Journal of Environmental Management 371 (2024) 123103

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Social targeting conservation subsidies in the Western Lake Erie Basin

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ARTICLE INFO

Handling Editor: Lixiao Zhang

Keywords:
Latent class
Constructed wetlands
Private land conservation
Voluntary conservation policy
Discrete choice experiment

ABSTRACT

Achieving public conservation objectives often requires voluntary conservation on private land. However, some landowners are reluctant to participate in voluntary conservation programs, even when offered financial incentives. Heterogeneity in willingness to participate suggests that policymakers can improve conservation outcomes by strategically targeting subsidy program outreach, messaging, and design to landowners who are more likely to enroll, which we call "social targeting." This paper informs social targeting a subsidy to farmers to construct wetlands in the Western Lake Erie Basin in the United States. We use a discrete choice survey and a latent class model to identify preference heterogeneity and farmer attributes associated with willingness to construct wetlands. Willing respondents prefer larger projects, but fully subsidized construction is vital for participation. Simulation results highlight that even the most willing farmers are unlikely to install a wetland if construction is not fully subsidized. Policy practitioners should target outreach to younger farmers and larger farms. Outreach strategies should focus on private benefits from the wetland, such as aesthetic values and hunting opportunities, highlight farmer responsibility for Lake Erie water quality, and promote positive social norms surrounding wetland construction.

1. Introduction

Voluntary conservation subsidy programs are an important tool to incentivize conservation on private lands, but they often face low enrollment. One way to increase enrollment is to increase subsidy levels, but this option is limited by budget constraints. Alternatively, policymakers may encourage enrollment by altering program attributes, such as changing conservation requirements or investing in outreach. This paper shows how policymakers can use social targeting to improve program design and outreach. Social targeting is designing policies and outreach strategies to cater to landowners who are most likely to accept voluntary conservation policy. A body of literature shows successful conservation programs promote a combination of awareness, financial incentives, and nudges (e.g., reminders) that acknowledge multiple barriers to adoption (Reddy et al., 2017). Physical targeting is an important complement to social targeting. It targets policy design and outreach to landowners whose land offers the greatest environmental benefits (Kast et al., 2021). Combined, social and physical targeting help move away from the homogenous, one-size-fits-all approach that is common in current conservation programs (Arbuckle, 2013a; Duff et al., 1992; McGrath et al., 2019; Ribaudo, 2015; Sims et al., 2019; Zwickle et al., 2021).

This paper shows how to socially target voluntary conservation policy using a discrete choice policy experiment and survey data on demographics and socio-psychological attributes. We use a three-step latent class model. The first step groups survey responses into classes based on policy preferences; policymakers can use these preferences to design conservation policy catered to likely accepters. The second step assigns respondents to classes and the third step describes respondent attributes. The third step results can be used to guide outreach strategies. We model heterogeneity at the class level because it is especially useful for social targeting; class-level resolution is precise enough to target willing respondents and coarse enough to produce results that policymakers can interpret as a heuristic guide for social targeting.

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https://doi.org/10.1016/j.jenvman.2024.123103
Received 18 November 2023; Received in revised form 4 October 2024; Accepted 25 October 2024
Available online 13 November 2024

Our case study focuses on a policy that incentivizes farmers in the US Western Lake Erie Basin (WLEB) to build constructed wetlands on their property. One hundred fifty years ago, a wetland known as the "Great Black Swamp" covered about one million acres of the WLEB (Kaatz, 1955). It is now functionally gone due to conversion of the basin to farmland, and, to a lesser extent, urban development (Mitsch, 2017). This dramatic reduction created an agriculturally productive region but also led to eutrophication and harmful algal blooms in Lake Erie, spurred by agricultural runoff (Michalak et al., 2013). Some have called for restoration of up to 10 percent (or 100,000 acres) of the Great Black Swamp to ensure the coexistence of agricultural productivity and local water quality (Mitsch, 2017). Restoration is possible but expensive. Estimates quote construction costs over $100,000 for a one-acre wetland or $700,000 for a 15-acre wetland (Kadlec and Wallace, 2008). Moreover, farmers who construct wetlands take on additional costs in terms of retiring land from production and regulatory risk.[1] Socially targeting landowners who are most willing to share this expense (or at least not add to it) can reduce the cost of restoration. But conservation practitioners in the region do not employ social targeting. Instead, policies are offered on a voluntary basis, at rates dependent on region (USDA, 2021). The results of our analyses can be used by practitioners in the WLEB to actively target constructed wetland subsidies.

We mailed a survey to WLEB farmers, including a discrete choice experiment that proposes subsidies for constructing wetlands. Each policy scenario offers a constructed wetland, with variation in levels of construction subsidy and annual per-acre subsidy for 15 years, wetland size, and quality of farmland to be converted. In addition to estimating the latent class model, we calculate how farmers trade off between construction and per-acre subsidies and simulate how the probability of acceptance for various policies differs between and within classes. The preferred model identifies four classes of survey respondents: (1) Willing to construct a wetland with sufficient subsidy ("pro-policy"), (2) unwilling to construct a wetland for any reasonable subsidy ("anti-policy"), and two classes that are ill-defined and omitted from postestimation analysis.[2] Conservation practitioners who want to maximize program uptake should design policies according to the preferences of the pro-policy class. Step one of our estimation shows that this class prefers larger wetlands and highly values construction subsidies, whereas annual per-acre subsidies are less important. Cost-effective policy design should focus on large projects with fully subsidized construction and a lower per-acre subsidy. As for outreach strategies, Step three shows that pro-policy respondents perceive more private benefits from wetlands, such as hunting and fishing opportunities, perceive less of a negative norm surrounding wetlands and more personal responsibility for Lake Erie water quality, are younger, and have larger farms. Effective outreach strategies should highlight wetlands' private benefits, note the impact of farmer decisions on Lake Erie, and push back on negative norms surrounding wetlands. Active outreach should target large farms with relatively unproductive lands.

[1] WLEB has a history of unexpected wetland regulation, contributing to distrust of regulatory authorities and likely also resulting in hesitance to construct wetlands.

[2] One class is composed of respondents who seemingly misinterpreted the survey, understanding "land productivity" to mean the wetland would produce a crop instead of describing the quality of farmland retired (see the question in Fig. 2). The wording of the question is admittedly ambiguous, though most answers were consistent with what was intended. The other class is a mix of unclassified respondents, who are characterized by misinterpreting the same survey question, preferring large subsidies, and having heterogeneous preferences for wetland size.

2. Background and literature

2.1. Wetland restoration and conservation in the western lake Erie basin

Wetland construction and restoration are a key requirement to improve environmental conditions near Lake Erie (Mitsch, 2017; Scavia et al., 2017). Given the hydrological history of this region as a one-million acre wetland feeding western Lake Erie (Kaatz, 1955), how much the region is now heavily tiled for rapid subsurface drainage (Jarvie et al., 2017), and the frequency and severity of harmful algal blooms in the lake (Michalak et al., 2013), it is clear that trapping the flow of water to help remove nutrients and sediments is necessary. Many organizations are working to target wetland creation where it may have the greatest environmental impact, including through federal programs, such as the National Resources Conservation Service Wetland Reserve Easement (USDA, 2021), and state programs, such as H2Ohio (Ohio Department of Natural Resources, n.d.). As most of the land in the basin is privately owned, individual landowners will have to construct wetlands to meet suggested targets (Mitsch, 2017). However, WLEB farmers have a unique and negative history with wetlands, with many being direct descendants of those who "drained the swampland" in that region (Dahl, 1990; Levy, 2017). Despite evidence that public attitudes toward wetlands have become more positive over time (Prince, 2008), wetlands are only a fraction of the acres enrolled in federal land retirement programs (Ferris and Siikamaki, 2009).

The primary approach to promoting conservation on private agricultural lands is voluntary incentive-based programs. However, a recent study in the region indicates that only one-quarter of farmers are participating in federal conservation programs and plan to continue (Téllez et al., 2021). Such programs function as a coalition of the willing, where interested farmers learn about the programs and apply to participate. If funding is not available to support every eligible applicant, the conservation office staff prioritize by maximizing environmental benefit within the pool of applicants (Claassen, 2009). The challenge is that this targeting to the areas of greatest need only occurs among those who sought out funding, sometimes called a "conservation policy of aggregation" (Nowak, 2009, 174A). Targeting the fields where conservation is needed across the full watershed would yield more efficient use of funds and potentially greater environmental impact (Berry et al., 2005; Delgado et al., 2005). Survey studies have found that farmers in the US Corn Belt tend to support proactive targeting policies and perceive them as beneficial for farming and the environment (Arbuckle, 2011). Although assessments of targeting benefits are limited, Kast et al. (2021) use process-based model simulations to compare environmental outcomes when subsidies are physically targeted (to fields with high phosphorus losses), socially targeted (to farmers having strong conservationist identities), or both. They find that subsidies can be distributed more efficiently by combining the two methods. Their model uses social-psychological variables to parameterize the simulation; our study adds to this literature by describing the characteristics of farmers willing to accept subsidies and heterogeneity in policy preferences among farmers in the study area.

