac{exp(\beta_s' X_{nj})}{\sum_{k=1}^{J} exp(\beta_s' X_{nk})} \tag{6}$$

where β_s is the vector of estimated coefficients associated with attributes X_{nj} in class s. We additionally use respondent-specific characteristics to inform the probability that farmer n belongs to class s. This probability is given by

$$Pr_n(s) = \frac{exp(\gamma_s Z_n)}{\sum_{s=1}^{S} exp(\gamma_s Z_n)}, \tag{7}$$

where Z_n is a vector of respondent-specific farmer and field characteristics and γ_s is a vector of coefficients associated with class *s*. Equation (6) describes a conditional logit model, where choice probabilities are determined by choice-specific attributes, while equation (7) is a multinomial logit model, where class probabilities are determined by individual-specific attributes (McFadden 1973). The unconditional likelihood that farmer *n* will choose a set of *T* policy alternatives *j* is

$$L_{LCA} = \sum_{s=1}^{S} \mathrm{Pr_n}(s) * \left(\prod_{t=1}^{T} \mathrm{Pr_n}(t = j \mid s) \right) . \tag{8}$$

The random parameters logit model also models heterogeneous preference parameters. Specifically, the vector of preference parameters is assumed to follow a random distribution described by Ω. Under this formulation, the probability that farmer *n* will choose policy alternative *j* is given by

$$Pr_n(j \mid \Omega) = \int_{\beta} Pr_n(j) f(\beta \mid \Omega) d\beta, \tag{9}$$

Where $Pr_n(j)$ is as defined in equation (5) and f (β | Ω) is the density function for the preference parameter vector. The unconditional likelihood that farmer *n* will choose a set of *T* policy alternatives *j* is then given by

$$\mathrm{L_{RPL}} = \int_{\beta} \left[\prod_{t=1}^{T} \mathrm{Pr_n}(t = j) \right] f(\beta \mid \Omega) d\beta. \tag{10}$$

In our model, we assume all preference parameters are normally distributed with the exception of program payment, which we assume follows a lognormal distribution. The model then estimates two distribution parameters for each attribute, a mean value for the preference parameter and a dispersion parameter which estimates the standard deviation for the preference parameter distribution.

Program attributes (X_{nit}) in our model are outlined in Table 2. They include the annual per-acre rental payment offered for land converted to filter strips, the required filter strip width in feet, the annual paperwork burden, measured in hours, associated with the program, the program length in years, and an alternative-specific constant denoting whether the choice was the status quo of not enrolling[2]. In the results that follow, we will compare marginal willingness-to-accept estimates from our three models. We will additionally examine four distinct sets of program cost estimates which we derive from the three models. These four estimates include a conditional logit estimate which assumes preference homogeneity; a random parameters logit estimate with continuously distributed preference parameters; a discrete latent class estimate in which each farmer is assumed to have preference parameters associated with the class they are most likely to be a member of (based on equation (7)); and a discrete-continuous latent class estimate. This estimate uses the latent class model, but in this formulation each farmer's preference parameters are estimated as a linear combination of the all class parameters, weighted by the farmer's estimated probability of membership in each class (again based on equation (7)).

Results

Coefficients and Marginal Willingness-to-Accept

[2] As there are three alternatives, it is possible to include two alternative specific constants. We chose to include only one on the basis that we don't expect any systematic difference between Program A and Program B, especially one that would influence the estimated coefficients of our variables of interest.

The estimations that follow in this section are obtained using Stata 14.2 statistical software. Table 3 presents side-by-side results from conditional logit (CL), latent class logit (LCL), and random-parameters logit (RPL) models. When using the latent class model, we find specifying two classes provides the best fit for our data by virtue of minimizing the BIC.[3] The CL, RPL, and majority class of the LCL (representing 68% of the data) all find that utility is increased by increasing payment and decreasing paperwork and filter strip width. While the signs of these coefficients are similar for the minority class in the LCL model, only the coefficient for paperwork is statistically significant.

