A Nationwide Comparison of Farmland Conservation Easement Valuation

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Abstract

Farmland loss is considered a serious problem by the public, and it is in part addressed by government initiatives to preserve farmland through the use of conservation easement programs. In order to prioritize which tracts are protected with these programs, it is important to understand and measure the non-market benefits of agricultural land. The contribution of this work is to provide national-level estimates of benefits as well as examine the possibility of geographic heterogeneity in preferences across states. This study uses choice experiment data on farmland attributes in the US, Georgia, Ohio and Maine. Sample selection was tested for and rejected. A random parameters logit model was estimated and significant preference heterogeneity was confirmed. This result indicates that although some variables may seem insignificant, they may actually be important to many individuals, but those individuals simply don't agree on the value of those attributes. Consequently, a broad-based funding mechanism such as taxes may be less popular than more targeted mechanisms. After testing for scale and parameter equality, it was found that the US and Maine had different underlying parameters, which indicates that federal-level policy may be inappropriate, as some states may have different preferences for which farmland attributes should be prioritized.

1 Introduction

Farmland loss is a serious problem to the public and the policymakers of the US. Since 1982, 14 million acres of prime farmland in the US has been lost, mostly to development (US Department of Agriculture, 2009). Public concern about farmland loss and development is reflected in the popular press with headlines decrying sprawl and praising preservation (Hellerstein et al., 2002). Policymakers have responded at all levels of government, creating farmland protection initiatives and measures against sprawl (Hellerstein et al., 2002).

Government intervention is justified on the basis of market failures due to the externalities agricultural land generates. Agricultural land has many non-market benefits, from cultural benefits such as maintaining the agricultural character of a region, to environmental benefits such as protecting water quality and biodiversity (Hall et al., 2004). Many of these non-market benefits have a public good nature, because they are non-excludable and non-rival (e.g., scenic views of

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the rural landscape). These non-market benefits are so well known that the term 'multifunctional agriculture' has arisen to describe the diversity of outputs agriculture can provide. The term has garnered so much attention in Europe that "multifunctionality has been identified as the way forward for European agriculture" (Hall et al., 2004), and it is emerging as an important issue in international trade (Moon and Griffith, 2011). As such, there is a pressing need to specifically identify and measure the public demand for the non-market outputs of agriculture (Hall et al., 2004; Moon and Griffith, 2011).

One form of farmland protection governments have instituted are conservation easement programs. In these programs, the farmland owner voluntarily and permanently retires development rights to a tract of his land in return for a lump sum payment or income tax deduction (Nickerson and Hellerstein, 2003). To optimize this form of protection, we need to know which farmland to prioritize, based on the non-market benefits it provides and the public preferences for different rural amenities. Hence, there is a need at all levels of government – state, local, national and international – to understand public preferences for non-market benefits of agriculture.

The last 30 years have seen a growing literature on answering that need (Bergstrom and Ready, 2009). The literature includes both stated preference and revealed preference methods; the latter includes a strong history in contingent valuation and more recently in choice experiments. These studies have found strong evidence that the public values farmland with more farmland acreage, regional farmland scarcity, alternative development intensity, public accessibility and productivity, and that individuals with greater income, age, education, visits to open or green space in the past and experiences with farms and farming tend to value farmland more (Bergstrom and Ready, 2009).

Despite a rich literature on public preferences for farmland, almost no studies have been conducted above the state level. It is important to conduct studies at the national level so that national support for farmland protection can be measured. This national support can then be represented in international relations, as the importance of multifunctional agriculture is represented in European trade talks, and can also be compared against federal spending on farmland protection, to check the appropriateness of the spending level. The only national-level study to date is a contingent valuation study which found an annual willingness-to-pay of $515 per taxpayer (Moon and Griffith, 2011). However, the authors admit that this measurement is too general to indicate where the money should be spent because it lacks detail about public preferences: which non-market benefits the public desire, how much of them and how good they should be.

It is also important to conduct studies across different states in order to account for geographic heterogeneity. Geographic heterogeneity could have important implications for regional customization of conservation easement programs, with each region having a custom list of priorities for conservation. If such heterogeneity is significant, then a one-size-fits-all policy approach at the federal level would be inappropriate. Instead, regionally-based programs which take into account the heterogeneity would be more efficient. The only study to date which considers more than one state compares only one pair of states and did not find them to be significantly different (Johnston and Duke, 2007). As a consequence, the study did not focus on the effects of geographic heterogeneity.

This study adresses both gaps in the literature by using national-level and state-level choice experiment data from three different state, each in a different region of the US. National-level choice experiment data allow for a more detailed look at public preferences for specific attributes of protected farmland. Data from three states in different regions of the US allow for three pairwise comparisons and provide stronger evidence about the presence or absence of geographic heterogeneity.

2 Literature review

In recent years, several excellent reviews of the farmland amenity valuation literature have been written (Bergstrom and Ready, 2009; Hall et al., 2004; Hellerstein et al., 2002; McConnell and Walls, 2005).

The seminal studies on estimating non-market benefits of farmland were contingent valuation studies (Halstead, 1984; Bergstrom et al., 1985; Beasley et al., 1986). Many more contingent valuation studies followed (see Bergstrom and Ready, 2009, for a complete list). These studies were all conducted in different regions in the US, but not the west coast. In these contingent valuation studies, models of valuation were based primarily on characteristics of the respondent, although some studies included alternative land uses that threatened farmland. In contrast, choice experiment studies allow a rich exploration of public WTP as a function of farmland attributes.