2.2. Farmer heterogeneity in wetlands acceptance

A range of individual and contextual factors can influence conservation enrollment (Epanchin-Niell et al., 2022). Some landowners are unwilling to engage with conservation agencies, perhaps due to distrust (Coulibaly et al., 2021; de Vries et al., 2019; Peng et al., 2020; Upadhaya et al., 2021) or negative perceived social pressure (Niemiec et al., 2020; Vaske et al., 2020). Some are unable to participate due to information gaps, such as regarding conservation implementation and maintenance costs or the need for training and technical support (Ranjan et al., 2019). Meta-analyses found significant relationships between conservation adoption and factors including personal motivation (e.g., concern about the environment, understanding of personal environmental impact) and capacity to act (e.g., access to quality information and supportive networks) (Baumgart-Getz et al., 2012; Prokopy et al., 2019). Interview studies with farmers in the Corn Belt have yielded similar conclusions (Zimmerman et al., 2019).

Evidence shows that farmers interested in government programs tend to be younger, be more educated, and have a greater belief in the effectiveness of on-farm actions for reducing nutrient loss and improving water quality (Téllez et al., 2021). Farmers with these characteristics are more likely to participate in programs when their capacity is high (e.g., they operate larger farms, have access to information about programs, and perceive programs to be compatible with their operation and land management approach).

Research on wetland construction in the WLEB finds that farmers who are willing to construct wetlands will even do so on productive land if they perceive additional private benefits, such as aesthetic value or hunting opportunities (Soldo et al., 2022). Research outside of this region indicates similar findings; landowners interested in wetlands are in the minority and less likely to be concerned about the potential financial costs (e.g., land taken out of production, cost of installation and maintenance) and magnitude of the payments (Yu and Belcher, 2011; Zhang et al., 2011). In addition, those who want to construct wetlands tend to perceive additional private or cultural benefits (Ghermandi and Fitchman, 2015; Hansson et al., 2012; Odgaard et al., 2017), perhaps due to their deep-rooted stewardship or conservation-based values (Hansson et al., 2012). A challenge to some farmers participating in wetlands programs is that enrollment of land is likely permanent or long term, either due to the high costs of returning wetland to agriculture or due to enrollment in a conservation easement, which often has a duration of 30 years to in perpetuity (e.g. USDA-NRCS Wetland Reserve Easement; USDA, 2021). Welsh et al. (2018) conduct interviews of landowners in northeastern New York State to determine factors that affect wetland program enrollment. They find program adopters are more likely to be retired or female. Their interviewees tended to have a conservation ethic and prior experiences with wetland restoration and preservation.

Collectively, this literature suggests that promoting constructed wetlands on private lands will have the highest uptake if targeted to those farmers with both the motivation and ability to act. These include farmers who already value wetlands for their various use and nonuse benefits and do not find program enrollment and participation too cumbersome. Accordingly, we hypothesized that perceiving non-conservation benefits of wetlands would predict greater wetland policy uptake.

2.3. Economic literature on stated preferences for private wetland management

An extensive body of literature on public valuation of wetlands has applied discrete choice experiments to reveal public willingness to pay (WTP) for government management (e.g., Birol et al., 2006; Birol and Cox, 2007; Newell and Swallow, 2013; see Brander et al., 2006 for a review). Less common are experiments testing private landowners' willingness to manage or create wetlands. Although our focus is on constructing wetlands on farms, related research has examined willingness to conserve and maintain existing wetlands and create riparian buffer zones. Yu and Belcher (2011) use a contingent valuation survey of private landowners' willingness to adopt wetland conservation practices on their property, coupled with measures of demographics and structural variables. They find that predictors of willingness to conserve are subsidy size, landowner experience, older age with shorter planning horizons, and perceptions of land values. Buckley et al. (2012) use a contingent valuation survey for willingness to establish a riparian buffer zone. They find that the main constraints to adoption are loss of productive farmland and nuisance effects. Wachenheim et al. (2018) survey participants in a private land wetlands conservation program (North Dakota's Working Wetlands Program), finding that farmers prefer shorter and more flexible management contracts. Czajkowski et al. (2021) use a discrete choice experiment to estimate farmers' preferences for protecting a nearby wetland and bird habitat, focusing on heterogeneity in private land use driving willingness to conserve. They also study the association between environmental knowledge and willingness to accept a conservation subsidy.

Our study differs from this literature in three major ways. First, we focus on wetland construction policies instead of conservation and preservation. Second, we model preference heterogeneity at the class level using a latent class model rather than continuous heterogeneity with a mixed logit model. Finally, we inform social targeting by focusing on results that correspond to actionable strategies for practitioners.

2.4. Hypotheses for latent classes

Given studies showing that a minority of landowners are willing to construct a wetland (Yu and Belcher, 2011; Zhang et al., 2011), we hypothesized that preferences would fall into two broad categories: (1) supporting wetland construction policies and tending to choose to participate and (2) failing to support wetlands and opting out of any policy. Predictions were made in accordance with the Theory of Planned Behavior (Ajzen, 2012), which states that behavioral intentions are influenced by attitudes related to that behavior. We hypothesized that respondents who support wetlands policies would have overall more favorable opinions of the benefits of wetlands and, consistent with these attitudes, prefer wetlands that are larger. However, given that even the most conservation-minded agricultural landowners are concerned with productivity and profit (Arbuckle, 2013b; McGuire et al., 2015), we predicted that both classes would prefer larger annual subsidies and fully covered construction costs.

3. Survey and variables

3.1. Survey description

We purchased a stratified, random sample of mailing addresses for WLEB agricultural operations (see Fig. 1) from Farm Market ID, yielding 1776 potential participants. Sampling was stratified by subbasin and farm size. Larger farms were oversampled to distribute the survey uniformly by land area. The farm size categories used for stratification were 20–249, 250–499, 500–999, and 1000+ acres. About 800 surveys were mailed to farms with over 500 acres. The Auglaize and Blanchard subbasins were oversampled because research identified them as high-priority locations for constructed wetlands to benefit Lake Erie water quality (Soldo et al., 2022). Approximately 400 surveys were mailed to each. The other subbasins (Cedar-Portage, Lower Maumee, Upper Maumee, Ottawa-Stony, Raisin, Sandusky, St. Joseph, St. Mary, and Tiffin) were sampled with equal frequency.

We sent each potential respondent a survey through the US postal service from August to September of 2019. The specific measures used in this analysis are detailed in the next section. We mailed 1) an initial letter; 2) a full mailing of the eight-page survey with a cover letter, including a return envelope and a $2 bill; 3) a reminder postcard; 4) a second full mailing with a cover letter and return envelope; and 5) a postcard (sent only to nonrespondents).[3] We received 613 out of 1776 responses, 491 of which were completed with full information and included in the analysis.

[3] As soon as a respondent returned a survey, no further Correspondence was issued. For those who indicated that they did not wish to participate by returning a blank survey or failing to respond after the full sequence of mailings, we deleted all contact information. All useable responses were assigned an identification number, thereby making responses anonymous and devoid of personally identifiable information. The data were stored and analyzed with a numerical code only.

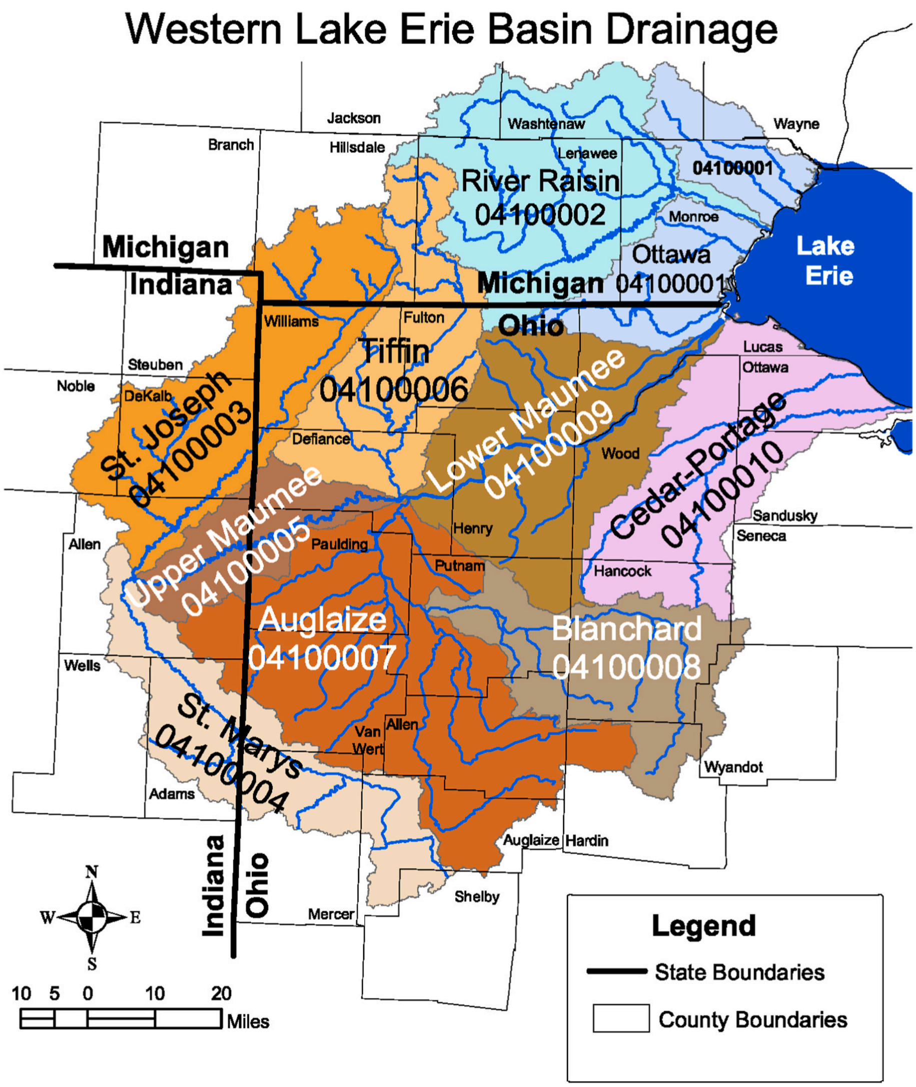

Fig. 1. Study area, comprising the WLEB drainage area (USDA Natural Resources Conservation Service). Different colored regions are the subbasins of the watershed. Just over 50 percent of responses in our survey are from Auglaize and Blanchard, in orange and light brown in the bottom of the map, which were oversampled due to their importance for wetland conservation. The other half of responses are distributed relatively equally throughout the other subbasins. Appendix Table A.1 reports the subbasin-level survey deliveries and response rates. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3.2. Description of survey variables