Program length has no significant impact in the CL and in both classes of the LCL models, while the RPL model finds a positive effect of program length on utility. The status-quo ASC, which measures preference for no program after controlling for program attributes, is positive, suggesting a general preference against opting into PES programs, for both the CL and RPL models. For the LCL model, the majority class has a significant negative coefficient (indicating a preference for program enrollment) while the minority class exhibits a significant positive status-quo coefficient. An examination of respondent-specific covariates in Table 4 reveals substantial differences between the majority and minority classes. The majority class, with its tendency toward program enrollment, has a higher education level (a lower proportion have a high school diploma or less), is less likely to engage in conventional tillage practices, is younger, and is more likely to already be enrolled in other conservation programs. Further, farmers in the majority class are more likely to have fields with a high slope, indicating greater erodibility potential. Lastly, while both classes have a similar proportion of farmers who classify themselves as willing to take risks in

[3] The two class model has a BIC of 1286.26. The BIC for three through class models are 1299.35, 1349.56, 1427.42 and 1443.09, respectively. Nylund *et al*. (2007) use Monte Carlo simulations to show that the BIC outperforms all other information criteria measures at predicting number of classes for LCA.

general, the majority class has a significantly higher proportion of farmers who are willing to take risks specifically in the realm of farming decisions.

The mixed logit model additionally estimates dispersion parameters for each attribute and finds significant heterogeneity for all variables except paperwork and the status-quo ASC. Goodness-of-fit statistics in Table 3 suggest that the RPL model provides the best fit for the data by virtue of maximizing log-likelihood as well as minimizing the Bayesian and Akaike Information Criteria. While it provides a worse fit than the RPL model, the LCL model still outperforms the homogeneous preference model.

Table 3 also displays marginal WTA estimates for filter strip width, paperwork and program length attributes. This measure is estimated as the negative ratio of the coefficient for the attribute in question to the coefficient for program payment. Statistical significance, obtained using the delta method, closely mirrors that of coefficient estimates. Across models, a one foot increase in filter strip width must be accompanied by an increase in per-acre annual payment of $1-2, while a one hour per-year increase in paperwork associated with the contract requires between $7 and $9 more in per-acre payment. As the RPL model predicts a preference for longer contracts, this model predicts that increasing contract length by one year can be combined with a decrease of $23 in annual payment. WTA values for the minority class in the LCL model are not statistically significant. This is likely a consequence of the non-significant effect of the payment coefficient.

These findings resemble those found in previous research: heterogeneous preference models outperform homogeneous preference models, but while there are clear differences between models, these differences are generally relatively minor. The issue with these analyses is that they tend to focus on comparing marginal changes around average affects. This focus, while it may uncover some differences between models, is unlikely to fully capture the important nuance lost when s model fails to account for distributional preference heterogeneity. A naïve policy-maker may examine these findings and reasonably conclude that, for policy purposes, these models make similar predictions about farmer receptiveness to filter strip programs and, by extension, the costs of implementing such a program. A more useful comparison, for the purposes of program design, would be a between-model comparison of the *total cost* of various programs. We perform this comparison in the next section.

Policy Simulation

With the goal of generating a relevant policy simulation for the region, we draw from the Ohio EPA's Western Lake Erie Basin Collaborative Implementation Framework document (Ohio EPA 2017). This document describes the Western Lake Erie Basin (WLEB) Initiative, which allocates $77 million in funding over three years for the purpose of reducing nutrient pollution in the WLEB. The document further cites an Ohio Department of Agriculture goal of "voluntarily establishing 67,000 acres of filter strips, riparian buffers, hardwood tree plantings, wildlife habitat and field windbreaks." (Ohio EPA 2017, p. 12). As filter strips are one component of this plan, we simulate the cost of using a voluntary PES filter strip program to achieve a subset of this 67,000-acre goal over three years. We specify the program to offer a three-year contract in which farmers establish a 25-foot filter strip on their field. We also specify an annual paperwork burden of five hours associated with the contract.