Two county-level choice experiment studies compared results from the hedonic price method to conjoint analysis. Accordingly, the choice scenarios in these studies were somewhat different from the format typical of later studies. In Johnston et al. (2001), respondents were asked to choose between two conservation programs. The three program attributes were the program cost and the amount of land remaining for each of two resources. In total, there were five resources in the experimental design: farmland, undeveloped land, wetlands, safe shellfishing areas and eelgrass. Program choice was modelled with conditional logit models. In Roe et al. (2004), respondents were asked to choose between houses rather than conservation easement programs. In this case, the farmland attribute was a neighbourhood attribute, and thus the choice experiment measured the value of proximity to farmland. Housing choice was modelled with a probit model.

Later choice experiment studies all asked respondents to choose between conservation easement programs. Two Delaware studies examined WTP by farmland attributes. In Duke and Ilvento (2004), the attributes included program cost, size of land conserved, land use allocation between cropland, forest cover and wetlands, and rate of development. Program choice was modelled with tobit models and grouped models. In Duke et al. (2007), the attributes included type of purchase (outright or easement), risk of development, type of use (poultry, vegetable, forest, grain or forest).

Two studies used data from two different states, Connecticut and Delaware. Johnston and Duke (2007) examined the effect of policy process attributes on public preferences, such as policy technique (preservation contract, outright purchase or conservation zoning) and implementing agency (state or land trust). Other attributes included acreage, land type (active farmland, differentiated among nursery, food crop, dairy and livestock; idle farmland, forest), public access (none, walking/biking, hunting), likelihood of development, and program cost. In this study, separate conditional logit models were estimated for the Connecticut and Delaware datasets, but the difference in parameter estimates was not significant, so the datasets were later pooled for a random parameters logit model. Johnston and Duke (2009) used the same dataset and random parameters logit model to examine the validity of benefit transfer across jurisdictional scales and across states.

A number of studies have used the same dataset that this study uses, although none of have used more than a single state in their analysis. The dataset includes data from Maine, Ohio, Georgia and the US. The attributes included in the survey were farmland use priority (hay, vegetables, pasture, forest, no priority), farmland location priority (near urban areas), land quality priority (prime farmland), acreage, and program cost. Özdemir (2003) and Boyle and Özdemir (2009) used the Maine dataset to investigate methdological questions about the design of choice scenarios and WTP with respect to farmland attributes. Volinskiy and Bergstrom (2007) and Johnston and Bergstrom (2011) used the Georgia dataset to develop a random parameters logit model with refinements and demonstrate the sensitivity of specification of random parameters logit models, respectively.

3 Analysis framework

Choice refers to whether an individual i chooses or does not choose an alternative j. In this paper, choice is modelled primarily by a binary outcome model, the probit model, and additionally by a multinomial model, the random parameters logit model. Using the probit model, econometric concerns such as sample selection and scale parameter comparison are addressed. The random parameters logit model is used to allow for correlation within individuals and preference heterogeneity across individuals.

3.1 Binary outcome model

A binary outcome model can be interpreted as a latent variable model, where there is an underlying unobserved continuous variable, but what is observed is a binary variable whose value depends on whether the continuous variable crosses a threshold:

$$y_{ij}^* = \beta x_{ij} + \epsilon_{ij} \tag{1}$$

$$y_{ij} = \begin{cases} 0, & \text{if } y_{ij}^* \leq 0 \\ 1, & \text{if } y_{ij}^* > 0 \end{cases} \tag{2}$$

where y_{ij}^* is the unobserved latent variable for individual i and alternative j, y_{ij} is the observed variable which takes on value 1 if individual i chooses alternative j and 0 otherwise, and ϵ_{ij} is the error. The distribution assumed for the error determines the particular model; in this case, we assume $\epsilon_{ij} \overset{\text{iid}}{\sim} N(0,1)$, the error form for the probit model.

3.2 Sample selection

Sample selection occurs when the observed sample is not representative of the desired population. It may arise when samples are based, intentionally or unintentionally, on the choices respondents make and nonrespondents would make (e.g., those who tend to support conservation easement programs may be more likely to respond). It can have serious consequences for the reliability of inferences when the causes of sample selection are correlated with the inferences in question, causing inconsistent parameter estimates. In this study, the presence of sample selection bias is evaluated with a Heckman-style bivariate probit model.

