Stripping Because You Want to Versus Stripping Because the Money is Good: A Latent Class Analysis of Farmer Preferences Regarding Filter Strip Programs

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Abstract: Governments in Ohio have attempted to limit nutrient runoff in the Maumee watershed from agriculture through the establishment of Payment for Ecosystem Services (PES) programs, in which farmers are paid to implement Best Management Practices (BMPs) such as grass filter strips. This paper seeks to understand which farmers are likely to opt into these PES programs and how farmer preferences for these programs are influenced by program attributes and farmer perceptions towards BMPs. We examine these questions using responses from a survey of Ohio farmers, where farmers choose between two PES programs and a status quo (no program) option. We allow for farmer heterogeneity using latent class analysis and find two classes of farmers. One class, denoted the "Environmental Steward" class, has a strong preference for opting into filter strip programs. Furthermore, increasing perceptions of filter strip effectiveness has no significant impact on program choice for this class. The second class, denoted the "Other" class, has a strong status quo preference. Increasing perceptions of filter strip effectiveness has a significant positive effect on members of this class. Both classes prefer programs with larger payments, smaller filter strips, and less paperwork, while program length is not significant.

Nutrient pollution has inflicted substantial damages to vital ecosystems both in the United States and worldwide, resulting in a reduction of deliverable ecosystem services (Kemp *et al*. 2005; Huisman *et al*. 2005; Rabalais *et al*. 2007; Lotze *et al*. 2006; Diaz and Rosenberg 2008). In recent decades, nonpoint source pollution, especially from agriculture, is responsible for an increasing share of nutrient loading (OEPA 2010). The increased incidence of severe storm events that are predicted with climate change (Milly *et al*. 2005, Moberg *et al*. 2006) are likely to exacerbate this problem (Jeppeson *et al*. 2009, Joseph *et al*. 2009). Governments have responded to these issues primarily by establishing voluntary programs that compensate farmers for adopting agricultural best management practices (BMPs). These are also called payment for ecosystem services (PES) programs.

There is a large literature dedicated to understanding farmer adoption of BMPs. Much of this research has focused on farmers adopting conservation practices without monetary incentives (Erven and Erven 1982; Gould *et al.* 1989; Bosch *et al*. 1995; Wu and Babcock 1998; Soule *et al*. 2000; Roberts *et al*. 2006; Davey and Furtan 2008). In addition to this literature, some work has examined farmer preferences for paid BMP programs. Zbinden and Lee (2005) and Lambert *et al*. (2006) consider actual program participation, while Purvis *et al*. (1989) and Ma *et al*. (2012) examine stated preference responses for hypothetical programs. This paper provides an analysis of farmer stated preferences for hypothetical filter strip programs and extends the previous literature in two important ways. First, our analysis allows for farmer preference heterogeneity through latent class analysis (LCA). It is common practice to assume that farmers are purely profit maximizers. This paper endeavors to focus on farmers as utility, rather than profit, maximizers. Our theoretical model treats farmer utility as a function of consumption, which is dependent on income and motivates the profit-maximization inclinations of farmers, and environmental services[1], which are influenced by environmental quality rather than profit or income. It is reasonable to posit that for some farmers, who we call environmental stewards, environmental services and environmental quality will have a greater impact on utility compared to other farmers (profit-maximizers). LCA accounts for this type of preference heterogeneity by assuming that the farmer population is comprise of several unobserved, or latent, classes. All farmers in a particular class possess homogeneous preferences, while preferences are allowed to vary across classes. We adopt a semi-parametric estimation of LCA in which the number of classes is not assumed *ex ante*, but is instead derived from the data and estimation model through the use of the Bayesian Information Criterion (BIC). This methodology is also being applied to farmer best management practices by Konar *et al.* (2012), although their working paper considers the impact of farmer and field characteristics on actual tillage choice, while this paper considers the impact of program characteristics on preferences toward hypothetical government filter strip programs.

Latent class analysis is one of several methods capable of addressing farmer preference heterogeneity. Perhaps the simplest method is the inclusion of interaction terms, which allows for heterogeneity based on observable characteristics. Unfortunately this method is of limited value when the source of heterogeneity is unobserved. In the absence of a variable that clearly delineates farmers into classes or otherwise specifies heterogeneity, the heterogeneity is latent or unobserved and thus controlling for heterogeneity through the use of interaction terms is insufficient. Random parameters (also called random coefficients or mixed) logit models also allow for heterogeneity by estimating variable coefficients and an individual-specific standard deviation parameter for each coefficient (McFadden and Train 2000, Train 1998, Columbo,

[1] This could be considered the consumption of environmental services, the provision of environmental services, or a combination of the two.

Hanley, and Louviere 2009). Peterson *et al*. (2012) use a random parameters model to estimate the transaction costs associated with hypothetical PES programs using farmers in a lab setting. The advantage of latent class analysis for the current study lies in the discrete rather than continuous nature of preference heterogeneity we anticipate in the farmer population. We suspect that a portion of farmers are environmental stewards, and the preferences of farmers within this group will be relatively homogeneous and will differ from the preferences of farmers who do not identify as environmental stewards but are instead pure profit maximizers. In addition, by avoiding the assumption of a continuous distribution of preferences, we are not forced to make assumptions regarding the shape of this distribution. Latent classes also improve communication of results to policy makers, who often find discussion of distinct classes of farmers more intuitively appealing than discussions of random parameters output or complex interaction terms. It has been argued that finite mixture approaches provide a more robust and tractable approach to representing preference heterogeneity than the random parameters approach (Greene and Hensher 2003; Hess *et al*. 2011; Shen 2009).

As a second contribution, this research examines how farmer perceptions of program efficacy in reducing runoff influence their preferences toward filter strip programs. Previous work has indicated that, in addition to larger payments, farmers are more likely to engage in conservation practices when they have higher incomes, larger farms, more education, lower quality soil, and when they express greater levels of concern for the environment (Lambert *et al*. 2006, Bosch *et al*. 1995, and Gould *et al*. 1989). However, to our knowledge no studies have been able to adequately isolate the degree to which farmers believe these practices will reduce runoff. It is reasonable to expect that farmers who believe BMPs to be effective would be more likely to adopt these practices, whether incentivized or not. Furthermore, this effect may differ from one latent class to another, thus indicating the need to control for preference heterogeneity. Ma *et al*. (2012) include controls in their estimation that capture farmer perceptions of ecosystem benefits from the considered BMP program. This measure is qualitative (a 5 point Likert scale), and as such is slightly different from the continuous quantitative measure undertaken here. More importantly, this variable is likely to be endogenous, as there are unobserved farmer attributes (social networks, for example) that are correlated with both perceptions of BMP efficacy and program choice. We test our measure and find that it is not endogenous. However, as a robustness check we also instrument for our efficacy measure using a two-stage control function estimation technique with field attributes as instruments. The results of this estimation are presented in the appendix.

We find that farmers do exhibit preference heterogeneity regarding filter strip program selection. Farmers fall into two latent classes. Both classes prefer programs that offer higher payment per acre, lighter paperwork burdens, and require smaller filter strips. The smaller class exhibits a strong status quo preference, suggesting that members of this class are generally less likely to enroll in conservation programs, while the larger class displays a strong preference toward PES programs. Furthermore, the class with a strong preference for PES programs shows no significant effect of increased perceptions of filter strip efficacy, while increases in these perceptions increase the probability of selecting a program for the class with a status-quo preference.

The rest of the paper proceeds as follows. The next section describes the survey and data from which our results derive. Subsequent sections outline the theoretical and empirical models utilized, results, and concluding remarks.

Data

Data presented in this study are from a 2012 mail survey of farmers in the Maumee watershed, located primarily in northwest Ohio. We received 817 responses from a total of 2000 surveyed corn and soybean farmers (40.85% 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 389 farmers for whom we have no missing variables of interest. Table 1 compares demographic information for the sample of 389, the broader sample of up to 596, and the entire farmer population for counties in the Maumee watershed (USDA, 2009). Our sample is skewed toward large farms with high gross sales and farmers who additionally earn off-farm income.[2] 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 it was pilot tested using 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

[2] The analysis presented in this paper uses the unweighted sample. Additional analysis using weights that produce the demographics in the final column of Table 1 was undertaken. The results using the weighted sample are qualitatively the same as those using the unweighted sample, and so are not presented here. They are available upon request from the authors.

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. After these questions, respondents were asked, "How likely is it that a 1-inch rainfall during a 30-minute storm event in mid-June would cause soil to run off into nearby surface water?" under three scenarios: 1) the field as it currently is with no filter strip, 2) the field with a 25-foot filter strip, and 3) the field with a 75-foot filter strip. Respondents were prompted to report this likelihood as a probability from 0% to 100%.

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 were allowed to differ, 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 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. 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.

Theory and Econometric Method

Theoretical Model

The theoretical specification of this paper assumes that farmers rank filter strip programs through a process of utility maximization in which utility is a function of consumption goods (C) and environmental services (E). The model is an adaptation of Dupraz *et al.* (2003) and Ma *et al.* (2012). Broadly speaking, consumption is bounded by income (I). Income is a function of farm profits (π) and off-farm income (R). Farm profits are influenced by farm output (Y), the level of variable inputs (X) (hired labor and planted land, for example), inputs like management and machinery that are fixed over the considered time period (F), environmental services (E) and prices (p). Without loss of generality, the cost of fixed inputs is assumed zero. This setup yields the following utility maximization problem:

$$max_{X,E} \quad U(C, E) \qquad (1)$$

$$where\ C \leq I = \pi + R$$

$$and\ \pi = p_y Y(E,X, F) - p_x X.$$

Off-farm income is treated exogenously in the model. The farm production function $Y(.)$ is increasing in X and non-increasing in E.[3] The levels of environmental services and inputs that maximize utility are given by (X^o, E^o). Implementing a filter strip program reduces runoff, but requires land and labor be diverted from farming, both to establish and maintain the filter strip and to complete paperwork and other compliance activities. In this way, a filter strip can be seen as a pair of changes (ΔE, ΔX), where ΔE is nonnegative and ΔX is nonpositive.

Noting that consumption can be written as a function of income, which is itself a function of inputs and environmental services, $C(I(X,E))$, a farmer's minimum willingness to accept (WTA) for the installation of a filter strip (ΔE, ΔX) satisfies the following equation:

$$U(C[I(X^o, E^o)], E^o) = U(C[I(X^o + \Delta X, E^o + \Delta E) + WTA], E^o + \Delta E). \qquad (2)$$

A filter strip program offer is modeled as a trio of changes (ΔE, ΔX, Z), where the first two terms capture the effects of the filter strip and Z is the program payment to the farmer. The farmer will accept the offered program provided $Z \geq WTA$, or

$$U(C[I(X^o + \Delta X, E^o + \Delta E) + Z], E^o + \Delta E) \geq U(C[I(X^o, E^o)], E^o). \qquad (3)$$

Empirical Model

[3] There may be instances where further provision of environmental services can increase farm production, but this is ignored for simplicity.

We now assume that utility obtained from individual n choosing alternative i is comprised of a systematic or observable element, denoted V, and a random error term ε, so the following equation holds:

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

Assuming the error terms are i.i.d. with a type 1 extreme value distribution and homogeneity of farmer preferences, the probability that a farmer will choose policy alternative i as the best (or highest ranked) from a set of policy alternatives $\{1,\ldots, I\}$ is given by

$$Pr_n(i) = \frac{exp(\beta' X_{ni})}{\sum_{i=1}^{I} exp(\beta' X_{ni})}, \tag{5}$$

where X_{ni} is a vector of attributes associated with program i for farmer n and β is the vector of estimated coefficients associated with these attributes. This is the standard conditional logit model. 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 is likely to be impractical. Potential heterogeneity of farming goals (environmental stewardship vs. profits) suggests that changes in program attributes may have different marginal impacts on program adoption for different farmer groups. For instance, farmers who place their emphasis exclusively on making a profit may be greatly influenced by changes in program payment while caring little about the environmental benefits of the program. Conversely, farmers who value environmental stewardship may care less about program payment and more about the environmental benefits of the program.

To allow for this potential preference heterogeneity, we also estimate a conditional logit using latent class analysis (Bhat 1997; Birol *et al*. 2006; Columbo *et al*. 2009). 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 a series of policy alternatives $\{i_{1\ldots}\ i_T\}$ from a set of policy alternatives $I \times I$, $I = \{1,\ldots, \mathrm{I}\}$, conditional on the farmer belonging to class *s*, is given by

$$Pr_n(i \mid s) = \prod_{t=1}^{T} \frac{exp(\beta_s{}'X_{nit})}{\sum_{i=1}^{I} exp(\beta_s{}'X_{nit})}, \tag{6}$$

where β_s is the vector of estimated coefficients associated with attributes X_{nit} in class *s*. We assume that one farmer's choice is independent of the choices of other farmers. However, because a farmer's choice is not independent of other choices made by the same farmer, equation (6) does not treat each choice as an isolated incident but instead describes the probability of a farmer making a series of *T* choices. The probability that farmer *n* belongs to class *s* 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 farmer-specific characteristics and γ_s is a vector of coefficients associated with class *s*. Equation (6) captures a conditional logit, where choice probabilities are determined by choice-specific attributes, while equation (7) captures a multinomial logit, where class probabilities are determined by farmer-specific attributes (McFadden 1973). Assuming independence of the probabilities outlined in equations (6) and (7), the unconditional probability that farmer *n* will choose a series of policy alternatives $\{i_{1\ldots}\ i_T\}$ is

$$Pr_n(i) = \sum_{s=1}^{S} \left[\frac{exp(\delta_s Z_n)}{\sum_{s=1}^{S} exp(\gamma_s Z_n)}\right] \times \left[\prod_{t=1}^{T} \frac{exp(\beta_s X_{nit})}{\sum_{i=1}^{I} exp(\beta_s X_{nit})}\right]. \tag{8}$$

In our data, farmers are presented with two sets of policy alternatives, so $T = 2$. The program attributes (X_{nit}) included in our estimations are outlined in Table 1. They include the per-acre payment given for land converted to filter strips, the required filter strip width, the annual paperwork burden 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. Additionally, we include a variable that captures farmers' perception of the efficacy of filter strips in reducing the likelihood of runoff. This variable is created by taking the difference of farmers' reported runoff probabilities with a filter strip on the field in question and without a filter strip. As an example, if a farmer reports the probability of runoff is A in the absence of a filter strip, B with a 25 foot filter strip, and C with a 75 foot filter strip, the perceived efficacy variable is $B – A$ for a 25 foot filter strip program, $C – A$ for a 75 foot filter strip program, and zero ($A – A$) for the status quo of no program.

It is reasonable to question whether this perceived efficacy variable poses an endogeneity problem. Unobserved farmer characteristics that are captured in the error term (like farmer social networks) may influence both perceptions of filter strip efficacy and program preferences. We use the Durbin-Wu-Hausman test and cannot reject the null of exogeneity. This is true both for the entire sample (p-value = 0.277) and when the sample is broken into the two latent classes found in our analysis (p-values of 0.790 and 0.224). We believe that the manner in which our variable was elicited lends credence to the assertion of exogeneity. The survey does not directly link the questions relating to our efficacy variable with specific programs in the choice exercises. This practice of disengaging perception and choice questions may limit the likelihood that unobservables will influence both questions, leading to an endogeneity problem. Despite this, and as a robustness check, we use a 2-stage control function estimation technique using exogenous field attributes as instruments for perceived efficacy. Field variables, also outlined in Table 2, include indicator variables for field slope of less than 2° and greater than 5°, an indicator variable for whether the field has working drainage tile and indicator variables for soil type and distance from the field to the nearest surface water. The details of this estimation are in the appendix.

Results

The estimations that follow are obtained using Latent Gold Choice 4.5 and Stata 11 statistical software. Results from the conditional logit estimation are presented in Table 3. The "pooled" column results assume preference homogeneity. In the language of LCA this is equivalent to assuming that all data fall into a single class. We will use this traditional estimation as a baseline for comparison with our LCA results. In the pooled estimation, increased payment per acre, decreased filter strip width, decreased paperwork burdens and increased perceptions of filter strip effectiveness all increase the probability of a program being selected. Program length has no significant impact. Additionally, the alternative-specific constant for no program, which we call the status quo, has no significant effect. This means that farmers have no statistically significant preference for or against enrollment in programs beyond what can be attributed to measureable program attributes.

When allowing for preference heterogeneity via LCA, a different and more nuanced story arises from the data. We find a two class model provides the best fit for our data by virtue of minimizing the BIC.[4] Table 4 presents a breakdown of the two classes by farmer-specific covariates included in the model. One class, which we call the "Environmental Stewards," comprises 62% of the sample. We label these farmers Environmental Stewards because they are less likely to use conventional tillage practices (and so are more likely to engage in either conservation tillage or no-till). As one would predict for Environmental Stewards, they are also more likely to be enrolled in conservation programs and more aware of algae issues on Grand Lake St. Mary's, although the differences are not statistically significant. Farmers in the Environmental Steward class are also younger, higher educated, are more likely to recreate in Ohio rivers, lakes and streams, and are less likely to be first generation farmers, although of these additional variables only age and recreation are statistically significant. Lastly, "Environmental Stewards" are also more risk tolerant regarding farming practices but less risk tolerant in general.

Both classes are qualitatively similar to each other and to the pooled estimation regarding program payment (positive and significant effect), paperwork (negative and significant effect), program length (no significant effect) and filter strip width (negative and significant effect). The difference between classes and between models is captured primarily in the status quo and filter strip efficacy variables. For the status quo variable, the "Environmental Steward" class has a large negative and marginally significant coefficient while the "Other" class has a large positive and significant coefficient. A positive coefficient is interpreted as preference for the status quo, even after controlling for program attributes, while a negative coefficient illustrates preference for enrolling in a filter strip program beyond what can be explained by program attributes. This

[4] The two class model has a BIC of 2289.83. BIC's for one and three class models are 2413.35 and 2365.86, 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.

stands in stark contrast to the pooled model, for which the status quo variable was insignificant. The efficacy variable, having been positive and significant in the pooled model, is positive for both classes but is only statistically significant for the "Other" class.

Reported marginal effects are the mean marginal effect in the sample, and significance is determined using the Krinsky Robb Procedure with 10,000 random draws (Krinsky and Robb 1986; Haab and McConnell 2002). Considering these marginal effects, we can identify further differences between classes. First, the marginal effect of increasing payment for the "Other" class is 75% greater than for the "Environmental Steward" class. Increasing payment per acre by $10 will increase the probability of program adoption by 0.8% and 1.4% for the "Environmental Steward" and "Other" classes, respectively. The marginal effect of decreasing paperwork is also larger for the "Other" class, with a reduction of one annual paperwork hour increasing the probability of program selection by 1.4% (compared to 0.7% for the "Environmental Steward" class). The marginal effect of increasing perceptions of runoff efficacy are about 3 times larger for the "Other" class, with a 10 percentage point increase in perceived efficacy corresponding to a 3.7% increase in the probability of program selection (compared to 1.1% for the "Environmental Steward" class).

Furthermore, the marginal effects of the alternative-specific constant are substantial for both classes. Even after accounting for program characteristics, being an alternative to the status quo increases the probability of selection by 66.8 percentage points for the "Environmental Steward" class and decreases the probability of selection by 35.9 percentage points for the "Other" class. These marginal effects are remarkably large. The results show that members of the "Environmental Steward" class will almost certainly select into one of the PES programs. In this way, marginal effects for program attributes illustrate preferences between programs rather than preferences between a program and the status quo. Members of the “Other” class, on the other hand, have a strong tendency to choose the status quo option, a tendency that can be mitigated by the adjustment of PES program attributes.

Using these results, we also derive willingness to accept (WTA) measures for each program attribute, presented in Table 5. As with marginal effects, significance for WTA measures are determined using the Krinsky Robb Procedure with 10,000 random draws. These measures can be interpreted as the change in per-acre rental payment that fully compensates a one unit increase in the program attribute being considered. We find that WTA for increases in annual paperwork hours is similar in both classes, between \$8 and \$10 per acre. Increases in program years have no significant effect. The “Environmental Steward” class WTA is about twice as large as that of the “Other” class for increased filter strip width (\$2.66 vs. \$1.35) but only half as large for increased perceptions of filter strip efficacy (-\$1.34 vs. -\$2.64). Further, WTA for increased perceptions of filter strip efficacy is not significantly different from zero for the “Environmental Steward” class.

Conclusion

This study examines the stated preferences of Ohio corn and soybean farmers in the Maumee watershed regarding government grass filter strip programs. When assuming preference homogeneity, our estimations suggest there is no “status quo preference,” meaning farmers do not demonstrate a preference for their current situation beyond what is explained by program characteristics. We also include a variable that captures how effective farmers believe filter strips are at reducing the probability of runoff. In models that do not allow for heterogeneity, we find that increasing this perception increases the likelihood of program adoption. Using latent class analysis to allow for preference heterogeneity, we find that farmers fall into two distinct classes. A majority of farmers (62% of our sample) fall primarily into what we call the "Environmental Steward" class, while the rest of the sample fall primarily into the "Other" class. We identify that in the "Environmental Steward" class tend to be younger, more risk tolerant in farming practices, more likely to recreate in Ohio waters, and already engaged in tillage BMPs when compared to their counterparts in the "Other" class.

In our latent class model, we find that the "Other" class of farmers possesses a strong and significant status quo preference. The "Environmental Steward" class demonstrates a negative status quo preference, or a preference for enrolling in government programs. We find a positive and significant effect of efficacy perceptions on filter strip choice for the "Other" class. The effect is positive but not significant for the "Environmental Steward" class.

Our results have important policy implications. First, this information can help policymakers predict which farmers are likely to enroll in conservation programs. Our research suggests that adoption rates can be increased and costs can be reduced if policymakers target farmer populations that are likely to be in the "Environmental Steward" class when soliciting conservation program enrollment. In addition, we find that farmers without strong tendencies toward program adoption (the "Other" class) are more likely to enroll in programs that they view as effective. There are potentially substantial gains to be made in this area. The average farmer in this class believes that a 25 foot filter strip will decrease the probability of runoff by 10.6 percentage points. Research has found that such a filter strip can actually reduce sediment runoff by 70-90% and can reduce nutrient runoff by 50-70% (Schmitt et al. 1999; Robinson et al. 1996; Blanco-Canqui et al. 2004). Our study suggests that informing farmers in this class of the real benefits of agricultural BMPs may go a long way toward increasing program adoption. Secondly, the broader goal of this research is to determine which farmers are likely to enroll in conservation programs. This information, when combined with land-use and natural system models, can be used to generate improved estimates of how conservation programs influence nutrient pollution in the Maumee watershed.

This research can be extended by applying this methodology to other BMP programs and watersheds. Given that the main difference between classes boils down to a willingness or hesitancy toward enrolling in government conservation programs, it may also be useful to examine whether attitudinal variables (toward politics, the government, etc.) are effective predictors of class membership.

References

Bhat, C. 1997. "An Endogenous Segmentation Mode Choice Model with an Application to Intercity Travel." *Transportation Science*, 13 (1): 34-48.

Birol, E., K. Karousakis, and P. Koundouri. 2002. "Using a Choice Experiment to Account for Preference Heterogeneity in Wetland Attributes: The Case of Cheimaditida Wetland in Greece." *Ecological Economics*, 60: 145-56.

Blanco-Canqui, H., C. Gantzer, S. Anderson, E. Alberts and A. Thompson. 2004. "Grass Barrier and Vegetative Filter Strip Effectiveness in Reducing Runoff, Sediment, Nitrogen, and Phosphorus Loss." *Soil Science Society of America Journal*, 68 (5): 1670-8.

Bosch, D., Z. Cook, and K. Fuglie. 1995. “Voluntary Versus Mandatory Agricultural Policies to Protect Water Quality: Adoption of Nitrogen Testing in Nebraska.” *Review of Agricultural Economics*, 17: 13-24.

Columbo, S., N. Hanley, and J. Louviere. 2009. “Modeling Preference Heterogeneity in Stated Choice Data: An Analysis for Public Goods Generated by Agriculture.” *Agricultural Economics,* 40: 307-22.

Davey, D. and H. Furtan. 2008. “Factors that Affect the Adoption Decision of Conservation Tillage in the Prairie Region of Canada.” *Canadian Journal of Economics,* 56: 257-75.

Dillman, Don. 2007. *Mail and Internet Surveys: The Tailored Design Method.* Hoboken, NJ, USA: John Wiley and Sons, Inc.

Diaz, R. and R. Rosenberg. 2008. “Spreading dead zones and consequences for marine ecosystems.” *Science* 321: 926-929.

Dupraz, P., D. Vermersch, B. De Frahan, and L. Delvaux. 2003. “The Environmental Supply of Farm Households: A Flexible Willingness to Accept Model.” *Environmental and Resource Economics,* 25 (2): 171-89.

Erven, C. and D. Erven. 1982. “Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence, and Policy Implications.” *Land Economics*, 58: 277-92.

Gould, B., W. Saupe, and R. Klemme. 1989. “Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion.” *Land Economics,* 65 (2): 167-83.

Greene, W. and D. Hensher. 2003. "A Latent Class Model for Discrete Choice Analysis: Contrasts with Mixed Logit." *Transportation Research Part B*, 37 (8): 681-98.

Haab, T. and K. McConnell. 2002. *Valuing Environmental Natural Resources: The Econometrics of Non-Market Valuation*. Northhampton, MA: Edward Elgar Publishing.

Heckman, J. and R. Robb. 1985. "Alternative Methods for Evaluating the Impacts of Interventions: An Overview." *Journal of Econometrics*, 30: 239-67.

Hess, S., M. Ben-Akiva, D. Gopinath and J. Walker. 2011. "Advantages of Latent Class over Continuous Mixture of Logit Models." Workin Paper.

Huisman, J., H.C.P. Matthijs, and P.M. Visser. 2005. *Harmful cyanobacteria*. Springer, Dordrecht, The Netherlands.

Jeppesen, E., B. Kronvang, M. Meerhoff, M. Sondergaard, K.M. Hansen, H.E. Andersen, T.L. Lauridsen, L. Liboriussen, M. Beklioglu, A. Ozen, and J.E. Olesen. 2009. "Climate Change Effects on Runoff, Catchment Phosphorus Loading and Lake Ecological State, and Potential Adaptations." *Journal of Environmental Quality* 38: 1930-1941.

Joseph, S.T., L.A. Chaimowitz, M.A. Quigley, R.A. Sturtevant, D.M. Mason, C.E. Sellinger, J. Wang, and C. DeMarchi. 2009. "Impact of climate change on the Great Lakes ecosystem. A NOAA science needs assessment workshop to meet emerging challenges – Summary report." NOAA Technical Memorandum GLERL-147. NOAA-GLERL, Ann Arbor, Michigan, 48 pp.

Kemp, W.M., W.R. Boynton, J.E. Adolf, D.F. Boesch, W.C. Boicourt, G. Brush, J.C. Cornwell, T.R. Fisher, P.M. Glibert, J.D. Hagy, L.W. Harding, E.D. Houde, D.G. Kimmel, W.D. Miller, R.I.E. Newell, M.R. Roman, E.M. Smith, and J.C. Stevenson. 2005.

Eutrophication of Chesapeake Bay: historical trends and ecological interactions. *Marine Ecology Progress Series* 303: 1-29.

Konar, A., B. Roe, and E. Irwin. 2012. “Do Farmers have Heterogeneous Preferences for the Environment and Does it Matter? A Latent-Class Approach to Explaining Field-Level Tillage Choices.” Working Paper prepared for presentation at 2012 AAEA Annual Meeting, Seattle, WA, August 12-14, 2012.

Krinsky, I. and A. Robb. 1986. “On Approximating the Statistical Properties of Elasticities.” *Review of Economics and Statistics*, 68: 715-9.

Lambert, D., P. Sullivan, R. Claassen, and L. Foreman. 2006. “Conservation-compatible Practices and Programs: Who Participates?” Economic Research Report No. 14. Economic Research Service, U.S. Department of Agriculture. http://ers.usda.gov/Publications/err14

Lotze, H.K., Lenihan, H.S., Bourque, B.J., Bradbury, R.H., Cooke, R.G., Kay, M.C., Kidwell, S.M., Kirby, M.X., Peterson, C.H., and Jackson, J.B.C. 2006. Depletion, degradation, and recovery potential of estuaries and coastal seas. Science 312: 1806-1809.

Ma, Shan, Scott Swinton, Frank Lupi and Maria Jolejole-Foreman. 2012 (forthcoming). “Farmers’ Willingness to Participate in Payment-for-Environmental-Services Programmes.” *Journal of Agricultural Economics*, 63 (3): 604-26.

McFadden, D. 1973. “Conditional Logit Analysis of Qualitative Choice Behavior.” In Zarembka, F. (Editor), *Frontiers in Econometrics*, Academic Press, New York, 105-142.

McFadden, D. and K. Train. 2000. “Mixed MNL Models for Discrete Response.” *Journal of Applied Econometrics*, 15: 447-70.

Milly, P.C.D., K.A. Dunne, and A.V. Vecchia. 2005. Global pattern of trends in streamflow and water availability in a changing climate. *Nature* 438: 347-350.

Moberg, A. and 39 others. 2006. “Indices for daily temperature and precipitation extremes in Europe analyzed for the period 1901– 2000.” *Journal of Geophysical Research*, 111: D22106, doi:10.1029/2006JD007103.

Nylund, K., T. Asparouhov and B. Muthen. 2007. “Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study.” *Structural Equation Modeling*, 14 (4): 535-69.

Ohio Environmental Protection Agency (OEPA). 2010. *Ohio Lake Erie Phosphorus Task Force Report.* Columbus, OH. 109p.

Peterson, J., C. Smith, J. Leatherman, N. Hendricks, and J. Fox. 2012. “Transaction Costs in Payment-for-Environmental-Service Contracts.” Working paper.

Petrin, A. and K. Train. 2010. “A Control Function Approach to Endogeneity in Consumer Choice Models.” *Journal of Marketing Research*, 47 (1): 3-13.

Purvis, A., J. Hoehn, V. Sorenson, and F. Pierce. 1989. “Farmers’ Response to a Filter Strip Programme: Results from a Contingent Valuation Survey.” *Journal of Soil and Water Conservation*, 44 (5): 501.

Rabalais, N.N., R.E. Turner, B.K. Sen Gupta, E. Platon, and M.L. Parsons. 2007. Sediments tell the history of eutrophication and hypoxia in the Northern Gulf of Mexico. *Ecological Applications* 17: 129-143.

Roberts, R., B. English, Q. Gao, and J. Larson. 2006. “Simultaneous Adoption of Herbicide-Resistant and Conservation-Tillage Cotton Technologies.” *Journal of Agricultural and Applied Economics*, 38 (3): 629-43.

Robinson, C., M. Ghaffarzadeh and R. Cruse. 1996. "Vegetative Filter Strip Effects on Sediment Concentration in Cropland Runoff." *Journal of Soil and Water Conservation*, 51 (3): 227-30.

Scarpo, R. and J. Rose. 2008. "Design Efficiency for Non-market Valuation with Choice Modelling: How to Measure it, What to Report and Why." *The Australian Journal of Agricultural and Resource Economics*, 52: 253-82.

Schmitt, T., M. Dosskey and K. Hoagland. 1999. "Filter Strip Performance and Processes for Different Vegetation, Widths, and Contaminants." *Journal of Environmental Quality*, 28 (5): 1479-89.

Shen, J. 2009. "Latent Class Model or Mixed Logit Model? A Comparison by Transport Mode Choice Data." *Applied Economics*, 41(22): 2915-24.

Soule, M., A. Tegene, and K. Wiebe. 2000. "Land Tenure and the Adoption of Conservation Practices." *American Journal of Agricultural Economics*, 82 (4): 993-1005.

Train, K. 2009. Discrete *Choice Methods with Simulation, Second Edition*. Cambridge University Press, Cambridge, MA.

Train, K. 1998. "Recreation Demand Models with Taste Differences over People." *Land Economics*, 74: 230-9.

United States Department of Agriculture. 2009. 2007 Census of Agriculture: Ohio State and County Data. Volume 1, Part 35. Online URL: http://www.agcensus.usda.gov/Publications/2007/Full_Report/Volume_1,_Chapter_1_State_Level/Ohio/ohv1.pdf

Wu, J. and B. Babcock. 1998. “The Choice of Tillage, Rotation, and Soil Testing Practices: Economic and Environmental Implications.” *American Journal of Agricultural Economics*, 80 (3): 494-511.

Zbinden, S. and D. Lee. 2005. “Paying for Environmental Services: An Analysis of Participation in Costa Rica’s PSA Programme.” *World Development*, 33 (2): 255-272.

Appendix: Two-Stage Control Function Estimation

Because the second stage of our estimation is nonlinear, traditional two-stage least squares (2SLS) methods are inconsistent. Instead we use a control function approach (Heckman and Robb 1985; Train 2009). The control function approach uses an identical first stage to what would be used in 2SLS, with the endogenous variable regressed on all exogenous variables and instruments. Results from this first stage regression are presented in Table 6. These variable coefficients are used to construct predicted values for the perceived efficacy variable in the presence of a filter strip, while perceived efficacy in the absence of a filter strip is set to zero. From these predicted values, we calculate residuals from the first stage regression. The second stage estimation includes the efficacy variable as well as the control function, which is comprised of the residuals from the first stage and a standard normal random variable (Petrin and Train 2010).

Results from the second stage estimation are presented in Table 7. The “pooled” column results assume preference homogeneity. In both the pooled and latent class estimations, the results are qualitatively similar to those found in the estimations presented in Table 3. The only major difference between the two models is the increased noise found in the control function estimations.

Table 1: Demographic Comparison

Variable		Analysis Sample (389)	Full Sample	Maumee	Weighted Analysis Sample
Planted Acres (% in each Category)	1-9	5.9	5.7 (456)	10	10.7
	10-49	16.5	17.3 (456)	28	30.3
	50-179	34.3	35.5 (456)	31	33.0
	180-499	25.2	24.1 (456)	18	17.7
	500 plus	18.1	17.3 (456)	8	8.3
% With Off-Farm Income		84.8	88.3 (806)	66	66.0
Farm Gross Sales (% in each Category)	Less than 50k	38.7	43.6 (438)	64	64.0
	50k-100k	16.5	16.0 (438)	10	10.0
	100k plus	44.8	40.4 (438)	26	26.0

Notes: In the "Full Sample" column, the number of observations is given in parentheses. The analyses presented in the paper have a sample size of 389.

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

Variable	Description	Mean	Standard Deviation	Min/Max
Program-Level Attributes				
Payment	$US per acre	126.45	96.12	0/250
Width	Filter strip width in feet	33.38	31.07	0/75
Paper	Hours of paperwork per year	3.77	3.77	0/10
Years	Program length	5.03	4.08	0/10
StatusQuo	= 1 if current program	0.33	0.47	0/1
Efficacy	Reduction in probability of runoff	11.37	18.29	-90/90
Individual-Level Attributes				
StMarys	Awareness of algal issues at Grand Lake St. Marys	1.44	0.62	0/2
HighRiskFarm	= 1 if risk tolerant in farming	0.23	0.42	0/1
HighSchool	= 1 if high school education or less	0.43	0.50	0/1
NormTill	= 1 if use conventional tillage	0.25	0.43	0/1
Age40	= 1 if 40 or younger	0.27	0.44	0/1
Enrolled	= 1 if enrolled in other conservation programs	0.58	0.49	0/1
Recreate	= 1 if respondent recreates in Ohio rivers, lakes or streams	0.39	0.49	0/1
FirstGen	= 1 if first-generation farmer	0.15	0.35	0/1
GeneralRisk	Likert-scale variable for general risk tolerance (10 = risk tolerant)	6.38	2.05	0/10
Organic	=1 if part of the farm is certified or in the process of being certified organic	0.02	0.15	0/1
Field-Level Attributes				
Drainage	= 1 if field possesses working drainage tile	0.86	0.34	0/1
25-75ft	= 1 if nearest surface water is 25-75 feet from field	0.20	0.40	0/1
75ft	= 1 if nearest surface water is more than 75 feet from field	0.24	0.43	0/1
SlopeLess2	= 1 if slope is less than 2 degrees	0.50	0.50	0/1
SlopeMore5	= 1 if slope is more than 5 degrees	0.09	0.29	0/1
ClayLoam	= 1 if soil type is clay loam	0.48	0.50	0/1
SiltyLoam	= 1 if soil type is silty loam	0.15	0.35	0/1
Loam	= 1 if soil type is loam	0.05	0.21	0/1
Sand	= 1 if soil type is sand	0.02	0.14	0/1
SandyLoam	= 1 if soil type is sandy loam	0.08	0.27	0/1
Width25	=1 if filter strip is 25 feet wide	0.34	0.47	0/1
Width75	=1 if filter strip is 75 feet wide	0.33	0.47	0/1

Table 3: Latent Class Analysis Estimates and Marginal Effects, No First Stage

Variable	Coefficients			Marginal Effects		
	Pooled	Environmental Stewards	Others	Pooled	Environmental Stewards	Others
Payment	0.0073*** (6.60)	0.0067*** (5.47)	0.0132*** (3.40)	0.0014***	0.0008***	0.0014***
Width	-0.0195*** (-8.33)	-0.0178*** (-6.00)	-0.0178** (-2.22)	-0.0038***	-0.0022***	-0.0019**
Paper	-0.0635*** (-3.96)	-0.0556*** (-3.02)	-0.1313** (-2.41)	-0.0123***	-0.0069***	-0.0139**
Years	-0.0117 (-0.66)	-0.0083 (-0.43)	-0.0451 (-0.86)	-0.0023	-0.0010	-0.0048
StatusQuo	0.3664 (1.26)	-5.3575* (-1.93)	3.3938*** (3.2054)	0.0712	-0.6678*	0.3594***
Efficacy	0.0230*** (4.89)	0.0090 (0.67)	0.0349*** (3.44)	0.0045***	0.0011	0.0037***

Notes: *, **, and *** indicate significance at the 90%, 95%, and 99% confidence level, respectively. Values in parentheses are z-statistics. Marginal Effects are the mean marginal effect and significance is obtained using the Krinsky-Robb Procedure with 10,000 draws.

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

Variable	Class 1 (Environmental Stewards)	Class 2 (Others)	P-value (difference)
StMarys	1.466	1.416	0.73
HighRiskFarm*	0.252	0.177	0.07
HighSchool	0.388	0.476	0.28
ConventionalTill***	0.187	0.372	< 0.01
Age40**	0.319	0.183	0.02
Enrolled	0.616	0.510	0.18
Recreate**	0.442	0.307	0.045
FirstGen	0.125	0.183	0.14
Organic	0.020	0.028	0.74
GeneralRisk*	6.396	6.416	0.09

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 1.

Table 5: Latent Class Analysis Implicit Per-Acre Compensation Values

Variable	Pooled	Environmental Stewards	Others
Width	$2.67***	$2.66***	$1.35**
Paper	$8.70***	$8.30***	$9.95**
Years	$1.60	$1.24	$3.42
Efficacy	-$3.15***	-$1.34	-$2.64***

Notes: *, **, and *** indicate significance at the 90%, 95%, and 99% confidence level, respectively. Significance is obtained using the Krinsky-Robb Procedure with 10,000 draws.

Table 6: First Stage Results, Control Function Estimation

Variable	Coefficient	t-statistic
Drainage	-3.8526***	-3.77
25-75ft	-2.7262***	-3.12
75ft	-4.2338***	-5.24
SlopeLess2	-5.0229***	-6.99
SlopeMore5	0.2442	0.24
Width	0.1181***	6.60
Payment	-0.0029	-0.30
ClayLoam	-1.6732*	-1.84
SiltyLoam	0.2914	0.25
Loam	-8.2307***	-4.68
Sand	-4.4278*	-1.94
SandyLoam	0.3226	0.24
Paper	-0.1912	-1.44
Years	-0.0161	-0.10
Current	-13.3091	-5.34

Notes: Estimation is OLS and the dependent variable is Efficacy. *, **, and *** indicate that coefficients are significant at the 90%, 95%, and 99% confidence level, respectively. Variable definitions are provided in Table 1. The excluded soil type is clay.

Table 7: Second Stage Latent Class Analysis Estimates and Marginal Effects, Control Function Estimation

Variable	Coefficients			Marginal Effects		
	Pooled	Environmental Stewards	Others	Pooled	Environmental Stewards	Others
Payment	0.0073*** (6.33)	0.0087*** (4.73)	0.0129*** (3.22)	0.0016	0.0009	0.0022
Width	-0.0188*** (-5.21)	-0.1017* (-1.85)	-0.0122 (-1.09)	-0.0040	-0.0059	-0.0016
Paper	-0.0657*** (-3.82)	-0.0789 (-0.87)	-0.1472*** (-2.58)	-0.0134	-0.0071	-0.0217
Years	-0.0123 (-0.66)	-0.0039 (-0.18)	-0.0512 (-0.95)	-0.0026	-0.0013	-0.0082
StatusQuo	0.3507 (0.82)	0.9235 (0.49)	2.6433** (2.04)	0.0581	-0.3511	0.4029
Efficacy	0.0187 (0.81)	0.7191 (1.52)	-0.0183 (-0.33)	0.0023	0.0312	-0.0100

Notes: Z-scores are in parentheses. The estimation is a conditional logit model where the dependent variable is an indicator equal to one if the program is selected as the best. For coefficients, the symbols *, **, and *** indicate significance at the 90%, 95%, and 99% confidence level, respectively. Variable definitions are provided in Table 1. The pooled column assumes one class in the data (preference homogeneity). Both components of the control function are not presented here, as they have no economic interpretation and were not significant in either estimation.