The primary purpose of our policy simulations is to generate a between-model comparison. For each model, estimating total program costs requires estimating individual contract costs for respondents in the sample and effectively extrapolating these sample costs to the entire watershed. The first step requires assigning preference parameters to each respondent. Using the CL, RPL, and LCL models, we generate four sets of these individual-specific preference parameter estimates. The CL model, as a homogeneous preference model, assigns the same preference parameter to each respondent. The RPL model generates preference parameter estimates as draws from the estimated normal[4] parameter distributions. The LCL model generates two different sets of estimates. One, which we denote discrete LCL (or LCL-D), assigns preference parameters for the class that the respondent has the highest estimated probability of belonging to. A separate estimate, which we denote probabilistic LCL (or LCL-P), assigns a preference parameter equal to the probability-weighted linear combination of class parameters.

Using these four sets of individual preference parameters, we estimate four minimum WTA values for each farmer by equalizing the utility associated with the program in question with utility from the status-quo option and solving for program payment. The equation below shows this equality:

$$\beta_{width}*25 + \beta_{paper}*5 + \beta_{years}*3 + \beta_{payment}*WTA = \beta_{StatusQuo}. \tag{11}$$

Rearranging this equality to solve for WTA yields:

$$WTA = \frac{\beta_{StatusQuo} - (\beta_{width}*25 + \beta_{paper}*5 + \beta_{years}*3)}{\beta_{payment}}\ . \tag{12}$$

This is a minimum WTA. It is possible that some farmers have a negative value for WTA. This can be interpreted as farmers who are willing to enroll in the program even if there was only a

[4] or lognormal in the case of program payment.

cost-share component to it. For these farmers, we set minimum WTA at zero. As many PES contracts are not designed to elicit prospective enrollees' minimum WTA, we further assume farmers may receive payments above their minimum WTA. The specific mechanics of this are described below.

Total program cost consists of three components: filter strip installation cost-shares, filter strip acreage rental payments, and technical assistance costs. For installation cost share estimates, we follow Ohio EQIP, which lists the cost of installing grass filter strips at $120.80 per acre for the 2018 fiscal year (Ohio EQIP 2017). Regarding rental payments, WTA estimates from equation (12) can be interpreted as the minimum annual per-acre rental payment needed to enroll a given farmer in the PES program. Total rental payments equal the annual rental payment multiplied by the three-year length of the contract. We estimate technical assistance costs to be 20% of total contract payments (rental payments plus cost share), following the practice outlined by the Ohio, Indiana, and Michigan Natural Resources Conservation Service in their assessment of the Western Lake Erie Basin (NRCS 2009).

In order to extrapolate from the sample to the watershed, we compare the acreage represented in the sample to total agricultural acreage in the Maumee watershed. The entire sample represents 38,181.8 acres, while the Maumee watershed contains 2,835,839 total acres in agriculture. Using these figures, each acre in the sample represents 74.27 acres in the watershed. We use this value as a sample-to-watershed multiplier when extrapolating impacts (acreage enrolled and program costs) from the sample to the watershed.

In addition to considering these four sets of model estimates, we run our simulation under a series of watershed acreage goals (specifically, 3,350 acres, 6,700 acres, 13,400 acres, and 26,800 acres, which are 5%, 10%, 20%, and 40%, respectively, of the 67,000-acre total goal) and under two different assumptions regarding the ability of farmers to extract rents from the program (or, conversely, the extent to which program officers can price discriminate in their design of PES contracts). In one series of simulations, we assume policy-makers have no ability to price discriminate, meaning they must offer a single per-acre payment to all farmers. We then identify the minimum payment that would enroll enough acres to achieve our goal. This payment is paid to all farmers with WTA at or below the payment level, and thus any farmers with WTA below the payment level receive rents (or surplus payments) from the contract. In another series of simulations, we allow for partial price discrimination. Specifically, we allow the policy-maker to offer individualized payments to farmers. We assume the policy-maker does not have full information on farmer WTA, and so cannot perfectly price discriminate, but instead we allow the policy maker to eliminate 50% of the surplus paid to farmers under the single-payment simulations.