In the Heckman-style sample selection models, sample selection is modelled using two latent variable equations, the selection equation and outcome equation, which are allowed to have correlated errors. The selection equation determines respondents and non-respondents in the sample, and the outcome equation determines choices made by the respondents, acknowledging that choices made by non-respondents are not observed.

$$\begin{aligned}
y_{is}^* &= \beta_s x_{is} + \epsilon_{is} && \text{(selection equation)} \\
y_{is} &= \begin{cases} 0, & \text{if } y_{is}^* \leq 0 \\ 1, & \text{if } y_{is}^* > 0 \end{cases} \\
y_{ijo}^* &= \beta_o x_{ijo} + \epsilon_{ijo} && \text{(outcome equation)} \\
y_{ijo} &= \begin{cases} -, & \text{if } y_{is}^* \leq 0 \\ 0, & \text{if } y_{is}^* > 0 \text{ and } y_{ijo}^* \leq 0 \\ 1, & \text{if } y_{is}^* > 0 \text{ and } y_{ijo}^* > 0 \end{cases}
\end{aligned}$$

where y_{is}^* and y_{os}^* are the latent selection and outcome responses, respectively, and y_{is} and y_{ijo} are the observed selection and outcome responses, respectively. y_{is} takes on value 1 if individual i is a respondent and 0 if a non-respondent. y_{ijo} takes on value 1 if individual i chooses alternative j, 0 if not, and is unobserved if the individual is not a respondent. Thus, y_{ijo} and x_{ijo} are only observed when $y_{is} = 1$.

Following the bivariate probit model, the error terms are assumed to be homoskedastic and jointly distributed as a standardized bivariate normal:

$$\begin{bmatrix} \epsilon_{is} \\ \epsilon_{ijo} \end{bmatrix} \overset{\text{iid}}{\sim} \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho' & 1 \end{bmatrix} \right)$$

where ρ is the covariance between ϵ_{is} and ϵ_{ijo}. If $\rho = 0$ then there is no sample selection and the two probit models can be estimated separately without inconsistency. Hence, the test for sample selection is a test of $\rho = 0$.

Note that the outcome equation in the sample selection model is identical to Equation 1, the original probit model. This sample selection model extends the original probit model to incorporate the presence of sample selection model.

3.3 Scale parameter comparison

One important limitation of the probit model is that the variance σ of the errors ϵ_{ij} cannot be identified because it is confounded with the model parameters. This unidentifiability is why the model specification normalizes the variance to 1. To see why the confounding occurs, consider, for example, $\Pr(y_{ij} = 1|x)$:

$$\begin{aligned}\Pr(y_{ij} = 1|x) &= \Pr(\beta x_{ij} + \epsilon_{ij} > 0) \\ &= \Pr(\epsilon_{ij} > -\beta x_{ij}) \\ &= \Phi\left(\frac{\beta x_{ij}}{\sigma}\right)\end{aligned}$$

Hence, the estimated coefficients are actually β/σ and not β. Since σ may vary across different datasets, comparison of probit estimates for different regions would be misleading without taking into account the possibility of differences in scale parameter.

Swait and Louviere (1993) describe a simple procedure to test whether observed parameter estimate difference occur because σ is different between two datasets. Swait and Louviere (1993) use the multinomial logit model to explain the importance of the normalized parameter, which in the MNL case is the scale parameter of the Gumbel distribution, μ. However, the same issue applies to the probit model as explained above.

The hypothesis of interest is

$$H_1 : \beta_1 = \beta_2 \text{ and } \sigma_1 = \sigma_2$$

where the subscripts indicate two datasets. The Swait-Louviere procedure tests H_1 in two stages:

$$\begin{aligned}H_{1A} &: \beta_1 = \beta_2 \\ H_{1B} &: \sigma_1 = \sigma_2\end{aligned}$$

H_{1A} tests for the equality of coefficient estimates while allowing for different scale parameters. In particular, an optimal value for σ_2 is found relative to σ_1 using log-likelihood values, and using this optimal value, H_{1A} is tested.

If H_{1A} is rejected, then H_1 is also rejected. If H_{1A} fails to be rejected, then H_{1B} is tested. H_{1B} tests for the equality of scale parameters, again by using the optimal value of σ_2 relative to σ_1. If H_{1B} is rejected, then H_1 is also rejected. Note that only in the case that H_{1A} is not rejected can the optimal σ_2 be interpreted as the ratio of the error variances of the two datasets.

Both subhypotheses are tested using likelihood ratio tests, which are summarized in Table 1. The table describes the notation for likelihood values under different assumptions about σ and the restricted and unrestricted models used to test each subhypothesis.

Thus, the test statistics for each subhypotheses are given by

$$-2\left(L_\sigma - (L_1 + L_2)\right) \sim \chi^2(k+1) \tag{H_{1A}}$$

$$-2(L_p - L_\sigma) \sim \chi^2(1) \tag{H_{1B}}$$

where k is the number of parameters in β_1 (or β_2).

3.4 Multinomial model

In addition to modelling choice with a binary outcome model, a multinomial model is also used. The random parameters logit model is a popular choice amoung multinomial models because of its flexibility of specification and comparatively relaxed assumptions compared to the traditional conditional logit and multinomial logit models. It can be viewed as a generalization of the conditional logit model which allows for individual preference heterogeneity, unrestricted substitution patterns between alternatives, and correlation between choices made by a given individual.

The random parameters logit model follows from the random utility model framework, where the utility of individual i choosing alternative j is specified as

$$U_{ij} = V_{ij} + \epsilon_{ij}$$

where V_{ij} is the systematic utility, the deterministic component of U_{ij}, and ϵ_{ij} is the error, the random component of U_{ij}. ϵ_{ij} is assumed to be iid and follow the type I extreme value distribution, as in the case of conditional logit models. It is usually the case that $V_{ij}(\cdot)$ is linear in parameters, so that

$$V_{ij} = X_{ij}'\beta_i$$

where β_i is a vector of coefficients which are allowed to vary over individuals. In the random parameters logit case, the researcher specifies a distribution for β_i, usually multivariate normal.

The probability that individual i chooses alternative j can thus be derived as

$$\begin{aligned} p_{ij} &= \Pr(U_{ij} > U_{im} \forall j \neq m) \\ &= \Pr(V_{ij} - V_{im} > \epsilon_{im} - \epsilon_{ij} \forall j \neq m) \\ &= \int \frac{\exp(x_{ij}'\beta)}{\sum_m \exp(x_{im}'\beta)} f(\beta_i) d\beta_i \end{aligned}$$

Note that the differencing of systematic utility casuse all individual-specific, alternative-invariant variables such as demographic variables to drop out of the estimation.

4 Data

The data used in this study is from a 2002 choice experiment on public preferences for conservation easement programs conducted across four geographic regions: Georgia, Maine, Ohio and the US. Participants were asked, in a mail survey, to choose between two conservation easement programs and the status quo. The conservation easements programs were defined as a bundle of five attributes: farmland use priority, farmland location priority, land quality priority, total acres of easement purchased and one-time cost to a household in 2002 (as an increase in state income taxes). Table 2 lists the attributes and their levels used in the survey.

The survey instrument, and in particular the program attributes and levels, were developed through a series of focus groups, pilot test and pretests. The survey development is described in detail in other studies (see Paterson et al., 2005; Özdemir, 2003; Boyle and Özdemir, 2009).

Each geographic region received 1000 survey instruments except for Maine, which received 500 survey instruments.The effective response rates are reported by region in Table 3. From this table it can be seen that Maine has an unusually high response rate, more than a third larger than the response rates from the other regions. This high response rate may be due to a more heightened awareness of and concern with farmland preservation issues due to a referendum on a bond issue to fund easement purchases, including of farmland.

The attribute levels were assigned using a random factorial design, and four choice questions were presented in each instrument. Each choice question presented two conservation easement programs with different attribute levels (programs A and B) as well as an option to choose neither program (status quo or opt-out). Thus, there were a total of 10,536 choice responses (878 respondents $\times$ 4 choice questions $\times$ 3 options).

Nonresponses and inconsistent respondents were not included in the dataset used for estimation. There were a total of 244 nonresponses to the choice questions. A respondent was labelled as inconsistent if he chose different programs in each part of the same choice question, and the difference was neither due to choosing the status quo option nor failure to respond. There were 61 such inconsistent respondents. After excluding nonresponses and inconsistent respondents, there were a total of 9,246 usable choice responses.

An auxiliary dataset from the USDA and the 2000 census was used to test for sample selection by including it as the data x_{is} for the selection equation. This dataset is aggregated at the zipcode level, so each observation is actually an aggregated value assigned to the nonrespondent based on his zip code. The variables in this dataset are listed in Table 4.

5 Results

5.1 Sample selection

The outcome equation was specified as a linear combination of the variables found in the attributes table (Table 2) [1]. The response variable in the outcome equation is a dummy for whether the respondent chose the alternative.

The selection equation was specified as a linear combination of the variables found in the selection equation variables table (Table 4). The response variable for the selection equation was a dummy variable for whether the individual was a respondent or not. This model was estimated using SemiParBIVProbit (Marra and Radice, 2011a,b; Marra and Radice) in the R environment (R Development Core Team, 2011). SemiParBIVProbit is a semiparametric package which fits the models by a penalized likelihood maximization, where the penalty prevents overfitting of the nonparametric components of the model.

Since the main goal of estimating the sample selection model is to test for the presence of sample selection, the model estimation results are presented in Appendix A. In this section, we present the Lagrange multiplier test results of $H_0 : \rho = 0$ in Table 5. From these results, it is

[1] Additional specifications with variables such as dummies for the order of the choice question and an 'in-the-market' dummy were also considered. However, the question order dummies were found to be insignificant, and a likelihood ratio test for joint significance failed to reject the null hypothesis of joint insignificance. The 'in-the-market' ASC, a dummy which indicates whether a respondent chose a program instead of opting out, could not be included because it induced perfect multicollinearity with the program size variables. Unlike the other program attributes, the size variable did not have a level in the experimental design which matched that of an opt-out design. That is, while the other program attributes could have a 'no priority' or zero level in a given program, it was not possible to present a program with a zero size. Hence, a zero size level would always correspond to opting out, thus resulting in perfect multicollinearity with the 'in-the-market' variable.

apparent that for every region, the null hypothesis that there is no sample selection bias cannot be rejected. Henceforth it is assumed that there is no sample selection bias, and the outcome equation can be estimated on its own with no bias.

5.2 Probit model

The probit model used the same specification as the outcome equation in the sample selection model. Because the omitted levels are those associated with the status quo option (not choosing either program), the interpretation of the coefficients is relative to the status quo option (of no program). For ease of comparison, the coefficient estimates of the probit model for each region is plotted in Figure 1. A tabular presentation of the estimates is in Appendix B. From the figure, it can be seen that there is considerable heterogeneity in the estimates across regions. Although most of the estimates have the same sign across regions, `useforest`, `usegrain`, `usepasture`, `size.categoricalmedium` and `size.categoricalsmall` don't. However, none of these variables are at significant at the 5% level except for `usegrain` in the US dataset. The standard errors on the estimates did not vary nearly as much across regions as the estimates themselves.

Among the farmland use priorities, all have a primarily positive impact relative to no priority except for `usehay`. Perhaps for aesthetic reasons, respondents seem to dislike farmland on which hay is grown. In focus groups, it was found that the orderly nature of row crops, such as due to growing vegetables and fruits, was desirable (Paterson et al., 2005). This finding was further supported by the significance of `usevegetable` in the US and GA datasets.

Prioritizing farmland near urban areas also had a positive impact, which makes sense because there is likely to be more (perceived and actual) development pressure on farmland near urban areas. Prioritizing prime farmland also had a positive impact, which is expected because one of the motivations for protecting farmland is as an agricultural resource. As expected, the coefficient on `cost` was both negative and significant for all regions.

Generally speaking, larger program sizes have a more positive impact; in fact, only the highest levels of sizes, `large` and `exlarge`, showed any significance. Participants may have a 'bigger is better' mentality, or perhaps believe that the program won't be worthwhile unless it has a large enough impact.

Because the model specification is linear in terms, the marginal willingness to pay for a given attribute can be simply computed as the ratio of the coefficient on that attribute and the negative of the coefficient on `cost` (Small and Rosen, 1981). A table of marginal willingness to pay by region is given in Table 6.

5.3 Scale parameter testing

The results of the Swait-Louviere procedure applied to each pairwise comparison of the regions in the dataset are summarized in Table 7. From these results it can be seen that all comparisons except for US vs ME do not present enough evidence to reject the hypothesis of parameter and scale equality. In these cases σ_2 can be interpreted as a relative variance factor. For example, the ratio 0.907 for the US vs GA comparison can be interpreted as GA having a variance 0.907 times that of the US variance. Thus, it can be seen that in general, regions with greater populations (or more responses) have greater variance. The only exception to this pattern is the GA vs OH comparison, in which Georgia, the smaller state and the one with fewer responses, has a greater variance than Ohio.

In the US vs ME comparison, the hypothesis of parameter equality (allowing for scale factor inequality) is rejected at the 95% confidence level. This result implies that Maine has an underlying model with different parameters from those of the US. However, the US does not have different parameters from those of other regions except for Maine; this contradiction unfortunately cannot be avoided when performing pairwise comparisons.

5.4 Random parameters logit

The estimation results of the random parameters logit model is presented in Table 8. Following convention, all the random parameters were assumed to follow a normal distribution. From the results, it is clear that most of the parameters exhibit strong preference heterogeneity, since almost all the standard deviation estimates are significant. Several variables have insignificant mean estimates but significant standard deviation estimates, such as `usegrain` and `size.categoricalmedium`. This indicates that although the variables seems insignificant when simply looking at the mean values, the preference heterogeneity yields a more nuanced picture: the distribution of the parameter may be centered near zero, but there is considerable spread away from zero, with some individuals having a positive preference for the attribute level and some individuals having a negative preference. This result indicates the possible presence of distinct market segments which have different – possibly opposing – preferences.

6 Conclusion

This study compared analyzed the preferences for farmland conservation program attributes accounting for the possibility of sample selection and geographic and individual heterogeneity. Using a Heckman-style bivariate probit model with sample selection, the null hypothesis of the absence sample selection failed to be rejected. A univariate probit model without sample selection was then estimated to investigate the effects of the farmland attributes. Prioritizing all types of farmland use excluding growing hay (growing grain crops, growing vegetable, fruity and nut crops, pasture land for grazing and forestd land), prioritizing farmland located near urban areas, prioritizing prime farmland and protecting larger tracts of land all had positive impacts on the choice probability.

To investigate geographic heterogeneity, a procedure outlined by Swait and Louviere (1993) was conducted to test for scale and parameter equality. That is, a test was conducted to see whether the differences in parameter equality were significant, allowing for the possibility that the parameter estimates differed only due to a scale parameter difference, because the scale parameter is not identified. The null hypothesis of scale and parameter equality failed to be rejected in all cases except in the comparison of the US to Maine. In that case the hypothesis of equal parameters even allowing for different scale parameters was rejected, which indicates that the US and Maine have different underlying parameters. This result indicates the importance of taking into account geographic heterogeneity when designing conservation easement programs.

To investigate individual heterogeneity, a random parameters logit model was also estimated.

The random parameters logit model showed the presence of significant preference heterogeneity. This result also indicates that the lack of significance on the mean estimates of most variables may be due to preference heterogeneity, since there may both be individuals with positive preferences as well as those with negative preferences. The preference heterogeneity masks the significance of the variable, indicating the importance of separating individuals into market segments with perhaps more homogenous preferences in order to better understand preferences over farmland conservation program attributes. This preference heterogeneity may also indicate that while a broad-based funding mechanism such as taxes may not receive much support, a more targeted funding source matching the market segments present may receive more support.

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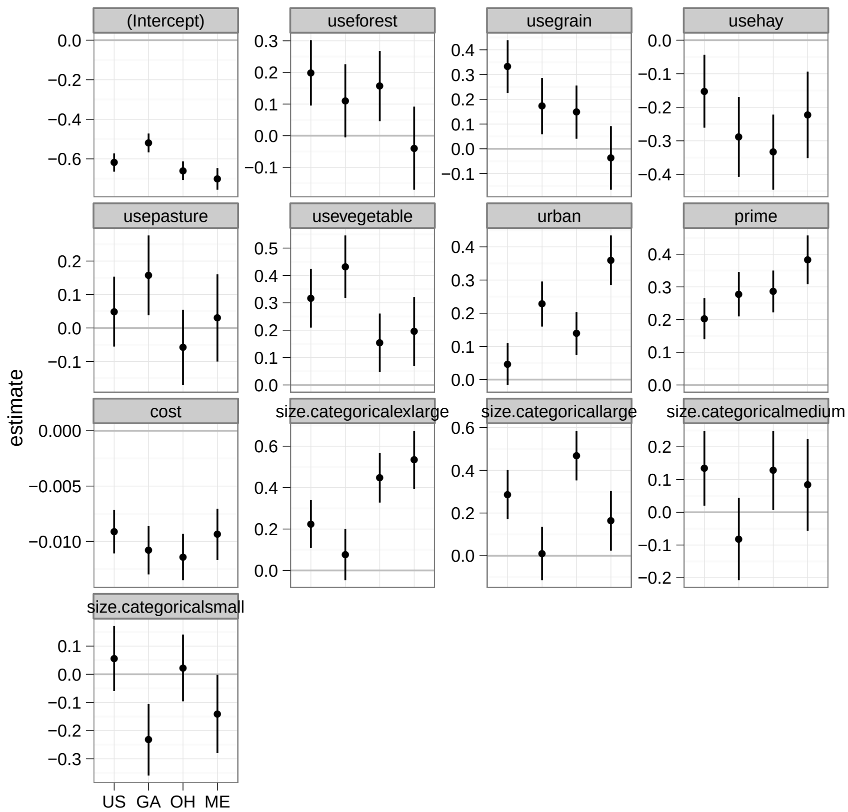

Figure 1: Plot of coefficient estimates from the probit model for each of the four regions in the dataset. Each point representes a coefficient estimate; each half of the line extending from the point is the length of the standard error on the coefficient estimate.

Table 1: Summary of likelihood ratio tests used in Swait-Louviere procedure

Log-likelihood	Dataset 1	Dataset 2
L_σ	$\sigma_1 = 1$	$\sigma_2 =$ optimal
L_1	$\sigma_1 = 1$	—
L_2	—	$\sigma_2 = 1$
L_p	$\sigma_1 = 1$	$\sigma_2 = 1$

Subhypothesis	Unconstrained log-likelihood	Constrained log-likelihood
H_{1A}	$L_1 + L_2$	L_σ
H_{1B}	L_σ	L_p

Table 2: Attributes and attribute levels present in choice experiment

Attribute	Level	Variable [a]
Farmland use priority	Growing grain crops	`usegrain`
	Growing hay	`usehay`
	Growing vegetables, berries, fruits and nuts crops	`usevegetable`
	Pasture for livestock	`usepasture`
	Forested land	`useforest`
	No priority	(omitted)
Farmland location priority	Near urban areas	`urban`
	No priority	(omitted)
Land quality priority	Prime farmland	`prime`
	No priority	(omitted)
Total acres of easement purchased [b]	Small	`size.categoricalsmall`
	Medium	`size.categoricalmedium`
	Large	`size.categoricallarge`
	Extra large	`size.categoricalexlarge`
One-time cost to household in 2002	\$3	`cost`
	\$5	
	\$7	
	\$10	
	\$25	
	\$50	

[a] All variables are dummies indicating presence of that level except for `cost`, which is continuous.
[b] The exact number of acres was reported in the choice question, but it depended on the size of the region, so is not reported here. It was approximately 1%, 5%, 10% or 20% of the total farmland in the region.

Table 3: Response rates by region

	US	GA	OH	ME	Overall
Surveys mailed	1000	1000	1000	500	3500
Surveys undeliverable	180	200	137	74	591
Surveys returned	244	213	248	173	878
Effective response rate	29.8%	26.6%	28.7%	40.6%	30.2%

Table 4: Variables in selection equation

Variable	Meaning
isresp	1 if responded to survey, 0 otherwise
pctmove	percent moved in last five years
pctmove_county	percent moved from different county in last five years
pctmove_state	percent moved from different state in last five years
pcths	percent with high school or better education
pctcol	percent with college or better education
pct_farm_earn	percent of earnings from farms
pct_renter	percent of residents who rent
ruc	rural urban continuum, from 0 (urban) to 9 (rural)
uic	urban influence code, from 1 (urban) to 9 (rural)
amenity	amenity scale, higher is better
popchange_nm_90	percent population change in nonmetro area since 1990
popchange_nm_80	percent population change in nonmetro area since 1980
popdensity_nm_00	population density in nonmetro area per square mile in 2000
popchange_90	percent population change since 1990
popchange_80	percent population change since 1980
popdensity_00	population density per square mile in 2000
Income	median income

[a] The dataset for these variables is at the zipcode level.

Table 5: Test for presence of sample selection

	US	GA	OH	ME
p-value [a]	0.722	0.923	0.451	0.886

[a] p-values for a Lagrange multiplier test of the hypothesis $H_0 : \rho = 0$.

Table 6: Marginal willingness to pay in dollars per household

	US	GA	OH	ME
useforest	21.8	10.2	13.8	−4.2
usegrain	36.4	16.0	13.0	−3.9
usehay	−16.7	−26.7	−29.2	−23.8
usepasture	5.4	14.5	−5.1	3.2
usevegetable	34.7	40.0	13.5	20.9
urban	5.1	21.1	12.2	38.4
prime	22.2	25.7	25.1	40.8
size.categoricalexlarge	24.5	7.1	39.2	57.0
size.categoricallarge	31.4	1.0	41.1	17.4
size.categoricalmedium	14.7	−7.6	11.2	8.9
size.categoricalsmall	6.1	−21.5	2.0	−15.0

Table 7: Summary of results from Swait-Louviere procedure

Comparison	Ratio [a]	p-value for H_{1A}	p-value for H_{1B}	Reject H_1 with $\alpha = 0.95$
US vs GA	0.907	0.394	0.473	No
US vs OH	0.860	0.755	0.165	No
GA vs OH	0.913	0.260	0.430	No
US vs ME	0.759	0.003	— [b]	Yes
GA vs ME	0.812	0.099	0.077	No
OH vs ME	0.908	0.102	0.320	No

[a] 'Ratio' refers to the optimal value of σ_2 when σ_1 is fixed at 1.
[b] The p-value for H_{1B} is not listed when H_{1A} is rejected.

Table 8: Estimation results for random parameters logit model

	US	GA	OH	ME
useforest	0.520*	−0.076	0.354	−0.364
	(0.264)	(0.436)	(0.311)	(0.453)
usegrain	0.573	0.139	0.129	−0.325
	(0.328)	(0.306)	(0.330)	(0.392)
usehay	−0.221	−0.820*	−0.944**	−0.621
	(0.299)	(0.347)	(0.328)	(0.359)
usepasture	0.141	0.213	−0.400	−0.117
	(0.314)	(0.328)	(0.312)	(0.421)
usevegetable	0.841**	0.910**	0.626	−0.087
	(0.291)	(0.328)	(0.387)	(0.398)
location	0.129	0.656***	0.545**	1.078***
	(0.170)	(0.193)	(0.193)	(0.246)
quality	0.565**	0.705***	0.813***	1.139***
	(0.175)	(0.196)	(0.199)	(0.259)
cost	−0.027***	−0.030***	−0.033***	−0.036***
	(0.006)	(0.007)	(0.007)	(0.009)
size.categoricalexlarge	0.035	0.058	0.945**	1.524***
	(0.310)	(0.354)	(0.348)	(0.449)
size.categoricallarge	0.341	0.054	0.881**	0.398
	(0.270)	(0.316)	(0.301)	(0.388)
size.categoricalmedium	−0.038	−0.506	−0.191	0.128
	(0.269)	(0.333)	(0.349)	(0.378)
size.categoricalsmall	−0.038	−0.598	−0.303	−0.561
	(0.275)	(0.307)	(0.300)	(0.380)
sd.useforest	1.526**	−3.131***	−1.698**	3.347***
	(0.564)	(0.796)	(0.562)	(0.879)
sd.usegrain	3.220***	−1.149*	2.054***	1.545*
	(0.729)	(0.580)	(0.614)	(0.741)
sd.usehay	1.668**	1.012	−1.108	−0.102
	(0.564)	(0.535)	(0.630)	(0.598)
sd.usepasture	2.292***	1.763**	1.239**	−3.514***
	(0.600)	(0.597)	(0.478)	(0.807)
sd.usevegetable	2.438***	1.987***	4.212***	2.908***
	(0.615)	(0.582)	(0.931)	(0.699)
sd.size.categoricalexlarge	2.467***	3.221***	3.238***	2.773***
	(0.527)	(0.699)	(0.602)	(0.567)
sd.size.categoricallarge	1.352***	1.953***	1.659***	1.817***
	(0.390)	(0.465)	(0.446)	(0.477)
sd.size.categoricalmedium	1.502***	1.755***	2.473***	2.407***
	(0.414)	(0.440)	(0.500)	(0.598)
sd.size.categoricalsmall	−0.989*	1.170**	−1.405***	1.330**
	(0.417)	(0.382)	(0.375)	(0.460)

A Sample selection estimation results

A.1 Selection equation results

	US	GA	OH	ME
(Intercept)	0.492**	−2.382***	1.018***	3.965***
	(0.157)	(0.209)	(0.153)	(0.289)
pctmove	1.901***	0.543	−1.410***	3.292***
	(0.250)	(0.282)	(0.233)	(0.563)
pctmove_county	−0.772***	−1.081***	0.706**	−2.929***
	(0.229)	(0.237)	(0.230)	(0.419)
pctmove_state	0.525	0.171	−0.778**	2.243***
	(0.270)	(0.257)	(0.292)	(0.489)
pcths	−1.341***	3.518***	−0.100	−2.183***
	(0.134)	(0.203)	(0.174)	(0.308)
pctcol	1.497***	−2.792***	2.014***	0.923***
	(0.176)	(0.205)	(0.196)	(0.270)
pct_farm_earn	0.519***	0.175	0.047	2.114***
	(0.088)	(0.104)	(0.081)	(0.229)
pct_renter	−0.646***	1.208***	−0.706***	−1.570***
	(0.183)	(0.186)	(0.145)	(0.263)
ruc	0.029***	0.011	0.021*	0.044***
	(0.008)	(0.008)	(0.009)	(0.012)
uic	−0.008	0.004	−0.019*	−0.115***
	(0.008)	(0.008)	(0.008)	(0.011)
amenity	0.027*	−0.059***	−0.011	−0.317***
	(0.013)	(0.011)	(0.011)	(0.020)
popchange_nonmetro_90	1.551*	−12.223***	−0.862	−4.744
	(0.609)	(0.757)	(0.865)	(3.162)
popchange_nonmetro_80	−2.252***	6.504***	0.362	0.717
	(0.333)	(0.428)	(0.452)	(1.679)
popdensity_nonmetro_00	−0.001	0.011***	−0.003***	0.051***
	(0.001)	(0.001)	(0.000)	(0.003)
popchange_90	0.356	12.374***	5.631***	−35.696***
	(0.708)	(0.735)	(1.048)	(3.498)
popchange_80	0.607	−4.717***	−2.571***	15.744***
	(0.315)	(0.367)	(0.441)	(1.336)
popdensity_00	0.001***	−0.002***	−0.000**	−0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
Income	0.000***	0.000***	0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)

A.2 Outcome equation results

	US	GA	OH	ME
(Intercept)	-0.577^{***}	-0.508^{***}	-0.690^{***}	-0.713^{***}
	(0.021)	(0.020)	(0.020)	(0.019)
useforest	0.176^{***}	0.072	0.137^{***}	-0.025
	(0.034)	(0.038)	(0.036)	(0.040)
usegrain	0.283^{***}	0.183^{***}	0.153^{***}	-0.046
	(0.036)	(0.037)	(0.035)	(0.039)
usehay	-0.137^{***}	-0.290^{***}	-0.327^{***}	-0.227^{***}
	(0.036)	(0.039)	(0.037)	(0.039)
usepasture	0.026	0.125^{**}	-0.066	0.029
	(0.035)	(0.039)	(0.037)	(0.040)
usevegetable	0.314^{***}	0.425^{***}	0.155^{***}	0.204^{***}
	(0.036)	(0.037)	(0.035)	(0.038)
urban	0.022	0.227^{***}	0.135^{***}	0.366^{***}
	(0.021)	(0.022)	(0.021)	(0.023)
prime	0.225^{***}	0.278^{***}	0.287^{***}	0.384^{***}
	(0.021)	(0.022)	(0.021)	(0.023)
cost	-0.010^{***}	-0.011^{***}	-0.012^{***}	-0.009^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
size.categoricalexlarge	0.138^{***}	0.065	0.473^{***}	0.541^{***}
	(0.039)	(0.040)	(0.039)	(0.043)
size.categoricallarge	0.228^{***}	-0.002	0.481^{***}	0.175^{***}
	(0.039)	(0.041)	(0.038)	(0.043)
size.categoricalmedium	0.087^{*}	-0.084^{*}	0.130^{**}	0.096^{*}
	(0.038)	(0.041)	(0.040)	(0.043)
size.categoricalsmall	0.045	-0.241^{***}	0.041	-0.123^{**}
	(0.039)	(0.041)	(0.039)	(0.043)

B Probit model estimation results

	US	GA	OH	ME
(Intercept)	-0.618^{***}	-0.519^{***}	-0.660^{***}	-0.701^{***}
	(0.046)	(0.048)	(0.047)	(0.055)
use: forest/none	0.199	0.110	0.157	-0.039
	(0.103)	(0.116)	(0.111)	(0.131)
use: grain/none	0.332^{**}	0.172	0.148	-0.037
	(0.107)	(0.114)	(0.107)	(0.128)
use: hay/none	-0.152	-0.288^{*}	-0.334^{**}	-0.223
	(0.109)	(0.119)	(0.112)	(0.129)
use: pasture/none	0.049	0.157	-0.058	0.030
	(0.104)	(0.119)	(0.112)	(0.130)
use: vegetable/none	0.317^{**}	0.432^{***}	0.154	0.195
	(0.107)	(0.114)	(0.107)	(0.126)
urban	0.047	0.228^{***}	0.139^{*}	0.360^{***}
	(0.063)	(0.068)	(0.064)	(0.075)
prime	0.203^{**}	0.278^{***}	0.286^{***}	0.383^{***}
	(0.063)	(0.068)	(0.064)	(0.075)
cost	-0.009^{***}	-0.011^{***}	-0.011^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
size.categorical: exlarge/none	0.224	0.076	0.447^{***}	0.534^{***}
	(0.116)	(0.124)	(0.119)	(0.141)
size.categorical: large/none	0.286^{*}	0.010	0.469^{***}	0.163
	(0.115)	(0.125)	(0.116)	(0.140)
size.categorical: medium/none	0.134	-0.082	0.128	0.084
	(0.114)	(0.126)	(0.121)	(0.140)
size.categorical: small/none	0.056	-0.232	0.023	-0.141
	(0.115)	(0.127)	(0.119)	(0.139)
Likelihood-ratio	90.963	107.014	156.617	158.350
Log-likelihood	-1585.268	-1395.836	-1525.707	-1121.927
AIC	3196.536	2817.671	3077.415	2269.854
BIC	3272.567	2892.169	3153.231	2341.910
N	2562	2277	2520	1887