We selected survey variables based on social-psychological and structural factors that have been found to correlate with adoption of conservation agriculture practices, participation in government programs, and support for wetlands (Lu et al., 2022). These works, and the corresponding social-psychological and economic theory, are outlined in sections A.5 and A.6 of the Appendix. The independent variables for Step three are characteristics of the farmer and their operation and measures of farmer identity (see Table 1). The latter are derived from the good farmer identity scale (Arbuckle, 2013b; McGuire et al., 2015), and the other beliefs are meant to largely replicate qualitative themes from Hansson et al. (2012) and include perceptions of private benefits from wetlands (e.g., hunting opportunities, aesthetic values), negative norms regarding wetland construction, concern for Lake Erie water quality, agricultural impacts on Lake Erie water quality, and agreement with whether a good farmer implements conservation practices or maximizes farm production capacity. The farmer identity and perception variables are aggregates, calculated as the mean of constituent items. The farm and farmer characteristics include age (years), education (college), off-farm income (dummy), farm size (log total farm acres), location (dummy-coded to indicate Ohioan), and the proportion of farm acres used for crops.

3.3. Discrete choice experiment description

The choice experiment asked respondents whether they prefer one of three offers for a subsidized constructed wetland or would choose not to build wetland. Fig. 2 shows how the discrete choice experiment was presented and the exact question wording. Each respondent answered three policy scenarios for a panel of answers. The policy offers varied on four dimensions: 1) the quality of the designated land, 2) the wetland size, 3) construction cost share level, and 4) an annual per-acre subsidy lasting 15 years. These parameters were chosen because wetland construction is often based on land topography, such that farmers have limited ability to choose the location. Furthermore, policies often set minimum wetland sizes in addition to defining the construction and per-acre subsidy.

Land quality is expressed as the probability of producing a good crop, with possible levels as 20 percent, 50 percent, or 80 percent of years (a

Table 1
Social-psychological aggregate variables and constituent items.

Variables	Constituent Items
Perceived Private Benefit[a]	Constructed wetlands would enhance the beauty of my farm Constructed wetlands would provide me with valuable hunting opportunities Constructed wetlands would attract desirable waterfowl to my property
Perceived Norm[a]	Other farmers I respect would not approve of me installing a wetland My neighbors would not approve of me installing a constructed wetland
Conservationist Identity (A good farmer is one who …) [b]	Scouts before spraying for pests/weeds/ disease. Puts long-term conservation of farm resources before short-term profits. Maintains or increases soil organic matter. Thinks beyond their own farm to the social and ecological health of their watershed. Minimizes nutrient runoff into waterways. Minimizes soil erosion. Manages for both profitability and minimization of environmental impact. Considers the health of streams that run through or along their land to be their responsibility. Minimizes tillage.
Productionist Identity (A good farmer is one who …) [b]	Has the highest profit per acre. Is willing to try new practices and approaches Has the highest yields per acre. Maximizes government payments
Lake Erie Concern (I am concerned about …)[a]	Nutrient loss from agriculture impacting Lake Erie. The public health impacts of harmful algal blooms (HABs) in Lake Erie. Nutrient loss occurring on my farm. The economic impacts of harmful algal blooms (HABs) in Lake Erie.
Lake Erie Responsibility[a]	My farming practices contribute to problems in Lake Erie Farming practices in the western Lake Erie Basin contribute to problems in Lake Erie.

Note: The aggregate variables are calculated as the mean of their constituent items.
[a] measured from strongly disagree (0) to strongly agree (4), where 2 equals neither disagree nor agree.
[b] measured from not important at all (0) to very important (4).

low, uncertain, or high chance of high yields). To test the effect of increasing wetland size on policy support, respondents were presented with policies that offered 1-, 5-, 10-, or 15-acre wetlands. To assess the impact of out-of-pocket costs on policy support, construction cost share is either 50 or 100 percent. The annual per-acre subsidy offered was \$300, \$750, or \$1500. For reference, a productive acre of corn or soy may yield about \$500 of profit, be as low as \$200–300 per year if the land is rented, or even have negative profit in an unproductive year.

The exhaustive set of alternatives (72) was offered. Each respondent answered three questions, with three alternatives per question (four including the no policy option), and we define eight groups of respondents. We use a fixed orthogonal design to pair alternatives and maximize efficiency for estimating the effects and interactions between policy attributes.

3.4. Justification of social-psychological variables

Psychological research has pointed to the importance of self-identity on behavior. Broadly, a person's identity, or how they define themselves, shapes their ongoing concerns and goals in everyday life. In turn, being committed to those goals helps a person to achieve them in the face of obstacles (Gollwitzer and Oettingen, 2012). For example, multiple meta-analyses have demonstrated that persons who identify as environmentalists are more concerned for the health of the environment and more likely to engage in actual conservation behaviors (Udall et al., 2021; Vesely et al., 2021). Inspired by this work, the field of farmer decision making has also studied how much farmers identify as conservationists.

Many farmers, including in the Corn Belt, continue to believe their primary duty is crop production (Leitschuh et al., 2022), which tends *not* to predict environmental concern (Sulemana and Harvey, 2014). However, farmers can simultaneously hold both productionist and conservationist identities (Arbuckle, 2013b; McGuire et al., 2015). Conservationist identity, or believing that a "good farmer" is one who cares about conservation, *does* predict greater concern for environmental issues (Sulemana and Harvey, 2014), adoption of more climate adaptation practices (Morton et al., 2017), and greater intentions to engage in management practices that are beneficial for water quality (Floress et al., 2017) and actual practice adoption (Denny et al., 2019; McGuire et al., 2013). Therefore, we hypothesize that greater conservationist identity corresponds with support for pro-environment policies (such as constructing wetlands).[4] In addition, because conservationist identity may not capture all aspects of environmental concern, we measure concern for Lake Erie water quality, specifically, and expect that those with greater concern are more likely to support wetland policy.

Beyond concern for an issue, having a sense of personal moral responsibility to address a problem predicts greater action (DeGroot and Steg, 2009), including willingness to improve water quality (Floress et al., 2017; Mills et al., 2017; 2018; Yoshida et al., 2018). Thus, we expect farmers with greater sense of personal responsibility toward addressing Lake Erie water quality to be more likely to participate in constructed wetlands policies. In addition, we expect that fairness beliefs about being asked to install a wetland will significantly predict wetlands support, as a sense of personal responsibility to address water quality issues may not specifically extend to feeling responsible for wetlands restoration.

Although a farmer may identify as a conservationist and feel responsible for improving the watershed, they could nevertheless be discouraged to install wetlands if they perceive negative social pressure. Social norms are perceptions about what others in one's social group tend to do and what actions they find acceptable (Cialdini et al., 1990; Fishbein and Ajzen, 2011). Norms have been shown to strongly influence pro-environmental intentions and behaviors (Farrow et al., 2017; Sparkman and Walton, 2017). These findings have been extended to agricultural contexts (Niemiec et al., 2020; Welch and Marc-Aurele, 2001), including the impact of perceived neighbor approval on management practice intentions (Läpple and Kelley, 2013; Vaske et al., 2020) and wetland conservation intentions (Valizadeh et al., 2021). However, more research on this topic is needed, as the effect of norms on conservation practices is mixed. For example, in Daxini et al. (2018), norms only showed a weak effect on intending to follow a nutrient management plan, and (Gao, 2022) did not find norms to predict actual in-field nutrient management practices.[5] We deemed it pertinent to examine the impact of perceived acceptance of wetlands and wetland policies among neighbors and fellow farmers. We expect that perceiving negative social pressure demotivates willingness to install wetlands.

Finally, separate from a farmer's pro-environment goals and beliefs, distrust in government entities acts as a barrier to engagement with

[4] Furthermore, because productionist identity does not preclude pro-environment action, we did not hypothesize a relationship with willingness to accept wetland policy but included this variable for exploratory purposes.

[5] Regarding intentions to implement wetlands, Lang and Rabotyagov (2022) concluded that social norms did not impact intentions. However, this study did not measure perceived social norms in terms of neighbor and farmer approval but rather beliefs that multiple agents are responsible for watershed management.

	□ Program A	□ Program B	□ Program C
Likelihood of the land designated for the wetland producing a good crop due to flooding and soil moisture	Good crop 20% of the time—or 2 out of every 10 years.	Good crop 80% of the time—or 8 out of every 10 years.	Good crop 80% of the time—or 8 out of every 10 years.
Constructed wetland size	1 acre	15 acres	1 acre
Granted subsidy (% of construction costs covered)	50% construction costs	100% construction costs	100% construction costs
Annual nutrient removal payments per acre	$1,500 per acre, per year	$300 per acre, per year	$300 per acre, per year

□ I would not construct a wetland on my property based on any of these options.

Fig. 2. Example choice experiment offered to survey participants.

conservation policies (Coulibaly et al., 2021; de Vries et al., 2019; Peng et al., 2020; Upadhaya et al., 2021). A baseline tendency to avoid policies would inhibit willingness to participate in a wetlands construction program. Moreover, farmers who distrust government are probably less likely to respond to our survey. This can be interpreted as selection bias, where farmers that trust government are overrepresented and distrust is an omitted variable that confounds the outcome variables. Nonetheless, the results are useful to interpret as the preferences of farmers who answer the survey, and may therefore be more trusting in government and more likely to enroll in a wetland restoration program. Also, although our survey did not measure trust in government directly, we can observe overall policy avoidance in the choice experiments where some respondents choose not to engage with any policy regardless of its attributes.

3.5. Justification of structural variables

Factors that enhance one's ability to enact conservation intentions contribute to conservation practice adoption, such that farmers with greater resources are more likely to adopt best management practices (Baumgart-Getz et al., 2012; Lu et al., 2022; Zimmerman et al., 2019). Consistent with this, we hypothesized that conservation intentions would be associated with more overall land and cropland, existing edge-of-field infrastructure, and higher farm and off-farm income. Other socioeconomic factors, such as educational attainment, also predict greater adoption, perhaps through lowered demands of management, increased risk perception of climate change, and higher perceived benefits of conservation (Barnes et al., 2013; Lo et al., 2021; Niles et al., 2016; Osmond et al., 2015).

Some demographic factors, such as age, show little support for a relationship with conservation practices (Knowler and Bradshaw, 2007; Niles et al., 2016) but are included for exploratory purposes, as observable factors can be useful for policy decisions. Farmers from Ohio were also included as a variable because the response rate from Ohioan farmers was higher than those from Michigan or Indiana. We hypothesize that a higher response rate will capture more farmers with lower conservation values, as they may be less likely to respond to a survey about wetland.

4. Empirical methods

We estimate class-level heterogeneity using a three-step latent class logit model, which is based on a random utility model (Greene and Hensher, 2003; McCutcheon, 1987; McFadden, 1974). We are faced with two primary modeling decisions. (1) How many classes should we specify? (2) Should class assignment depend on both policy preferences and respondent attributes (a one-step model) or only on policy preferences, with respondent attributes connected post-estimation (a three-step model)?

The number of classes can be specified based on social science theory or using an inductive approach leveraging various fit metrics (Nylund-Gibson and Choi, 2018; Weller et al., 2020). Using theory has the benefit of ensuring relevant and interpretable results, but it is ad hoc, and the estimated policy preferences may not conform to expectations. Using a purely inductive approach ensures the estimation fits the data but also may overfit the data and can risk uninterpretable or uninformative results (Eger and Hjerm, 2022). We choose the number of classes based on social science theory, guided by fit metrics and estimated outputs. We use Bayesian Information Criterion (BIC) and Consistent Akaike Information Criterion (CAIC) to assess overall model fit and rely on entropy for separation between classes. We evaluate whether to include interactions between the policy variables in the same way.

We select a three-step model because it is more informative for social targeting. Although a one-step model achieves stronger segmentation regarding respondent attributes, this comes at the expense of segmenting policy preferences, as it weighs both factors in assigning the class probabilities. On the other hand, a three-step model segments classes only using policy preferences. Thus, the individual attributes associated in the third step will more reliably predict who is willing and unwilling to construct a wetland.

Bolck et al. (2004) propose a three-step model as follows.

(1) Run a latent class estimation of policy preferences,
(2) Assign respondents to classes based on their observed preferences, and
(3) Use a multinomial logit model to regress class assignment on individual attributes.

They and Vermunt (2010) show that the variation introduced in Step two leads to biased and inconsistent coefficient estimates in Step three. We correct Step three using the method proposed by Bolck et al. (2004), leveraging the equivalent and simpler formulation proposed by Vermunt (2010).

4.1. Estimation

Survey respondent i receives random utility U from alternative j in choice experiment k:

$$U_{ijk} = \mathbf{x}_{ijk}\boldsymbol{\beta}_i + \epsilon_{ijk}, i = 1, \dots, N, j = 1, \dots, J, k = 1, \dots, K_i,$$

where $\mathbf{x}_{ijt}$ is a vector of alternative-specific attributes, $\boldsymbol{\beta}_i$ is an individual-specific vector of coefficients for the marginal utility from each alternative attribute, and ϵ is an idiosyncratic error term. In a mixed logit model, β_i may be a random parameter unique to each respondent with a user-parameterized distribution of β. In the latent class model, all β_i is specific to classes of individuals. Let T represent the number of classes. A latent class model estimates class-specific coefficients on the policy attributes such that $\beta_i = \beta_t$ for all i in class t.

In the first step, we have respondents choosing K policies, denoting each choice situation Y_{ik}, the decision chosen $Y_{ik,j}$, and the vector of choices $\boldsymbol{Y}_i$. Every respondent answered all three choice experiments, so $K_i = 3$ decisions per respondent. Responses are assumed to be independent conditional on class membership, so we can write

$$P(\boldsymbol{Y}_i | X = t) = \prod_{k=1}^{K_i} P\left(Y_{ik,j} | X = t\right).$$

The central logit model is the probability of individual i choosing $Y_{ik,j}$ in choice situation k:

$$P(Y_{ik} | X = t) = \frac{\exp\left(\boldsymbol{x}_{ik,j}\boldsymbol{\beta}_t\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{x}_{ik,j}\boldsymbol{\beta}_t\right)},$$

where $\boldsymbol{\beta}_t$ is a *class-specific* vector of coefficients. The full step one log-likelihood function is then

$$\ln L_1 = \sum_{i=1}^{N} \ln P(Y_i) = \sum_{i=1}^{N} \ln\left[\sum_t w_{it} \prod_{k=1}^{K_i}\prod_{j=1}^{J}\left(\frac{\exp\left(\boldsymbol{x}_{ik,j}\boldsymbol{\beta}_t\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{x}_{ik,j}\boldsymbol{\beta}_t\right)}\right)^{y_{it,j}}\right], \tag{1}$$

where w_{it} is the probability that respondent i is in class t, such that $\sum_t w_{it} = 1$ for all i. Class probabilities do not depend directly on individual attributes in the three-step approach. The first step model is estimated by maximizing the log likelihood with respect to the parameter vector $\theta = (\boldsymbol{\rho}, \boldsymbol{\beta})$. The maximum likelihood procedure is implemented using the gmnl package in R (Sarrias and Daziano, 2017). Convergence is a challenge for implementing a latent class model using maximum likelihood estimation (Bhat, 1997). To address this, each model takes as start values a vector randomly sampled from a uniform distribution on $(-1.5, 1.5)$. This procedure is repeated one million times for each model run, and the best-fitting model, as evaluated by BIC, is taken to be the global optimum. We use Wald tests to test whether policy preferences differ significantly between classes.

The number of classes must be prespecified to run the model. Our a priori expectation, from theory, is that 2–3 classes will be optimal: "never adopters," "always adopters," and possibly "adopts with sufficient incentive." We also suspect a priori that some respondents may misinterpret the survey or respond haphazardly, requiring a residual category that captures these respondents. We test 2–6 classes to test these hypotheses. We evaluate the models based on BIC, CAIC, entropy, and comparing the results to our hypotheses, following a hybrid approach to model selection (Nylund-Gibson and Choi, 2018).

The second step assigns respondents to classes based on the estimation results and their policy choices. The posterior probability of class membership $P(X_i = t \mid \boldsymbol{Y}_i)$ is calculated as

$$\widehat{\pi}_{it} = \frac{\widehat{w}_{it} \prod_{k=1}^{K_i}\prod_{j=1}^{J}\left(\frac{\exp\left(\boldsymbol{x}_{ik,j}\widehat{\boldsymbol{\beta}}_t\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{x}_{ik,j}\widehat{\boldsymbol{\beta}}_t\right)}\right)^{y_{it,j}}}{\sum_{t}^{T} \widehat{w}_{it} \prod_{k=1}^{K_i}\prod_{j=1}^{J}\left(\frac{\exp\left(\boldsymbol{x}_{ik,j}\widehat{\boldsymbol{\beta}}_t\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{x}_{ik,j}\widehat{\boldsymbol{\beta}}_t\right)}\right)^{y_{it,j}}} \tag{2}$$

Denote the class assigned to a respondent as W_i. Two primary class assignment methods exist: modal and proportional. Modal assignment sets $P(W_i = t \mid \boldsymbol{Y}_i) = 1$ if class t is the maximum posterior probability for respondent i and 0 otherwise. Proportional assignment sets $P(W_i = t \mid \boldsymbol{Y}_i) = \pi_{it}$. Both methods allow us to construct weights for consistent and unbiased estimates in Step three, so we opt for modal assignment for simplicity.

The third step is to relate assigned class membership W_i to individual-specific covariates $\boldsymbol{z}_i$ using a weighted multinomial logit on an expanded dataset (Bolck et al., 2004; Vermunt, 2010). The procedure accounts for uncertainty introduced by the possibility of misassignment in Step 2. Without the weights, the estimated coefficients are biased toward 0. To construct the weights, we first calculate the probability of assignment to class s conditional on a true latent class of t:

$$P(W = s \mid X = t) = \frac{\sum_i P(X = t \mid Y_i) P(W_i = s \mid Y_i)}{P(X = t)} \approx \frac{\sum_i \widehat{\pi}_{it} \ \widehat{W}_{is}}{\sum_i \widehat{\pi}_{it}}.$$

Using these estimates, we construct a $T \times T$ matrix D where the (t, s) element is $d_{ts} = P(W = s \mid X = t)$, and a matrix $D^* = D^{-1}$. The unbiased and consistent Step 3 model is calculated by maximizing the following likelihood function:

$$\ln L_3 = \sum_{i=1}^{N} \sum_{t=1}^{T} w_{it}^* \log P(X = t | \boldsymbol{z}_i), \tag{3}$$

where $w_{it}^* = \sum_{s=1}^{t} w_{is} d_{st}^*$ equals d_{st}^* for modal assignment (Vermunt, 2010). This is implemented by using a weighted multinomial logit to regress class assignment on respondent attributes, with $N*T$ rows such that every respondent is assigned a probability for every class, each row corresponds to a respondent and class, and the multinomial logit is weighted by d_{st}^*. Standard errors are clustered at the individual level by resampling individuals and bootstrapping the t-statistic (Cameron et al., 2008). The Stage 3 model is implemented using the R packages mlogit and clusterSEs (Croissant, 2020; Esarey and Esarey, 2022).

4.2. Trade-off between the construction subsidy and annual per-acre subsidy

A key question for constructed wetlands subsidy design is how to split the budget between construction cost subsidies and annual per-acre subsidies for land retirement. The discrete choice experiment proposes contracts with varied levels of both subsidy types. We calculate the value of construction cost sharing in terms of the per-acre annual subsidy. The survey offered two levels of construction cost subsidy: 50 or 100 percent. Construction costs are coded as a dummy variable indicating a 50 percent cost share. Therefore, the ratio of the coefficients, $\beta_{constr,t}/\beta_{annual,t}$, is the average value of a 50 percent cost share, instead of a full subsidy, in terms of a dollar-per-acre subsidy. In other words, it answers the question of what annual per-acre subsidy combined with a 50 percent cost share is indifferent to a full construction subsidy. Confidence intervals are calculated using the delta method to estimate asymptotic variance of the ratio value. These estimates are multiplied by 2 to indicate the implied willingness to accept for annual per-acre subsidy to cover construction costs.

Furthermore, assuming various discount rates to calculate the net present value of the subsidy, we calculate farmers' estimates of total wetland construction costs. This is important because, with known values of wetland construction costs, this informs class-level heterogeneity in the quality of information farmers have about them.

4.3. Policy uptake simulations

We simulate how the probability of policy acceptance varies between the pro-policy and anti-policy classes and for different policies. We use the policy coefficient estimates from the first-step model to predict mean within-class acceptance probabilities for various policies. This highlights which policy parameters are driving decisions and how that varies by class. A conservation practitioner could use this information to understand what drives decisions for the class of respondents willing to construct wetlands.

Additionally, we estimate a null model—a conditional logit model—effectively masking the heterogeneity in the sample. This informs the extent to which policy outreach directed at the pro-policy class is more cost-effective than outreach to a random respondent (i.e., the typical respondent when targeting outreach on expected environmental benefits). The null model is calculated with respondents assigned only to the pro-policy and anti-policy classes, so the null predicted probability is a weighted average of the class-level probabilities.

4.4. Imputing total acres

The survey had a high response rate for acreage of the farm designated to corn and soy but a lower response rate for total farm acres. However, total farm acreage is a more relevant measure for constructing a wetland. We impute total farm acreage by regressing total acreage on corn and soy acreage and an intercept for the sample of respondents reporting both measures. We extrapolate the results to the 16 respondents who skipped the question. The regression results are in Appendix A.5.

5. Results

5.1. Respondent attributes

Table 2 shows summary statistics for the sample included in the policy simulation analyses. Farmers averaged 62 years old, with about 59 percent at least 60 years old. The majority responded that they received off-farm income in 2018 (76 percent). The average farm size was 937 acres, with a long right tail on the distribution; 43 percent were 300–1000 acres and 31 percent larger than 1000 acres. Seven percent of the farmers already had a constructed wetland on their property. Most respondents were in Ohio (84 percent).[6] A narrower majority were college educated (56 percent). Most already used edge-of-field conservation practices (71 percent).

[6] Michigan and Indiana are the other states in the WLEB that received surveys. This variable is included because an analysis of response rates showed that recipients in Ohio were more likely to respond.

Table 2
Sample summary statistics.

	Variable	
Structural	Age (share over 60)	0.59
	College (share)	0.56
	Off-farm income (share)	0.76
	Farm acres (mean)	937.75
	Proportion crop (mean)	0.96
	Ohioan (share)	0.84
	Edge conservation (share)	0.71
	Variable	
Socio-psychological (grand mean of Likert scale, with 0 indicating disagree and 4 indicating agree; see Table 1)	Good farmer conserves	3.09
	Good farmer maximizes production	2.30
	Private benefit	1.49
	Negative norm	1.57
	Lake Erie concern	2.41
	Lake Erie responsibility	1.79

Farmers indicated strong agreement with statements indicating that a good farmer is a conservationist. Consensus was weaker that a good farmer maximizes production, but a general agreement still existed. Respondents reported, on average, worse than neutral agreement that wetlands provide private benefits, such as hunting, fishing, and recreational opportunities, natural beauty, or desirable biodiversity. Respondents sought information about conservation opportunities from private sources (other farmers in the community, certified crop advisers) more than public sources (land grant extension service, local conservation district, USDA Natural Resources Conservation Service, county engineers), on average. The average perception of a norm regarding wetland construction was neutral, tending toward no negative norms. Farmers were concerned about the water quality in Lake Erie but did not necessarily feel personally responsible for it, on average.

5.2. First-step estimation, number of classes, and policy preferences

Attributes for selecting no policy were coded as 0 (the annual per-acre subsidy and wetland size would equal 0). Regarding the land quality variable, the likelihood of land being productive is unspecified under no-policy conditions and coded as 0. Last, if a person indicated that they would not build a wetland, their construction costs would not exist and therefore be covered 100 percent (50 percent cost share = 1).[7]

Following conventions in behavioral science (Weller et al., 2020), the number of classes was guided by fit metrics (Nylund-Gibson and Choi, 2018) and selected based on social science theory and interpretable estimated coefficients (Múthen and Múthen, 2000). Model fit and separation metrics are reported in Table 3, the estimation results from Equation (1).[8] The four-class model fits the data best based on BIC and CAIC. Entropy indicates the two- and three-class models have better class separation. Table 4 reports the coefficient estimates associated with the classes for each model and can be used to verify that results are consistent with social science and economic theory. The two-, three-,

[7] This choice could be interpreted differently, that a person rejected a wetland program but would still build their own wetland; if so, construction costs would not be covered at all. Such an interpretation would require a three-category dummy variable that represents cost coverage (0, 50, and 100 percent); we explored this in a separate four-class model that compared preference for 0 and 100 percent to 50 percent. The direction of coefficient estimates did not change, and 100 percent was still preferred to 50 percent, suggesting that our interpretation is accurate.

[8] We also test interacting variables with wetland size (e.g., interacting annual per-acre subsidy with wetland size), but the interactions strictly worsen model fit and do not affect class separation.

Table 3
Comparing the fit and separation, varying number of classes.

Classes	BIC	CAIC	Entropy
2	2665	2676	0.87
3	2658	2675	**0.91**
4	**2645**	**2668**	0.83
5	2661	2690	0.85
6	2683	2718	0.83

Note: Fit metrics and separation metrics for models with different number of classes. The policy attributes included in the model are a policy dummy variable, good year probability, construction cost proportion, per-acre subsidy, and wetland size. Bayesian Information Criterion (BIC) and Correct Akaike Information Criterion (CAIC) measure model fit, with a lower number indicating a better fit. Entropy measures class separation on the unit interval. A heuristic for well separated classes is entropy greater than 0.8.

and four-class models all identify the two classes predicted by social science theory (pro-policy and anti-policy).

The three- and four-class models also separate respondents into an "unclassified" group. Visual examination of choice sets shows that for some in this class, responses were characterized by preferring high subsidies but heterogenous preferences for wetland size. Others showed little preference based on wetland size or subsidy but, surprisingly, preferred wetlands to be built on better, more productive land. In the four-class model, another group was identified that also preferred wetlands on land with higher productivity. This "survey misinterpreted" class seemingly misinterpreted the land quality attribute to mean that the wetlands themselves would result in higher productivity.

The good year probability variable is surprisingly insignificant in the two- and three-class models and significant in the expected direction for both classes in the four-class model. The four-class model shows that the annual and construction subsidy are valued more similarly by the pro-policy and anti-policy respondents, as expected by economic theory. Variables that were significant with two classes remain significant with four classes but with a larger magnitude.

The four-class model is supported based on the fit metrics, such as BIC (Nylund-Gibson and Choi, 2018), and social science and economic theory. This model is also straightforwardly interpretable (Múthen and Múthen, 2000), so it is our preferred specification (Weller et al., 2020), with the caveat that only two classes are of interest for postestimation analyses. As shown in Table 4, the standard errors around preference estimates for the unclassified class are large and not useful for drawing inferences. Relatedly, the preferences of the survey misinterpreted class are not realistic to a real-world farming context and thus not useful for modeling policy uptake. Therefore, we included only respondents classified within the hypothesized pro-policy and anti-policy classes and discuss only these classes henceforth.

The four-class step 1 results are shown in more detail in Table 5. The coefficients are estimated with Equation (1) and the class membership percents from Equation (2). Both the pro-policy and anti-policy class prefer to place wetlands on less productive land, but that preference is stronger for the latter. We use Wald tests to test for significant differences between the pro-policy and anti-policy preference coefficients (Table 6). The difference is only significant for the policy dummy variable and wetland size. The significant intercept also indicates significantly fewer pro-policy respondents.

5.3. Determinants of willingness to construct a wetland

[Fig. 3 ABOUT HERE]

Fig. 3 shows the results from the third step, Equation (3), connecting class assignment to respondent attributes. The estimation sets as a baseline the mean attributes of the anti-policy class and plots the multinomial logit coefficient estimates for the mean attributes of the pro-policy class. It plots 95 percent confidence intervals, indicating a significant nonzero difference between the classes. The variables are standardized such that the magnitude of the associations can be compared apples to apples.

Table 5
Step one results for the four-class model with coefficient estimates and SEs.

	Pro-policy	Anti-policy	Survey misinterpreted	Unclassified
Policy	1.33***	−2.61***	0.72	−198.2
	(0.37)	(0.68)	(0.48)	(455,560)
Good year probability	−2.85***	−1.93**	1.91***	269.71
	(0.44)	(0.86)	(0.50)	(494,310)
50 percent construction cost share	−2.01***	−0.96**	−0.55**	−183.3
	(0.34)	(0.44)	(0.24)	(421,230)
Per-acre subsidy ($1k)	1.60***	1.09**	0.38*	129.18
	(0.27)	(0.45)	(0.23)	(431,220)
Wetland size (acres/10)	0.57***	−2.35***	−0.92***	−69.12
	(0.20)	(0.67)	(0.21)	(109,960)
Class intercept		0.78***	−0.27**	−1.21***
		(0.78)	(-0.12)	(0.14)
Percent of Respondents Assigned Modal Class	23.87%	51.22%	16.53%	8.37%
N = 1436				
Respondents = 490				
Log Likelihood = −1251.3				
AIC = 2553.0				
CAIC = 2697.2				
BIC = 2674.2				
Entropy = 0.828				

Significance levels: * = 0.1, ** = 0.05, *** = 0.01. Standard errors clustered at the respondent level.

Table 4
Comparing the coefficient estimates, varying number of classes.

	Class name (average posterior probability)	Policy dummy (1, 0 for no policy)	Good year probability (0.2, 0.5, 0.8, 0 for no policy)	50% construction cost share (0 for full subsidy, 1 for 50% cost share, 0 for no policy)	Per-acre subsidy ($1k) (0.3, 0.75, 1.5, 0 for no policy)	Wetland size (acres/10) (0.1, 0.5, 1, 1.5, 0 for no policy)	Class intercept
Two-Class	Pro-policy (44%)	1.10***	−0.32	−1.30***	0.91***	−0.21**	−0.25***
	Anti-policy (56%)	−4.54***	0.67	−1.00***	1.75***	−1.21***	
Three-Class	Pro-policy (41%)	1.21***	−0.62***	−1.17***	0.87***	−0.21**	
	Anti-policy (53%)	−3.46***	−0.57	−0.54	1.43***	−2.60***	0.25***
	Unclassified (6%)	−180.06	274.03	−257.31	161.64	−78.51	−2.13***
Four-Class	Pro-policy (24%)	1.33***	−2.85***	−2.01***	1.60***	0.57***	
	Anti-policy (51%)	−2.61***	−1.93**	−0.96**	1.09**	−2.35***	0.78***
	Unclassified (7%)	−198.20	269.71	−183.30	129.18	−69.12	−1.21***
	Survey misinterpreted (18%)	0.72	1.91***	−0.55**	0.38*	−0.92***	−0.27**

Significance levels: * = 0.1, ** = 0.05, *** = 0.01. Standard errors omitted for brevity.
Note: Coefficient estimates for two-, three-, and four-class models.

Table 6
Wald test for significantly different coefficients between pro-policy and anti-policy classes.

Preference	*Wald Chi-sq*	P-*value*
Policy	25.39	0.00***
Good year probability	0.88	0.35
Construction cost proportion	3.60	0.058*
Per-acre subsidy	0.97	0.33
Wetland size	17.37	0.00***

Significance levels: * = 0.1, ** = 0.05, *** = 0.01.

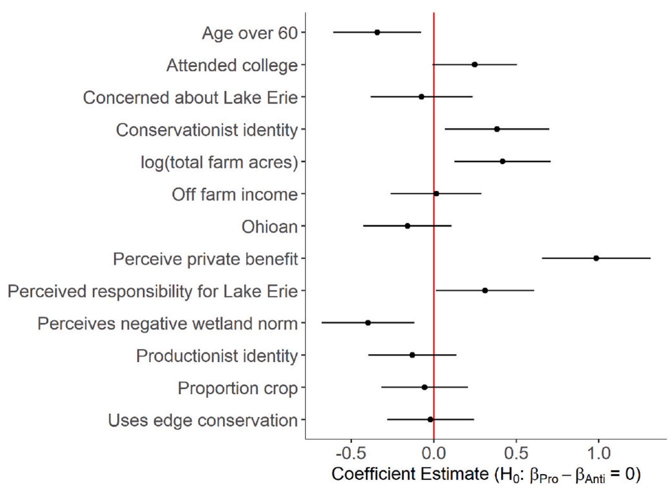

Fig. 3. Coefficient plot for the Step 3 multinomial logit regression.
Note: The variables are standardized in the regression. Includes coefficients for the pro-policy class only; 95 percent confidence intervals are calculated using heteroskedastic-robust SEs clustered at the individual level.

Compared to their unwilling counterparts, pro-policy farmers perceive more private benefit from farmland conversion, such as aesthetic value or hunting and fishing opportunities from wetland, and less of a negative norm surrounding wetland construction. They identify more strongly as conservationists and feel directly responsible for Lake Erie water quality. They have larger farms and are younger, on average.

5.4. Trade-off between per-acre subsidy and construction subsidy

Table 7 shows the estimates of the trade-off between construction cost subsidies and annual per-acre subsidies. An average participant in the pro-policy class is indifferent to receiving a full construction cost subsidy and paying 50 percent coupled with a $1250 annual payment per-acre. The unwilling respondents' (anti-policy class) indifference level is lower, about $875. Assuming a 2 percent discount rate, the net present value of an average willing respondents' trade-off between the cost share and annual subsidy is $16,366 per acre, implying an estimated wetland construction cost of about $32,700 per acre. This is likely less than the actual cost. A model developed by Kadlec and Wallace (2008) estimates the construction cost for a free water surface wetland in 2010 USD as $\$194,000{*}A^{0.69}$, where A is the area of the wetland measured in hectares. This corresponds to construction costs of about $109,000 for a one-acre wetland, $63,100 per acre for 5 acres, $50,900 per acre for 10 acres, and $44,900 per acre for 15 acres. This does not include the operations and maintenance costs, which too can be substantial (Irwin et al., 2018). Although both groups seem to underestimate total wetland construction costs, the lower indifference level of unwilling respondents may reflect that group being even less informed about wetland costs. The indifference level for both groups could increase if landowners were fully informed of construction and annual maintenance costs. These indifference levels also could have implications for program costs, as offering annual subsidies rather than the cost share could be less costly for the program, based on these indifference levels, so long as respondents are not deterred by construction costs or can construct wetlands at lower costs than Kadlec and Wallace (2008) estimated.

Table 7
Class-level construction cost values in terms of annual subsidy per acre.

	Annual per-acre subsidy required to compensate a 50% cost share (95 percent confidence interval)
Pro-policy	$1252.26 (1236.90, 1267.61)
Anti-policy	$874.98 (826.78, 923.18)

Note: 95 percent confidence intervals reported in parentheses calculated using asymptotic variance estimates from the delta method.

5.5. Policy simulations

Fig. 4 shows the predicted probability of enrollment in various constructed wetlands policies. Pro-policy respondents would most likely accept any policy that fully subsidizes construction, even one with only a modest per-acre annual subsidy, and those with sufficiently poor farmland would most likely accept any policy, even one with construction cost sharing and a modest subsidy. So, the enabling conditions for acceptance are fully subsidized construction or sufficiently poor land. When neither of these conditions hold, an annual per-acre subsidy of $1500 is required. The anti-policy class is unlikely to accept any contract, even for a heavily subsidized small wetland with free construction.

6. Discussion

6.1. Alignment with the literature

Consistent with similar literature on conservation subsidies and our *ex-ante* expectations, belonging to the pro-policy class is associated with greater perceived benefits of wetlands and identifying as a conservationist and negatively associated with perceived social disapproval (Ghermandi and Fitchman, 2015; Hansson et al., 2012; Odgaard et al., 2017; Soldo et al., 2022). Overall, these results suggest that negative social pressure and the perceived benefits of wetlands are strong drivers of policy acceptance and that only some structural factors are related to typologies of acceptance. Consistent with conservation agriculture practices more broadly (Prokopy et al., 2019), one of the most important structural correlates of support may be farm size, perhaps because larger farms have more options for favorable wetland locations.

However, some findings did not align with the literature or our expectations. Regarding structural variables, latent class had no relationship with existing edge-of-field practices, the proportion of farm designated for cropland, or off-farm income (Baumgart-Getz et al., 2012; Prokopy et al., 2019; Zimmerman et al., 2019). This may be because, although the first two factors may relate to greater on-farm resources and crop revenue, they are not direct indicators of the resources that would be needed to install a wetland. Furthermore, off-farm income may provide perceived security against unexpected costs of installing a wetland but also lower the necessity to supplement with subsidies. Contrary to expectation, concern for Lake Erie water quality also had no relationship with membership in the pro-policy class (Irwin et al., 2018), suggesting that many do not view wetlands as a solution to Lake Erie concerns.

6.2. Applying the results to Social targeting

WLEB conservation practitioners offer subsidies to walk-ins to the conservation office. When budget constraints preclude everyone receiving their desired subsidy, practitioners offer subsidies to those

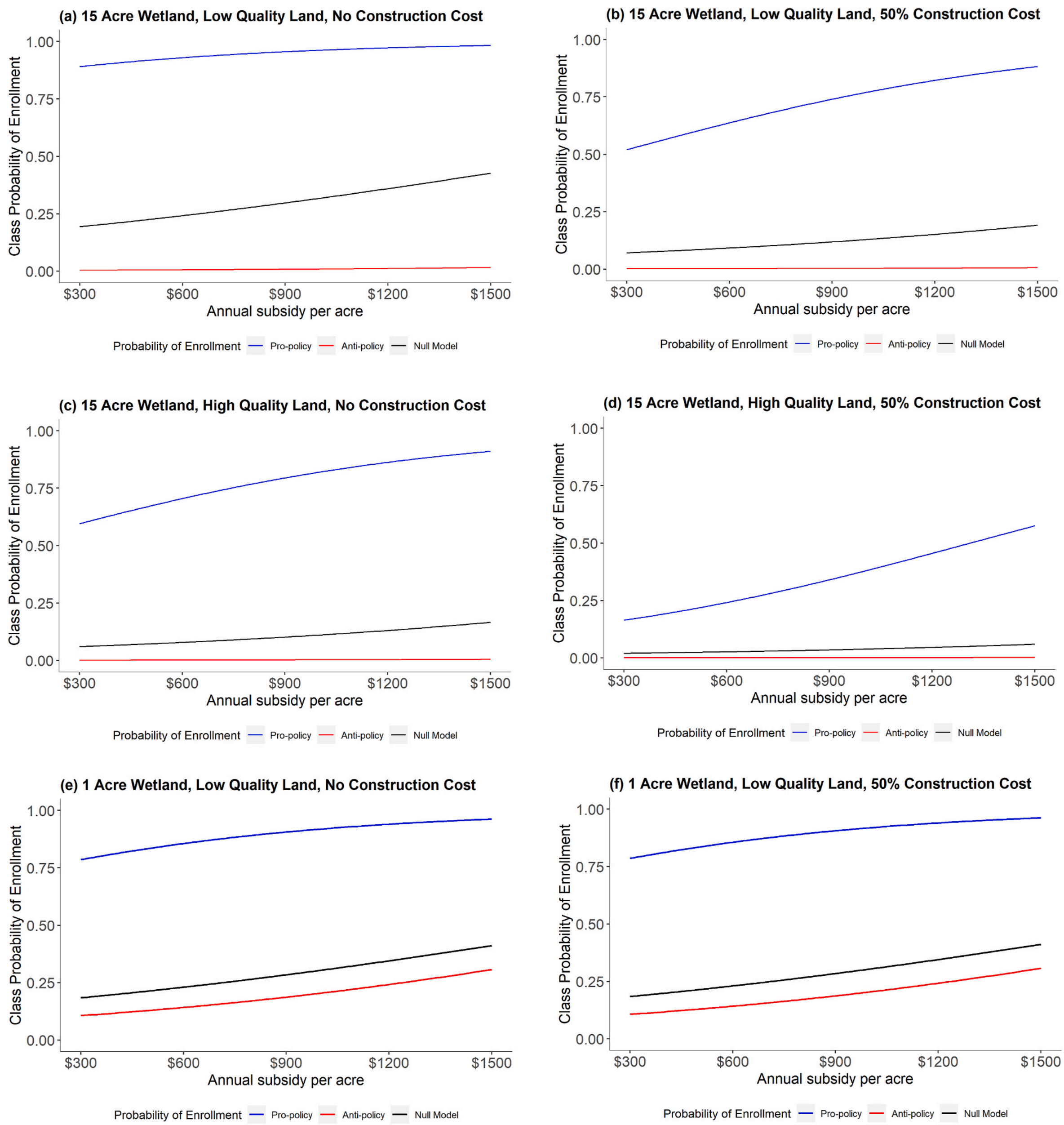

Fig. 4. Graphs of predicted probabilities of agreement to various constructed wetlands contracts.
Note: Predicted probabilities of enrollment are on the y-axes, varying the level of per-acre subsidy on the x-axes. Results for policies with a 100% construction cost subsidy are shown on the left, and 50% construction cost subsidy policies are on the right.The null model is from a conditional logit model using the sample of respondents classified as pro-policy or anti-policy. See Appendix for the results.

with land that has the greatest conservation benefit. Social targeting implies a more active approach to conservation policy. A practitioner may design a wetlands policy based on the preferences of the pro-policy respondents in the first step and increase the number of walk-ins by advertising it based on attributes associated with pro-policy respondents in the third step. It would not be beneficial to limit farmer participation based on these attributes, as some farmers categorized as non-willing may nonetheless opt to enroll. However, this social targeting may increase the effectiveness of outreach and overall program participation.

Another type of social targeting based on the results is to use the pro-policy class's preferences to guide how to trade off between the level of construction cost subsidy and the annual per-acre subsidy payment. For example, we estimate that a pro-policy respondent has about a 60 to 90 percent probability of accepting an offer that fully subsidizes construction and pays a $300 per-acre, per-year subsidy (the lowest per-acre subsidy in our survey) for constructing a 15-acre wetland. However, if the program only partially covers construction costs, the socially targeted policy would need to offer $1500 per acre per year to achieve the same probability of acceptance from pro-policy farmers.

The four-class model suggests heterogeneity in preference for wetland size, with the pro- and anti-policy groups tending to prefer larger and smaller, respectively. However, the two- and three-class models find both groups prefer smaller wetlands. Thus, this result is not robust to model misspecification in the number of classes. Moreover, size preference may be heterogenous *within* the pro-policy class. Given the uncertain direction on this coefficient, we recommend that practitioners allow farmers to choose the size.

Our results also help inform how to frame policies in active outreach strategies, such as advertising campaigns. Active outreach should advertise constructed wetlands as enhancing beauty and providing opportunities for hunting and fishing, based on the result that perceiving private benefits is an important attribute of pro-policy respondents. Effective outreach may also inform farmers about their impacts on Lake Erie water quality. Outreach should foster positive norms around wetlands, which may shift more farmers to the pro-policy class. Finally, outreach should target farmers with larger farms and low-quality land, as the pro-policy class tends to have larger farms and prefers wetlands on lower-quality land.

7. Conclusion

We use a three-step latent class model to guide social targeting of a WLEB constructed wetlands policy. The first step identifies policy preferences with class-level heterogeneity, which is useful to design policies that policymakers' constituents are likely to accept. The third step characterizes these classes, which can inform active outreach strategies. The first step finds two meaningful classes of respondents—willing to construct a wetland with a reasonable subsidy and unwilling barring an exorbitant subsidy.

The pro-policy respondents have larger farms and are younger, on average. They perceive less social pressure discouraging wetland construction, more personal responsibility for water quality in Lake Erie, and more private nonmonetary benefits from wetlands, such as aesthetic value and hunting opportunities. Simulations demonstrate socially targeting policy results in a substantially higher probability of acceptance. Targeted policies also require lower subsidy levels than nontargeted policies.

Overall, social targeting recommendations for WLEB include 1) emphasizing the private aesthetic and recreational benefits of wetlands to attract those who value these benefits; 2) targeting areas that already have wetlands installed, which could indicate lower negative social norms regarding wetlands; 3) combating negative norms by engaging with community leaders who support wetlands; and 4) targeting those with larger farms and low-productivity land.

CRediT authorship contribution statement

Matthew Ashenfarb: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis. **Carrie Dale Shaffer-Morrison:** Writing – review & editing, Writing – original draft. **Robyn Wilson:** Writing – review & editing, Writing – original draft, Funding acquisition, Data curation, Conceptualization. **Sandra Marquart-Pyatt:** Conceptualization, Writing – review & editing. **Rebecca Epanchin-Niell:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization, Funding acquisition.

Declaration of competing interest

The authors declare no competing interests.

Acknowledgements

Funding for this research was provided by Resources for the Future and the National Socio-Environmental Synthesis Center (SESYNC) under funding received from the National Science Foundation (NSF) DBI-1639145. This work was also supported by the Nature Conservancy and Joyce Foundation through award OSU D'Ambrosio 09/19–01.

Appendix

A.1 response rate analysis

The response rate overall was 29.1 percent, after accounting for deceased respondents and undeliverable surveys. To investigate for selection bias, conditional response rates are reported at the watershed (Table A.1), farm size (Table A.2), and state (Table A.3) levels. The response rate denominator in the tables also excludes deceased and undeliverable surveys.

Higher response rates were observed for surveys delivered to farmers in Ohio, which is expected given that the survey was cosponsored by Ohio State University. However, when we consider if Ohioan and non-Ohioan respondents differ in their conservationist identity, we do not find a significant relationship. Moreover, the coefficient on Ohioan is insignificant between the classes, suggesting no significant difference in wetland policy preferences when controlling for the other included variables.

A.2 Null Model Mixed Logit

Fig. 4 uses a null model, a conditional logit model using the subsample of respondents modally classified as pro-policy or anti-policy. The results are shown in Table A.4.

A.3 step 3 coefficient plot for unclassified and survey misinterpreted classes

Fig. 3 in the main text plots the multinomial logit coefficients that test for significant differences between the pro-policy and anti-policy classes. The same regression also produces coefficients that test for significant differences between the survey misinterpreted and unclassified classes, still using the anti-policy class as a baseline. Figures A.1 and A.2 show the coefficient plot for the survey misinterpreted and unclassified classes, respectively. The former perceives more private benefits and has larger farms, on average. The latter is less likely to be from Ohio, more likely to have off-farm income, and more concerned about Lake Erie water quality, on average.

A.4 coefficient plot results for the two-class model

Although the four-class model is the preferred specification based on the fit metrics, economic theory predictions, and social-psychological predictions, the two-class model may still be a valid specification. The first step results for the four- and two-class models are somewhat qualitatively different: the coefficient on wetland size for the pro-policy class is negative for the two-class model but positive for the four-class model. Also, the coefficient on land quality is insignificant in the two-class model but significant with a large magnitude in the four-class model. The four-class model suggests pro-policy respondents prefer a larger wetland, as long as it is sufficiently low quality. The two-class model suggests they prefer smaller wetlands, but land quality is not a significant decision factor. The third-step results are similar for the four- and two-class models, shown in Fig. 3 and A.3, respectively. From the two-class model, th4e pro-policy respondents are younger, are more likely to have attended college, have larger farms, are more likely Ohioan, perceive private benefits from wetland construction, and perceive that they are personally responsible for Lake Erie water quality.

A.5 imputing total acres

Described in Section 4.3, for 16 respondents, we impute total farm acres using data on corn and soy acres. This increases the sample size from 497 to 512. The regression results for interpolation are in Table A.5. The mean imputed total farm acreage is 879.14 acres, and the mean for the non-imputed is 876.90 acres. The respective standard deviations are 1018.08 and 1024.53.

	☐ Program A	☐ Program B	☐ Program C
Likelihood of the land designated for the wetland producing a good crop due to flooding and soil moisture	Good crop 20% of the time—or 2 out of every 10 years.	Good crop 80% of the time—or 8 out of every 10 years.	Good crop 80% of the time—or 8 out of every 10 years.
Constructed wetland size	1 acre	15 acres	1 acre
Granted subsidy (% of construction costs covered)	50% construction costs	100% construction costs	100% construction costs
Annual nutrient removal payments per acre	$1500 per acre, per year	$300 per acre, per year	$300 per acre, per year

☐ I would not construct a wetland on my property based on any of these options.

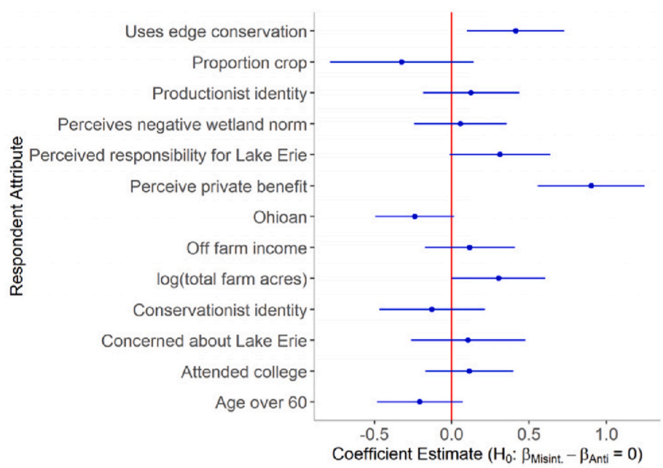

Fig. A.1. Coefficient plot for the survey misinterpreted class from the four-class model

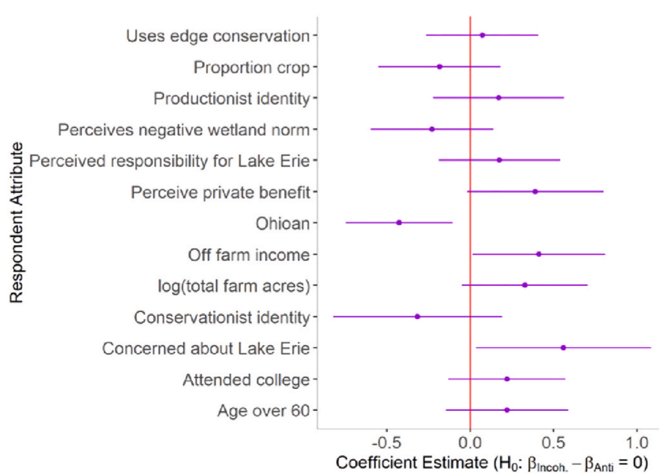

Fig. A.2. Coefficient plot for the unclassified class from the four-class model

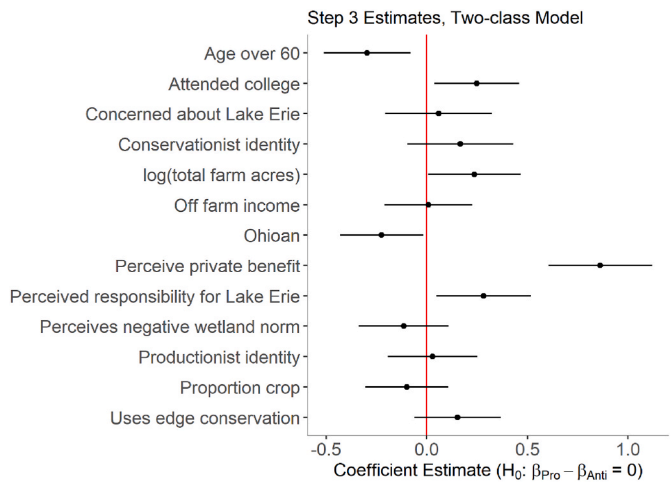

Fig. A.3. Step three coefficient plot for the two-class model (equivalent of Fig. 3, but using the latent class model with two instead of four classes)

Table A.1
Response rates by watershed of farmer address

Watershed (HUC8) Name	Surveys Delivered	Reponses	Response Rate
Auglaize	474	173	0.36
Blanchard	394	159	0.40
Cedar-Portage	106	44	0.42
Lower Maumee	65	22	0.34
Ottawa-Stony	74	23	0.31
Raisin	89	23	0.26
Sandusky	102	42	0.41
St. Joseph	107	31	0.29
St. Marys	107	40	0.37
Tiffin	100	32	0.32
Upper Maumee	98	34	0.35

Table A.2
Response rates by farm size

Farm Size	Surveys Delivered	Responses	Response Rate
20–249	449	170	0.38
250–499	478	170	0.36
500–999	432	159	0.37
1000+	357	124	0.35

Table A.3
Response rate by state

State	Responses	Surveys Delivered	Response Rate
IN	60	196	0.31
MI	51	194	0.26
OH	512	1326	0.39

Table A.4
Conditional logit model results

	Policy Choice
Policy	−1.31***
	(0.149)
Good year probability	−1.03
	(0.180)

(*continued on next page*)

Table A.4 (*continued*)

	Policy Choice
50% construction cost share	−1.942***
	(0.189)
Per-acre subsidy ($1k)	0.75***
	(0.091)
Wetland size (acres/10)	−0.35***
	(0.084)
N = 1436	
Respondents = 490	
Log Likelihood = −1574.6	

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table A.5
Farm acreage imputation regression

	Total Acres
Corn and Soy Acres	−1.31***
	(0.149)
Constant	−1.03
	(0.180)
N = 497	
$R^2 = 0.621$	
Adj. $R^2 = 0.621$	
F Statistic = 946.489	

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Data availability

Data will be made available on request.

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