Table 5 provides policy simulation results. The first key trend is that there is substantial variation between estimated cost of the homogeneous preference model (CL) and the heterogeneous preference models. This stands in contrast to estimates of marginal WTA, where homogenous/heterogenous model disparities were on a much smaller order for several individual program attributes. Also noteworthy, and similar to what intuition would suggest, is that the there is no persistent gap between CL and the heterogeneous preference models. Instead, CL program cost estimates are substantially larger than the other models when considering relatively small-scale programs and substantially smaller than the other models when comparing the larger-scale programs. This follows intuition because the CL model miss-specifies both the low- and high-WTA portions of the data, assuming instead that every farmer has relatively moderate WTA.

Table 5 also illustrates how the models make different predictions of the cost saving effects of price discrimination. A homogeneous preference model like CL specifies that all farmers have the same minimum WTA. In this scenario, there are no surplus payments to be had by farmers, so follows that the model would find no cost reductions as a result of price discrimination on the part of the policy-maker. Conversely, models that accommodate preference heterogeneity can also estimate the surplus that accrues to farmers from a single-payment policy and find substantial cost reductions from price discrimination, especially for large-scale programs where the marginal program participant is likely to have very high WTA. The LCA-D model provides a curious example. It is a heterogeneous-preference model that finds no cost reductions from price discrimination for all but the largest programs considered here. This is a function of the discrete nature in which heterogeneity is captured in this model. The majority class in this model, by virtue of a large and statistically significant negative coefficient for the status-quo ASC, produced negative minimum WTA estimates for all farmers in the class. In this model, it is possible to reach the 5%, 10% and even 20% acreage goal by enrolling only farmers who fall into this class. As such, total program cost for these simulations is made up of only cost shares and technical assistance costs. Since these costs are not affected by our modelling of price discrimination, we find no cost reductions from price discrimination until the 40% acreage goal, at which point we start enrolling farmers in the minority preference class.

Conclusion

This is a preliminary draft. Draw your own conclusions.

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Table 1: Demographic Comparison

Variable		Sample	Maumee	Weighted Sample
Planted Acres (% in each Category)	1-9	6.0	8.6	8.5
	10-49	16.4	27.2	27.5
	50-179	33.6	31.3	31.7
	180-499	24.8	19.7	18.8
	500 plus	19.2	13.3	13.5
Farm Gross Sales (% in each Category)	Less than 50k	32.0	54.5	50.2
	50k-100k	15.4	10.6	13.1
	100k plus	52.6	34.9	36.7

Table 2: Program-, Individual-, and Field-Specific Variable Summary Statistics

Variable	Description	Mean	Standard Deviation	Min/Max
Program-Level Attributes				
Payment	$US per acre	124.96	96.13	0/250
Width	Filter strip width in feet	33.19	31.14	0/75
Paper	Hours of paperwork per year	3.75	3.78	0/10
Years	Program length	5.01	4.09	0/10
StatusQuo	Alternative specific constant for = current field use	0.33	0.47	0/1
Individual- and Field-Level Attributes				
HighRiskFarm	= 1 if risk tolerant in farming	0.24	0.43	0/1
HighSchool	= 1 if high school education or less	0.41	0.49	0/1
Conventional Till	= 1 if use conventional tillage	0.28	0.45	0/1
Age40	= 1 if 40 or younger	0.25	0.43	0/1
Enrolled	= 1 if enrolled in other conservation programs	0.55	0.50	0/1
HighRiskGen	= 1 if risk tolerant in general	0.35	0.48	0/1
High Slope	= 1 if slope is more than 5 degrees	0.12	0.33	0/1

Notes: Summary statistics calculated using the weighted data sample.

Table 3: Latent Class Analysis Coefficients and Marginal Effects with Weights

Variable	Coefficients					Marginal WTA			
	Conditional Logit	LCA: Class 1 [66.2%]	LCA: Class 2 [33.8%]	Mixed Logit Mean	Mixed Logit Sd Dev	Conditional Logit	LCA: Class 1 [66.2%]	LCA: Class 2 [33.8%]	Mixed Logit
Payment	0.0109*** (< 0.005)	0.0143*** (< 0.005)	0.0177 (0.180)	0.0330*** (< 0.005)	0.0198** (0.010)	-	-	-	-
Width	-0.0177*** (< 0.005)	-0.0164*** (< 0.005)	-0.0298 (0.274)	-0.0484*** (< 0.005)	0.0695*** (< 0.005)	$1.63*** (< 0.005)	$1.14*** (< 0.005)	$1.69 (0.342)	$1.47*** (< 0.005)
Paper	-0.0854*** (< 0.005)	-0.1170*** (< 0.005)	-0.2310** (0.013)	-0.3032*** (< 0.005)	0.1088* (0.061)	$7.87*** (< 0.005)	$8.16*** (< 0.005)	$13.04 (0.164)	$9.18*** (< 0.005)
Years	-0.0142 (0.422)	-0.0735 (0.923)	-0.0122 (0.972)	0.7634** (0.013)	1.5466*** (< 0.005)	$1.31 (0.420)	$5.13 (0.922)	$0.69 (0.971)	-$23.12*** (0.003)
StatusQuo	0.6541** (0.032)	-2.2593*** (0.763)	4.053** (0.034)	3.211** (0.017)	0.2143 (0.615)	-	-	-	-
BIC	1501.43	1275.04		1252.79		1501.43	1275.04		1252.79
Log-L	-731.33	-583.68		-587.62		-731.33	-583.68		-587.6237
AIC	1472.66	1203.37		1195.25		1472.66	1203.37		1195.25

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% confidence level, respectively. Values in brackets are the percent of the sample that falls in each given class. P values in parentheses. Inference for Payment parameters in the Mixed Logit model as well as all marginal WTA estimates are obtained using the delta method. As the Payment variable is assumed to have a lognormal distribution, the mean effect is estimated as $e^{\mu+\frac{\sigma^2}{2}}$ and the standard deviation is estimated as $\sqrt{(e^{\sigma^2}-1)*e^{2\mu+\sigma^2}}$, where μ and σ are the estimated mean and standard deviation parameters, respectively. BIC and AIC are the Bayesian Information Criterion and Akaike Information Criterion statistics, respectively, for which a lower value implies a superior model fit. Variable definitions are provided in Table 2. In the mixed logit model, all variables have a normal distribution except for Payment, which has a log normal distribution.

Table 4: Mean Values of Farmer-Specific Covariates by Class

Variable	Class 1 (Environmental Stewards)	Class 2 (Others)	P-value (difference)
HighSchool***	0.3720	0.4876	< 0.005
ConventionalTill***	0.1835	0.3908	< 0.005
Age40***	0.2909	0.1714	< 0.005
Enrolled***	0.6285	0.4955	< 0.005
HighRiskGen	0.3929	0.3883	0.8960
HighRiskFarm***	0.3008	0.2054	< 0.005
High Slope***	0.1338	0.0552	< 0.005

Notes: *, **, and *** indicate that differences in mean values between classes are significant at the 90%, 95%, and 99% confidence level, respectively. Variable definitions are provided in Table 2.

Table 5: Policy Simulation

	CL	LCA-D	LCA-P	MixL
	No Price Discrimination			
5% of goal (3,350 acres)	$2,258,265	$517,623	$489,839	$646,126
10% of goal (6,700 acres)	$4,521,044	$1,100,188	$1,455,610	$1,643,337
20% of goal (13,400 acres)	$8,915,954	$2,114,002	$4,478,496	$4,170,967
40% of goal (26,800 acres)	$17,818,340	$36,907,434	$23,355,042	$41,545,540
	50% Surplus Reduction Price Discrimination			
5% of goal (3,350 acres)	$2,258,265	$517,623	$489,839	$542,479
10% of goal (6,700 acres)	$4,521,044	$1,1000,188	$1,245,751	$1,409,342
20% of goal (13,400 acres)	$8,915,954	$2,114,002	$3,670,400	$3,597,220
40% of goal (26,800 acres)	$17,818,340	$21,942,088	$16,742,110	$27,546,021

Notes: