COST-EFFECTIVE CONSERVATION PROGRAMS TO ENHANCE ECOSYSTEM SERVICES IN AGRICULTURAL LANDSCAPES

By

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ABSTRACT

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Conservation programs promote voluntary adoption of agricultural management practices that can mitigate nutrient runoff and generate ecosystem services (ES) in working landscapes. However, despite billions of dollars spent on conservation programs annually, agricultural pollution remains a persistent problem. Using experimental auctions and behavioral models that integrate economic and ecological information, the first two essays of this dissertation identify how conservation programs can be designed to cost-effectively improve aquatic ecosystem services in agricultural landscapes. The third essay estimates some of the benefits from successful conservation programs in terms of averted welfare loss when beach closures are caused by harmful algal blooms resulting from agricultural nutrient runoff.

Essay one analyzes farmer preferences for different types of conservation incentives, including payments, green insurance, tax credits, and price premiums. I estimate how the type of incentive offered affects farmer willingness to adopt agricultural management practices that reduce nutrient runoff from cropland in the Maumee watershed to help abate damaging algal blooms in western Lake Erie. I evaluate how the cost-effectiveness of various incentive types depends on farmer willingness to enroll in the program and the level of payment or other financial incentive they require. In general, the most cost-effective contracts are ones that spatially target high priority areas of the watershed and offer financial incentives with low transaction costs for farmers such as payments and tax credits.

Essay two identifies barriers and deterrents to participation in conservation auctions and explores how participation affects cost-effectiveness. Outcomes are reported from two conservation auctions that were implemented in two counties in NW Ohio as part of an ongoing effort to reduce harmful algal blooms in Lake Erie. Bids were evaluated based on their expected environmental benefits -- specifically their estimated reductions in bioavailable phosphorus loadings to Lake Erie as predicted by biophysical models. Only 1% of landowners submitted bids. A follow-up survey revealed three barriers to bidding: knowledge about the auction program, ineligibility, and transaction costs of participation. Three policy scenarios are simulated using a mathematical programming model to demonstrate how transaction costs reduce farmer participation and erode cost-effectiveness of conservation auctions relative to uniform payment programs. Cost-effectiveness is greatest in policies with low transaction costs that can spatially target environmentally vulnerable parcels.

Essay three uses two benefit transfer approaches to estimate welfare losses from beach closures in Lake Erie caused by harmful algal blooms. I identify how estimates differ between the two transfer approaches – value transfer and function transfer – and evaluate conditions under which the more time-consuming and data-intensive function transfer is worth the effort compared to a simple value transfer. In this study, benefit function transfer was essential to estimate beach demand (trips) and demand elasticity (change in trips), but when evaluating individual beach closures with known trip demand, the function transfer and value transfer yielded similar results for individual beach closures. Results from the two transfer methods deviated (up to 106%) when multiple beaches closed because value transfer did not account for the loss of beach substitutes. This result emphasizes the importance of using transfer methods that account for changes in trip demand to estimate welfare loss from regional beach closures.

I dedicate this dissertation to my parents, Cheryl and Ronald Harris.
Your endless love, support, and encouragement motivate me every day.
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KEY TO ABBREVIATIONS

AAA	American Automobile Association
ACS	American Community Survey
ARS	Agricultural Research Service
BDM	Becker-DeGroot-Marschak
Bio P	Bioavailable phosphorus
BMP	Best (or beneficial) management practice
BT	Benefit transfer
CB	Cost-benefit
CRP	Conservation Reserve Program
DNR	Department of Natural Resources
EBI	Environmental Benefit Index
EQIP	Environmental Quality Incentives Program
ES	Ecosystem services
FSA	Farm Service Agency
GLPF	Great Lakes Protection Fund
HAB	Harmful algal bloom
IIA	Independence of irrelevant alternatives
IJC	International Joint Commission
IV	Inclusive value
KBS	Kellogg Biological Center

LTER	Long-term Ecological Research
MAC	Marginal abatement costs
MDEQ	Michigan Department of Environmental Quality
NASS	National Agricultural Statistics Service
NL	Nested logit
NPS	Nonpoint source
NRCS	Natural Resources Conservation Service
ODH	Ohio Department of Health
ODNR	Ohio Department of Natural Resources
OP	Organic phosphorus
PES	Payments for environmental (ecosystem) services
PIP	Particulate inorganic phosphorus
RMA	Risk Management Agency
RUM	Random Utility Model
SRP	Soluble reactive phosphorus
SWAT	Soil and Water Assessment Tool
SWCD	Soil and Water Conservation District
TC	Transaction cost
TNC	The Nature Conservancy
TP	Total phosphorus
USDA	United States Department of Agriculture
WLEB	Western Lake Erie Basin

WTA	Willingness to accept
WTP	Willingness to pay

INTRODUCTION

Agricultural productivity has grown tremendously over the last century in part because of increased fertilizer use, but overuse and improper application of nutrients degrades aquatic resources. Improving nutrient management and integrating agricultural conservation practices into conventional management systems can reduce the negative impacts of crop production on surrounding ecosystems (e.g., water pollution) (Sharpley et al. 2006; Rao et al. 2009). Using conservation best management practices (BMPs) can also generate a suite of non-marketed ecosystem services (ES), including pollination, flood mitigation, nutrient cycling, and recreation (Swinton et al. 2007). Due to the public good nature of many ES and the increased costs and effort often necessary to adopt BMPs, financial incentives are used to promote voluntary adoption of conservation practices (Lambert et al. 2007). Cost-share programs like the USDA Environmental Quality Incentives Program (EQIP) and land retirement programs like the Conservation Reserve Program (CRP) are widely recognized for promoting land stewardship. However, agricultural nonpoint source (NPS) pollution remains a persistent problem, despite the federal government spending nearly seven billion dollars a year to promote conservation and BMP adoption (Ribaudo 2015).

Harmful algal blooms (HABs) in Lake Erie are a prime example of agricultural phosphorus runoff wreaking havoc on water quality after a partial recovery of the lake in the mid-1990s (Johnson et al. 2014). HABs produce a toxin called microcystin that poses dangers to humans and wildlife, negatively affects ecosystem health, and degrades recreational amenities. In the 1960s and 70s, point source polluters (e.g. factories, water treatment plants) were primarily responsible for pollution in Lake Erie, but recent eutrophication is attributed to excess NPS runoff, primarily from agriculture (International Joint Commission 2014).

Cost-effectively mitigating nutrient runoff requires an understanding of biophysical characteristics of agricultural land as well as the behavioral and economic factors that drive land management decisions. The first two essays of this dissertation explore farmer willingness to participate in conservation programs aimed at mitigating HABs in the Western Lake Erie Basin (WLEB). The third chapter examines the impact of HABs on Lake Erie beaches and estimates the welfare loss that could be avoided by using runoff abatement programs to reduce the occurrence of beach closures caused by algal blooms. Results from this body of research will help policymakers understand farmers' willingness to engage in conservation programs and will inform the development of policies that improve water quality in the Great Lakes.

Previous research on incentives for BMP adoption largely focuses on two contract types – cost-share and annual stewardship payments (Claassen, Cattaneo and Johansson 2008); however, other types of transactions can also promote conservation. In Essay 1, I use experimental conservation auctions to empirically analyze farmer preferences for four different conservation incentives, 1) direct payments, 2) BMP insurance, 3) tax credits, and 4) price premiums tied to stewardship certification. Using a within-subjects design, I determine the relative cost-effectiveness of each incentive contract by comparing the cost (bid) and resulting environmental benefits across auctions for the four incentives. Farmers submit lower, more cost-effective bids for contracts that they find attractive, whereas they demand more (bid higher) for incentive contracts that they dislike. Payments and tax credits that target high impact areas of the watershed are more cost-effective than untargeted price premiums for product certification.

Farmers demand higher payments for contracts offering green BMP insurance due to anticipated transaction costs.

In a world free of transaction costs, auctions can cost-effectively allocate conservation payments by targeting projects that provide the most benefit per dollar spent, but when costly participation restricts the number of bids submitted, cost-effectiveness is limited. In Essay 2, I report outcomes from two conservation auctions designed to abate nutrient runoff in the Tiffin Watershed, located in the WLEB. Farmer bids were evaluated based on the cost to reduce bioavailable phosphorus runoff as predicted by hydrological models applied to individual fields. One percent of landowners who were invited to participate actually submitted a bid. Due to low participation, the actual conservation auction made payments for phosphorus reduction that were surprisingly costly at the margin. I report results from a follow-up survey that identified participation barriers and deterrents. A farmer behavioral model is used to simulate participation choice and cost-effectiveness of environmental outcomes in auctions compared to uniform payment programs. Results reveal that when the perceived transaction costs of bid preparation are high, auction programs that rank bidders are less cost-effective than spatially targeted, fixed conservation payments that attract higher participation.

An influx of funding to abate nutrient runoff has spurred demand for timely information about the potential value of mitigating HABs. Benefit transfer methods are widely recognized as an approach to estimate resource values when time and funding constraints inhibit primary data collection (Boyle et al. 2010; Johnston et al. 2015). In Essay 3, I analyze how HABs impact the value of Lake Erie beaches. I use two benefit transfer methods – a value transfer and function transfer – to estimate welfare loss from hypothetical beach closures. In addition to informing policymakers about the recreational losses from HABs, this research also contributes to the benefit transfer literature by analyzing how results from function transfers and value transfers differ depending on the scale of beach closures within the region. The two transfer methods estimate similar welfare losses for individual beach closures. However, results deviate exponentially with the number of beaches closed due to HABs, because the value transfer does not account for the loss of beach substitutes. Not only does the function transfer capture the effect of substitutes, but it also accounts for differences between the policy setting and the original study site, including differences among beach characteristics and between the two populations of beach users. In this essay, I also describe three ways that researchers can increase the value of original valuation studies by making them more amenable to future transfers.

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ESSAY 1. EXPERIMENTAL AUCTIONS TO EVALUATE INCENTIVES FOR COST-EFFECTIVE AGRICULTURAL PHOSPHORUS ABATEMENT IN THE GREAT LAKES[1]

1.1 Introduction

Financial incentives such as payments for environmental services (PES) are commonly used to promote voluntary adoption of so-called "best management practices" (BMPs) in the United States, where farmers generally hold the property rights to manage their land as they deem appropriate (Lichtenberg 2004; Kroeger and Casey 2007; Norris, Schweikhardt and Scorsone 2008). A substantial amount of research has examined PES programs for cost-share or annual stewardship payments (Reichelderfer and Boggess 1988; Lambert et al. 2007; Claassen, Cattaneo and Johansson 2008), but little is known about farmer preferences for other types of transactions, such as tax incentives, green (BMP) insurance, and stewardship certification programs. Using experimental conservation procurement auctions, this research evaluates farmers' preferences for different incentive designs.

Despite the reported benefits of agricultural conservation, widespread adoption of many BMPs has not occurred. For example, it is estimated that cover crops are only planted on 3-7% of farms in the United States, which translates to about 1% of crop acreage (Wallander 2013). Many factors impact farmers' adoption decisions, including attributes of the innovation, farm and farmer characteristics, social influences, and farmers' risk perceptions and beliefs about how actions on their farm impact the environment (Feather and Amacher 1994; Edwards-Jones 2006;

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[1] A version of this chapter has been submitted for publication: Palm-Forster, LH., S.M. Swinton, and R.S. Shupp. Farmer preferences for conservation incentives that promote voluntary phosphorus abatement in agricultural watersheds. In review.

Prokopy et al. 2008; Wilson, Howard and Burnett 2014). Some conservation BMPs require additional management effort and may reduce profits due to higher operating costs or lower yields, especially in the first few years of adoption while the farmer is learning how to successfully incorporate the new practice(s) (Lambert et al. 2007). Other BMPs, like filter strips and buffers, displace cropland, creating high opportunity costs due to profits foregone on those parcels.

As long as farmers hold the property rights to manage their land as they choose, economic incentives will continue to be an important tool to motivate adoption of voluntary conservation practices. Determining what kind of economic incentives are most cost-effective is an essential step in maximizing environmental benefits from limited funds. Cost-effectiveness can be achieved by allocating payments to the subset of conservation projects that result in the highest benefit per dollar spent. The measure of benefit depends on the goals of the program. For example, some programs focus on increasing biodiversity of native species, whereas others target reductions in soil erosion (sedimentation) or nutrient runoff (marine hypoxia and freshwater eutrophication). For algal blooms and eutrophication, the expected benefit is strongly related to reducing phosphorus runoff (Michalak et al. 2013). A cost-effective program would select and fund projects that result in the highest reduction in phosphorus loss per dollar (or, equivalently, the lowest cost per unit of phosphorus reduction). Selecting such programs requires the ability to predict changes in phosphorus loss from a particular conservation practice on a specific field and requires knowledge of the financial incentive that the farmer would demand to implement that practice.

Research on conservation incentives largely focuses on two contract types: uniform cost-share payments and annual stewardship payments (Lambert et al. 2007; Claassen et al. 2008).

Cost-share payments (e.g., under the USDA Environmental Quality Incentives Program, EQIP) offset a portion of the cost to implement a conservation action and are typically based on average costs in the state or region. Stewardship payments, like those disbursed under the U.S. Department of Agriculture (USDA) Conservation Reserve Program (CRP), offset the opportunity costs of managing land in a manner that promotes positive environmental outcomes. For example, landowners can receive payments for maintaining natural prairie habitat instead of producing crops. Both programs provide farmers a direct payment for land management changes.

Direct payments may not be the most attractive type of transaction for some farmers. Depending on their tax liability, attitudes toward risk, and marketing strategies, alternative transaction types that may be attractive include tax credits, green insurance, and price premiums for stewardship certification. If farmers' preferences affect their willingness to accept payment for BMP adoption, certain transactions may be relatively more cost-effective and hence able to expand the impact of a limited conservation budget.

Evaluating alternative transactions is also interesting from a political standpoint because these transactions involve a variety of payers, some of whom may be able to mobilize funding outside of public conservation budgets. For example, price premiums for stewardship certification are a market-based PES financed by consumers in the private sector. Tax credits, on the other hand, would be allocated through legislative decisions and do not require funding from conservation agency budgets. If farmer preferences about transaction types affect their willingness to participate in a conservation program, then those preferences will also impact the success and cost-effectiveness of the conservation initiative.

By comparing bids submitted in hypothetical conservation auctions, this research explores cost-effective ways to induce adoption of BMPs that reduce phosphorus loss by evaluating farmers' willingness to accept conservation contracts offering four different incentives: 1) direct payment, 2) direct payment with cost-free green BMP insurance, 3) tax credit, and 4) a price premium tied to stewardship certification. Results indicate that the options with BMP insurance (#2) and stewardship certification (#4) were less cost-effective than the ones that offered a direct payments or tax credit. Farmers perceived BMP insurance to have high transaction costs, so they demanded greater compensation (via higher bids) to accept this incentive. Although farmers were willing to accept modest product price premiums for stewardship certification, this incentive was less cost-effective because it was not targeted to fields where the new conservation practices would have greatest environmental impact. As with most certification programs, all farmers willing to obtain the certification by adopting the required conservation practices were permitted to do so and enrolled in the program regardless of farm characteristics and baseline management practices. In general, the most cost-effective contracts were ones that could spatially target high priority areas of the watershed and offer financial incentives with low transaction costs for farmers.

1.2 Theoretical framework

A theoretical model is used to elucidate the effect of farmer preferences on the cost-effectiveness of different types of conservation incentives. Using a limited budget, a conservation agency seeks to maximize environmental benefits by providing financial incentives for voluntary adoption of agricultural management practices that generate desirable environmental outcomes. To implement a targeted conservation program, the conservation agency makes two decisions. First, the agency chooses which incentive transaction it will offer to motivate voluntary conservation actions. Second, the agency selects the set of farmers that will be accepted into the program and paid for their conservation actions.

Research has shown that heterogeneous costs and benefits of BMP implementation make uniform payments inefficient, as some farmers are overpaid for their actions while others decline to enroll due to inadequate compensation (Horowitz, Lynch and Stocking 2009; Selman et al. 2008), but information asymmetries limit the ability to write contracts that increase participation without paying information rents to farmers with low BMP adoption costs. Conservation procurement auctions provide agencies with a way to allocate scarce funds among the most cost-effective projects by having farmers compete for contracts and accepting offers that provide the most environmental benefit per dollar spent (Claassen et al. 2008).

By comparing bids submitted in hypothetical conservation auctions, this research explores cost-effective ways to induce adoption of BMPs that reduce phosphorus loss by evaluating farmers' willingness to accept conservation contracts offering four different incentives: 1) direct payment, 2) direct payment with cost-free green BMP insurance, 3) tax credit, and 4) a price premium tied to stewardship certification.

1.2.1 The farmer's problem

A farmer will only enroll in a conservation program and implement conservation action a_1 if the utility derived from being in the program (u^1) is greater than their status quo utility (u^0) with baseline conservation effort a_0. A farmer's expected indirect utility from participating in a conservation program is,

$$u(a_1, \theta, \boldsymbol{\rho}) = m[\pi(a_1) + \theta] + v(a_1) - \psi(\boldsymbol{\rho}) \tag{1.1}$$

where, m is the farmer's marginal utility of income, a is the conservation action required to participate in the program, and $\boldsymbol{\rho}$ a set of attributes of the conservation program. To simplify this analysis, assume that farmer utility is linearly separable. $\pi(a_1)$ is farm income, and θ represents the financial incentive from program j. $v(a)$ accounts for utility derived from personal and reputational benefits of adopting conservation practices (e.g., pride in actions that help the environment and respect from neighbors). $\psi(\boldsymbol{\rho})$ represents disutility from enrolling in and complying with the conservation program.[2]

Participation in the program affects profitability through changes in productivity and costs. Assume each farmer manages a homogeneous unit of land with crop output $y(x, z)$, which is a function of purchased inputs x and z. Input x is a productive input (e.g. fertilizer)and input z is a conservation input (e.g. conservation tillage, variable rate technology). Purchased inputs are functions of, 1) conservation action a, such that $x_a \leq 0$ and $z_a > 0$, and 2) the location and other physical characteristics of the field that impact soil fertility and BMP performance, denoted by l. Input cost is $c(x, z)$ and is nondecreasing in each input.

After tax expected profit, presented in Eq. (1.2), equals total expected revenue from crop production minus expected costs of production that have been normalized by the output price, accounting for income tax rate t.

$$\pi = (1 - t)\left\{ y\,(x(a, l), z(a, l)) - c\left(x(a, l), z\,(a, l)\right)\right\} \tag{1.2}$$

Participating in a conservation program affects farmer utility by changing agricultural profit, but program attributes and conservation outcomes also influence utility. Peterson and coauthors (2014) show that transaction costs arising from contract stringency can increase the minimum payment farmers are willing to accept to adopt new management practices. I posit that transaction costs linked to different types of incentives and farmer attitudes about incentive type can have similar effects on farmers' willingness to enroll in conservation programs. Following

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[2] Farmer utility is likely influenced by the existence of ecosystem services (ES) that enhance productive resources (e.g., soil fertility) or provide nonmonetary benefits (e.g., recreation). ES are impacted by agricultural practices over time; however, in this static framework, the potential benefits that actions today will generate in the future are ignored. Research extensions should consider the dynamic decision making process of farmers when actions in one time period can generate ecological or agronomic benefits in future time periods.

Peterson et al. (2014), $\boldsymbol{\rho}$ is a vector of attributes of a conservation incentive program. Attributes include the perceived complexity of enrolling in the program and complying with the conservation contract (i.e., transaction costs of participation).

Conservation actions also provide personal and reputation benefits that contribute to utility, represented by $v(a_1)$. For example, farmers who value the environment receive utility from knowing that they are improving ecological outcomes through their conservation actions. Juutinen et al. (2013) found that conservation motives decrease rental payments required by landowners participating in a Finnish conservation program. Wilson et al. (2014) found that farmers who are more concerned about negative environmental impacts of nutrient loss were more willing to take additional conservation actions on their land.

Consider N heterogeneous farmers that are eligible to submit an offer (bid) in a discriminatory price reverse auction to enroll in the conservation program. In discriminatory price auctions, farmers with selected offers are paid the amount of their bid.[3] The offer amount θ and predicted environmental benefits e are used to determine the cost benefit scoring index, $\beta = \theta/e$, which is the bid amount per unit of environmental benefit. After ranking the β's from lowest to highest, the conservation agency accepts the set of offers with the lowest β's that exhausts the conservation budget. Offers are rejected if the associated cost benefit index exceeds some cutoff level $\tilde{\beta}$. The probability that the farmer's offer is accepted is $P(\beta \leq \tilde{\beta})$ and depends on the distribution of $\tilde{\beta}$, which is determined by the complete set of offers (bids and corresponding environmental benefits) from N farmers. Each bidder submits an offer, θ, but

[3] First-price discriminatory auctions are not incentive compatible, meaning that it is not a dominant strategy for the participant to bid her true cost. However, in practice, most conservation auctions involve a discriminatory payment mechanism in which winning bidders are paid the amount of their offer (bid) (Horowitz, Lynch and Stocking 2009; Stoneham et al. 2003). See Hellerstein, Higgins, and Roberts (2015) for an overview of conservation auction design.

does not know the exact level of environmental benefit that their actions will provide. Instead, the bidder has a subjective expectation about his cost benefit score, $\ddot{\beta} = \theta/\ddot{e}$, where $\ddot{e}$ is the subjective belief about the environmental benefits provided by conservation actions a_1. Furthermore, I assume that an individual farmer n does not know the true distribution of bids and benefits but instead holds a subjective belief about the probability of bid acceptance that The perceived probability of bid acceptance is $\ddot{\sigma}$, which depends on the farmer's expectations about their own cost-benefit index score relative to expected cost-benefit scores of competing project tenders.

A farmer will only submit an offer if the expected payoff of participating in the auction is greater than his *status quo* utility,

$$u(a_1, \theta, \boldsymbol{\rho})\, \ddot{\sigma} + u(a_0)[1 - \ddot{\sigma}] > u(a_0) \tag{1.3}$$

where, $u(a_0)$ is the status quo utility. Farmers face a tradeoff when choosing their bid – a higher bid increases their potential payment, but it increases the agency's cost per unit of environmental benefit, thus decreasing the probability that the bid will be accepted, such that ${}^{\partial \ddot{\sigma}}/_{\partial \theta} \leq 0$. Offer θ is selected to maximize the expected net utility,

$$\max_{\theta} \; [m(\pi(a_1) - \pi(a_0) + \theta) + \; v(a_1) - v(a_0) - \psi(\boldsymbol{\rho})\,] \;\; \ddot{\sigma} \tag{1.4}$$

It must be true that $\theta \geq 0$ because otherwise, the farmer would have adopted the BMP voluntarily without the presence of an incentive program.

The monetary "expected net cost" of adopting conservation action a_{nj} without financial incentives is $E[\pi(a_0) - \pi(a_1)]$, which accounts for changes in direct costs as well as opportunity costs of any foregone revenues. The expected net cost is the value that a farmer would be expected to bid for conservation payment if the farmer is either, a) indifferent to other arguments in the utility function, or b) perceives no changes in their levels. Consider the effect on utility of conservation action a_{nj} given an incentive program with financial incentive θ and program attributes $\boldsymbol{\rho}$. If $[v(a_1) - \psi(\boldsymbol{\rho})] > v(a_0)$, then it is possible that the farmer would accept an incentive payment less than the expected net cost of the BMP, $\theta < E[\pi(a_0) - \pi(a_1)]$.[4]

Using this utility-based framework, one can analyze how bids differ for different types of conservation incentives. Consider four alternative transaction types $j \in \{s, \tau, g, \phi\}$, where s is a direct payment, τ is a tax credit, g is BMP insurance, and ϕ is a price premium tied to stewardship certification. If farmers were to submit bids for each type of incentives, the amount of the bid may differ among the four incentive transactions. Analyzing relative bids reveals information about farmer preferences for the alternative transactions.

For example, farmers may simply dislike taxes, either because they are loss averse (Ericson and Fuster 2011) or because they dislike financing the government. In this case, the disutility from the attributes of the tax credit program would be less than the disutility from a payment program, such that $\psi(\boldsymbol{\rho_s}) > \psi(\boldsymbol{\rho_\tau})$. If true, the bid for tax credits (θ_τ) would be less than the bid for a direct payment (θ_s), meaning that conservation programs could be more cost-effective by offering tax benefits (deductions or credits) or fee reductions instead of making direct payments.

If the farmer perceives higher risks from BMP adoption, they may insist upon a risk premium in the form of higher PES compensation. BMP insurance protects farmers from down-

[4] Using a utility maximization framework instead of the classic profit maximizing framework, one can show how environmental attitudes impact bid amounts. I posit that strong environmental preferences place downward pressure on bids, inducing farmers to bid below their full cost of participation. This is not the focus of this essay, but the theoretical implications are meaningful and should be explored in future research about conservation auctions.

side profitability risk tied to BMP adoption. Crop yield insurance linked to BMP implementation may be more cost-effective than payments when farmers are risk averse, especially if the farmer perceives exaggerated downside risk of BMPs on farm profitability (Mitchell and Hennessy 2003). Green insurance is designed to encourage farmer experimentation with BMPs, typically with the expectation that farmers will learn how to implement the BMP successfully over several growing seasons and then will no longer require the BMP insurance. But for green insurance to be successful, farmers must first be willing to participate in the program. In principle, if a risk averse farmer was provided with fully subsidized (i.e., free) green insurance, then one would expect a bid for a payment with free green insurance (θ_g) to be less than a bid for a direct payment without insurance (θ_s) because θ_s would include a risk premium, whereas θ_g would not.

Certification of environmental stewardship represents a third alternative means to induce improved agro-environmental management. Programs that certify environmental stewardship can induce conservation actions if farmers value benefits resulting from certification (e.g. price premiums, increased market access, social recognition, protection from future regulation). Benefits to farmers could take the form of price premiums for sustainably produced agricultural goods or increased access to markets. In this model, I assume that benefits from stewardship certification take the form of a product price premium if a farmer adopts conservation practices that exceed a designated threshold, $a \geq \tilde{a}$.

A certification to recognize producers using conservation practices may evoke a sense of pride in farmers, meeting nonmonetary objectives that would provide additional utility. In turn, farmers may adopt BMPs for a price premium that pays less than a direct payment made privately, $\theta_\phi < \theta_s$ (where $\theta_\phi = y * \phi$ such that y denotes the farmer's crop production in bushels and ϕ is the per bushel price premium demanded). Even without financial benefits, some farmers may seek certification for social recognition or because the standards align with their personal preferences for environmental stewardship.

The bidding mechanism used to elicit farmer willingness to enroll in a certification program with price premiums differs from the discriminatory price reverse auction used for payment and tax credit programs. In this auction experiment, farmers enroll in a stewardship certification program if they are willing to accept the premium provided by the program. This enrollment rule can be mimicked using a Becker-DeGroot-Marschak (BDM) mechanism (Becker, DeGroot, and Marschak, 1964) in which farmers bid the minimum price premium they would accept to enroll in the certification program. Then, a random price is drawn from a known distribution and this price sets the price premium for the program. If the bid is less than the premium drawn, the farmer enrolls in the program, adopts the specified BMPs, and receives the per bushel premium[5]. If the bid is greater than the premium drawn, the farmer is not enrolled because he demands a higher price premium. Unlike discriminatory price auctions, the BDM mechanism has been shown to be incentive compatible, meaning that the mechanism induces truth-telling such that a bidder reveals his true willingness-to-accept (Lusk and Shogren 2007; Lusk, Alexander and Rousu 2007).

1.2.2 The conservation agency's problem

Using a limited budget for conservation incentives, a conservation agency seeks to maximize environmental benefits by providing incentives for voluntary adoption of agricultural management practices that generate desirable environmental outcomes. The environmental

[5] The per bushel premium requested would likely differ among crops. Here I consider a premium for a single crop or one can imagine that the premium is weighted for multiple crops.

impacts of agricultural conservation practices vary greatly, depending on the location and characteristics of each farm. Conservation procurement auctions provide agencies with a way to allocate scarce funds among projects that offer the most environmental benefit per dollar spent. The agency makes two decisions. First, the agency decides the characteristics of the conservation program (i.e., select $\boldsymbol{\rho_j}$), which includes the type of financial incentive that will be available. Second, the agency decides which offers $n = 1, \dots, N$ will be accepted in the program. The two-stage problem is analyzed by backward induction, starting with the second stage.

Assume the agency receives N offers $\theta_{nj}, \dots, \theta_{Nj}$ indicating the financial transaction requested in exchange for implementing conservation actions a_j. Heterogeneity among farmers, farms, and conservation practices creates considerable variability among auction tenders. The conservation agency can predict the environmental benefit from each offer, e_{nj}, using a biophysical model that predicts site-specific benefits based on land attributes and management practices. Consider an agency targeting a single environmental endpoint – reduced total phosphorus (TP) runoff.

Bids are ranked based on the cost to procure one unit of environmental benefit, $\beta_{nj} = \frac{\theta_{nj}}{e_{nj}}$, which is defined as the cost-benefit index of the offer for transaction j. The conservation agency ranks farmers' offers and funds the offers with the lowest cost per unit of environmental benefit (i.e., pound of TP reduction). Let $b(k, \boldsymbol{\rho_j})$ denote the kth order statistic of the distribution of βs. For a conservation incentive program with attributes $\boldsymbol{\rho_j}$, the vector $[b(1, \boldsymbol{\rho_j}) \dots . b(N, \boldsymbol{\rho_j})]$ is the set of all bidders' β values sorted in ascending order. Assume each bidder has a distinct β so that the sorted values increase in a strictly monotone way such that $b(1, \boldsymbol{\rho_j}) < b(2, \boldsymbol{\rho_j}) < \cdots < b(\mathrm{N}, \boldsymbol{\rho_j})$. After ranking bids, the agency accepts as many offers as it can afford to fund with its constrained budget G_j, starting with the most cost-effective offer $b(1, \boldsymbol{\rho_j})$ and ending with $b(\widehat{K}, \boldsymbol{\rho_j}) = \tilde{\beta}$, which is the highest cost-benefit index that is accepted. The agency's enrollment decision rule can be written,

$$d_{nj} = \begin{cases} 1 & \text{if} \quad b(k, \boldsymbol{\rho_j}) \leq b(\widehat{K}, \boldsymbol{\rho_j}) \\ 0 & \text{if} \quad b(k, \boldsymbol{\rho_j}) > b(\widehat{K}, \boldsymbol{\rho_j}) \end{cases} \tag{1.5}$$

Total agency expenditures is $\sum_{n=1}^{N} d_{nj}\theta_{nj} \leq G_j$ and total environmental benefits procured is $\sum_{n=1}^{N} d_{nj}e_{nj} = E_j$. The cost-benefit score of the conservation program is,

$$CB_j = G_j/E_j \tag{1.6}$$

In the first stage of the conservation agency's decision-making process, the agency selects the most cost-effective incentive program (i.e., program with the lowest CB_j) by choosing $\boldsymbol{\rho_j} \in \{\boldsymbol{\rho_s}, \boldsymbol{\rho_g}, \boldsymbol{\rho_\tau}, \boldsymbol{\rho_\phi}\}$. Assuming that the fixed budget G_j is exhausted, the cost-effectiveness of each program is determined by the amount of environmental benefits procured, which depends on the cost to obtain each unit of benefit. Lower offers θ_{nj} reduce the cost per unit of benefit procured and thus improve cost-effectiveness by lowering CB_j.

Figure 1-1 presents the environmental contract curves that are created by plotting the ranked cost-benefit index β_{nj} associated with each offer and the cumulative benefits procured E. At a given level of environmental benefits, E, the area underneath the supply curve equals the budgetary outlay required to fund accepted bids in a program with attributes $\boldsymbol{\rho_j}$. Area b is equivalent to area c such that the budgetary expenditure for program $\boldsymbol{h}$ (i.e., $G_h = a + b$) equals the budgetary expenditure for program $\boldsymbol{j}$ (i.e., $G_j = a + c$). E_j and E_h represent the total benefits procured with a fixed budget G in programs offering incentive j and h, respectively. The agency chooses program attributes $\boldsymbol{\rho_j}$ that result in the highest total environmental benefits procured with budget G – i.e., the agency selects the incentive type that will result in the most cost-effective program.

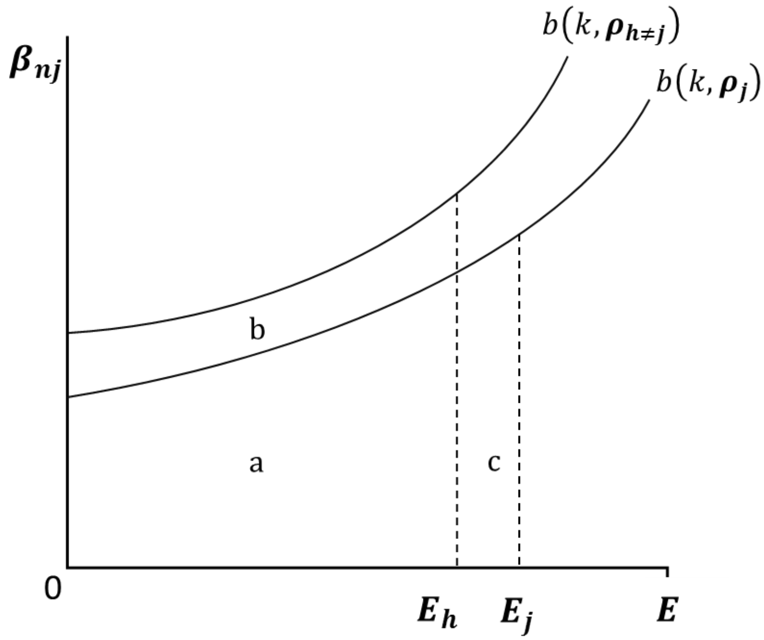

Figure 1-1. Contract supply curves show the level of environmental benefit, E_j, that can be procured in conservation program j with attributes $\boldsymbol{\rho}_j$, given a limited budget $G = a + b = a + c$.

1.3 Auction experiments

Using experimental conservation procurement auctions, I evaluate farmer preferences for different conservation incentives by comparing bids for contracts offering four types of financial transactions, 1) payment, 2) payment coupled with green insurance, 3) tax credit, and 4) price premium tied to stewardship certification. In the experiments, farmers submit offers to adopt agricultural management practices that reduce TP runoff from corn and soybean farmland in a stylized watershed. Participants earn money in the experiment based on the profitability of their mock farms; however, their decisions in the experiment are not linked to real actions on farmland they own.

Experiments were conducted in the Maumee watershed, which drains into western Lake Erie. Eighty percent of the land in the Maumee is dedicated to agriculture, and it is the single largest watershed draining into the Great Lakes, spanning parts of Ohio, Michigan, and Indiana (Stumpf et al. 2012). Recent research suggests that spring phosphorus loading from the Maumee River is the primary driver of algal bloom intensity and area in western Lake Erie (Stumpf et al. 2012; Johnson et al. 2014). In 2011, a record setting harmful algal bloom (HAB) in Lake Erie drew attention to land management in the Maumee Watershed. Subsequent HABs[6] have further focused attention on the region and have pushed stakeholders to address the chronic nutrient-loading problem. Unlike eutrophic conditions in the 1960s and 1970s that were primarily fueled by point source polluters (e.g. municipal sewage treatment plants), current phosphorus loadings are being driven by nonpoint source nutrient loss from agriculture and other sources (Michalak et al. 2013; International Joint Commission 2014).

Lake Erie HABs threaten human health and wildlife by producing microcystin, a harmful toxin that contaminates drinking water sources (Stumpf et al. 2012). Furthermore, HABs reduce the value of lake recreation and associated tourism revenues. Harder to quantify, hypoxic conditions caused by decaying algae may negatively affect fish communities and harm high-valued fisheries in Lake Erie (Scavia et al. 2014). To significantly reduce HABs in the lake's western basin, experts estimate a need to reduce annual total phosphorus (TP) loads from the Maumee River and other western basin tributaries by 40-46% (Johnson et al. 2014). Identifying cost-effective conservation programs to abate TP runoff associated with HABs is clearly needed to augment the impacts from limited conservation budgets.

[6] In August 2014, microcystin – a toxin produced by HABs – contaminated drinking water near Toledo, Ohio affecting more than 500,000 people.

1.3.1 Development and pretesting

Auction protocols were developed in three stages. The first stage involved the development, pre-testing, and implementation of a simplified auction that was conducted with 72 students at Michigan State University. The second stage involved the development of the farmer experimental auction protocols, directions, and information handouts about mock farms and conservation practices. Comparing conservation incentive designs requires controlling for other factors that may influence the cost-effectiveness of phosphorus abatement. Past research has shown that farmer willingness to accept PES depends on direct costs and benefits, opportunity costs, personal beliefs, and capital stock (Ma et al. 2012). To test preferences for different transactions a questionnaire was used to identify farmer characteristics and then controlled for farm characteristics by presenting auction participants with hypothetical, "mock" farms at specific locations in the Maumee watershed. Mock farms allowed replication of the same farm settings at different auction sites; they also facilitated the real-time ranking of bids using previously simulated environmental data for each farm. As described in the results section, panel data resulting from the auctions were subsequently used to compare the preference effect for a given transaction type with random effects regression techniques using the mock farms to control for otherwise unobservable farm characteristics.

Sixteen mock farms were developed to represent corn and soybean farms in the Maumee Watershed. Experts provided input about common cropping systems and practices in the region. For simplicity, each mock farm is 200 acres divided between two 100-acre fields[7]. I assumed one field was planted in corn and the other in soybeans to represent a typical corn-soybean rotation. Farms were clustered in four groups as depicted in Figure 1-2.

[7] Average farm size in the Ohio portion of the Maumee Watershed is approximately 240 acres (USDA - NASS 2014).

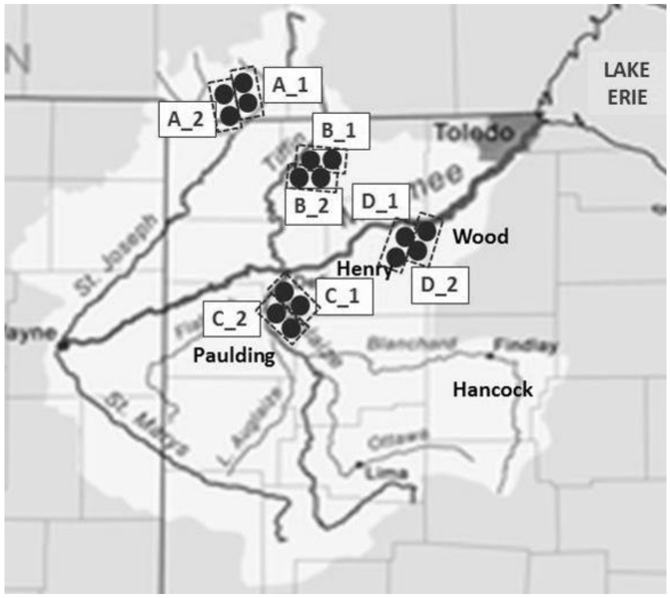

Figure 1-2. Locations of mock farms in experimental auctions

Within the group of four farms, pairs of farms had unique soil types and average crop yields, meaning that there were eight unique geographic farm characteristics among the 16 mock farms (see Table 1-1). Soil type was assigned based on the two predominant soil types in each farm cluster. Crop yields for each farm were estimated using the Soil and Water Assessment Tool (SWAT) model (Gassman et al. 2007; Bosch et al. 2011) and were calibrated to align with the average yield of farms in the county to which each farm was assigned.

Auction participants were provided with a map that identified the location of their farm within the watershed.

Table 1-2 presents the additional information provided to participants about their mock farm, including acreage, soil type, cropping system, average crop yield and prices, and cost of conservation practices.

Table 1-1. Information about mock farm location, soil type, and crop yields

Farm ID	Farm Cluster	Sub basin	Soil Type	Soil Description	Average Yield
1 & 2	A_1	St. Joseph	Miami	fine, moderately well-drained	Corn – 174 bu/ac. Soybeans – 45 bu/ac.
3 & 4	A_2	St. Joseph	Glynwood	fine-loamy and well-drained	Corn – 170 bu/ac. Soybeans – 45 bu/ac.
5 & 6	B_1	Tiffin	Colwood	fine-loamy, poorly-drained	Corn – 177 bu/ac. Soybeans – 46 bu/ac.
7 & 8	B_2	Tiffin	Ottokee	fine, moderately well-drained	Corn – 157 bu/ac. Soybeans – 46 bu/ac.
9 & 10	C_1	Lower Auglaize	Paulding	very fine, very poorly-drained	Corn – 167 bu/ac. Soybeans – 44 bu/ac.
11 & 12	C_2	Lower Auglaize	Toledo	fine, very poorly-drained	Corn – 167 bu/ac. Soybeans – 44 bu/ac.
13 & 14	D_1	Lower Maumee	Hoytville	fine, very poorly-drained	Corn – 172 bu/ac. Soybeans – 48 bu/ac.
15 & 16	D_2	Lower Maumee	Mermill	fine-loamy, very poorly-drained	Corn – 169 bu/ac. Soybeans – 48 bu/ac.

Acreage, cropping system, and average crop prices were held constant across farms while soil type, average yield and cost of conservation practices varied among mock farms to account for the heterogeneity among farms in the region and control for factors that may influence farmers' willingness to adopt conservation practices, specifically the location effect on payment (soil type, location in watershed), yield risk and opportunity cost of land (yield, price), and direct cost of conservation practices. Other hypothesized determinants of adoption decisions and willingness to accept PES are either unobservable or captured in bidder traits.

Table 1-2. Example information card for mock farms assigned in the experimental auction

Farm ID	Farm A-1
Acreage	You own 200 acres, which is divided into two 100ac fields.
Soil Type	Miami -- fine, moderately well-drained
Cropping System	corn-soybean rotation – assume that each year you grow 100 acres of corn and 100 acres of soybeans[a]
Average yield and prices	Corn – 174 bu/acre ($6/bu) Soybeans – 45 bu/acre ($12/bu)
Cost of conservation practices[b]	Cover crop: $20/acre Conservation tillage: $16/acre *No fall fertilizer* (spring fertilizer instead): $0/acre *Filter strips:* $28 for one acre of filter strips

[a] Details were attached and are shown in Table 1-3
[b] Does not include costs or benefits of yield changes

Information about baseline production practices was provided to auction participants, including 1) planting and harvesting dates, 2) fertilizer application rate, source, and timing, 3) tillage practices, 4) cover crops, and 5) filter strip placement. The baseline cropping system is presented in Table 1-3. The same baseline cropping system was assumed for all mock farms.

Table 1-3. Baseline crop production system for mock farms

DESCRIPTION OF CROPPING SYSTEM: You own and farm 200 acres. Your land is divided into two 100-acre fields. Each year you produce corn on one field and soybeans on the other field. Following soybean harvest, corn land is field cultivated and fertilized in fall. Corn also receives starter and sidedress fertilizer. Soybeans are no-till drilled into corn stubble with no fertilization. No cover crops. Details below.

Corn Field	Soybean Field
Plant: mid-April to mid-May	Plant: May
Fertilizer Application: (starter fertilizer) **Type:** UAN 28% and Liquid Ammonium Polyphosphate mixed to: N-P-K 17-20-00 **Rate:** 18 gallons/acre **Time:** day of planting	Harvest: October Tillage (before corn): **Type:** Field cultivator **Time:** October or November
Fertilizer Application: (side dress) **Type:** UAN 28%: N-P-K 28-00-00 **Rate:** 41.5 gallons/acre **Time:** 6 weeks after planting **Harvest:** end of October - November	Fertilizer Application (before corn): (broadcast) **Type:** 08-15-00 + potash; mixed to: N-P-K 08-15-45 **Rate:** 200 lbs. /ac **Time:** October or November (after fall tillage)
*No filter strips	*No filter strips

Costs of conservation practices were selected based on information from two sources, 1) the cost-share payment schedule for conservation projects in Ohio funded by Natural Resources Conservation Service's (NRCS) Environmental Quality Incentives Program (EQIP) and 2) opinions from farmers interviewed at the Michigan State Ag Expo (East Lansing, MI, July 18, 2013). Costs were selected to be representative of the typical costs faced by Maumee producers when adopting each of the four BMPs.[8] A main-effects orthogonal design was used to assign four levels of BMP implementation costs to the 16 mock farms as presented in Table 1-4.

[8] Conservation practice implementation costs for the mock farms range roughly from 50% to 150% of the EQIP payment levels. This range was selected to reflect the heterogeneity of costs among farmers.

Table 1-4. Costs of conservation practices assigned for mock farms

Cost Levels	Cover Crops $/acre/yr.	Conservation Tillage $/acre/yr.	Spring Fertilizer $/acre/yr.	Filter Strip[a] $/acre/yr.
1	20	16	0	28
2	24	20	1	30
3	28	24	2	32
4	32	28	3	34

[a] Only includes cost of implantation/installation

The final stage of pretesting involved vetting the mock farm descriptions and auction directions both with farmers and with knowledgeable experts. Experts from The Ohio State University Extension, a crop and soil science professor at Michigan State University, and a nutrient management consultant from a northwestern Ohio agricultural retailer were consulted to develop and approve the baseline cropping system and characteristics of the mock farms. Additionally, three farmers were recruited during the Michigan Ag Expo to review the auction directions and mock farm descriptions. Farmer feedback was used to improve the design of the auctions.

1.3.2 Design of experimental conservation auctions

Farmers were mailed personalized invitations to the experimental auction meeting with a cover letter explaining the purpose of the auction experiment. To enhance credibility, the cover letters were co-signed by leaders in the agricultural communities where each auction was held. Producer addresses were obtained from four sources, 1) the local Soil and Water Conservation District (SWCD) office, 2) the Ohio Farm Bureau, 3) an agricultural input supplier in northwest Ohio, and 4) county property tax records.

Upon arrival, participants were asked to sign a consent form, were paid a $50 participation honorarium, and were provided with a folder that included details about their mock farm and general instructions (Appendix 1-A). The auction leader presented an introduction and review of the general instructions. Farmers were told the purpose of the auctions and informed about how the auctions would be conducted, but were not told the exact number or type of auctions in which they would participate.

In a series of auctions, farmers submitted bids for different types of financial transactions. Farmers were asked to make decisions for the mock farms as if the farms were really their own. Five protocols were consistently followed across all auctions. First, farmers were invited to submit bids for the annual payment they would require to adopt one or more of the following in field conservation practices, 1) cover crops, 2) conservation tillage, and 3) spring fertilization instead of fall fertilization.[9] If a farmer bid on more than one practice, then the group of practices was evaluated as a package[10]. Second, the predicted TP runoff reductions from adopting the conservation practices proposed in each bid were calculated using the Soil and Water Assessment Tool (SWAT) model. Third, bids were always ranked based on the cost per pound of reduced TP runoff. Fourth, contracts were offered to the farmers who made the most cost-effective bids until the budget was exhausted. The budget for each auction was set at 100,000 experimental dollars, but was unknown to farmers. Fifth, bids were sealed and no information about outcomes was provided between rounds. Farmers learned about bid acceptance at the end of the session.

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[9] Participants had the option to bid on filter strips in the payment and tax credit auction, but filter strips were not an option in the green insurance and certification premium auctions. Therefore, I focus the analysis on in-field practices so that I can compare bidding behavior for the same practices across all four auctions.

[10] Combinations of practices were evaluated together for computational tractability because I could estimate environmental benefits for all possible practice combinations in SWAT before the auction. However, future work should be designed to evaluate parts of the combinatorial bid so that acceptance is not "all or nothing." For a comprehensive review of design issues associated with combinatorial auctions see (Iftekhar, Hailu and Lindner 2012).

In addition to the $50 participation honorarium, participants were paid based on their performance in the auctions, which was measured by the total income generated by their mock farm in all auction rounds. Net winnings in each round equaled the difference in farm profits with and without the conservation program. Farm profits equaled the net revenue minus the costs of adopting the conservation practice(s) plus the income provided by the conservation incentive (e.g., payment, tax credit, or price premium). Mock farm income was calculated for each auction round and then summed to calculate the total earnings. Actual payments to farmer participants were determined by relative mock farm earnings from all rounds. Payments for auction performance ranged from $38 to $68.25, with an average payment of $52.

1.3.3 Treatments

In this essay, outcomes are reported from four auctions in which farmers submitted individual bids for conservation contracts offering different incentives to motivate adoption of conservation practices.[11] To familiarize farmers with the auction process, the first round involved farmers bidding for a direct payment, which is the most straightforward transaction. After the direct payment auction, farmers were asked to submit another bid for a direct payment if they were also provided with green insurance free of cost. In the following rounds farmers submitted bids for a tax credit and then a price premium per bushel that was tied to an environmental stewardship certification (example bid sheet are presented in Appendix 1-B).

The direct payment auction represented a typical conservation auction in which farmers bid the payment that they would require to adopt one or more conservation practices. After the

[11] In this research, I also explored the impact of joint bidding on auction performance. Auctions with joint bidding were conducted after the four auctions testing conservation transactions and thus these experiments do not impact the results reported in this essay.

payment auction was completed, farmers were informed about “green insurance” that they would automatically receive if their bid for a payment was accepted in the second auction. Farmers were told that green insurance would protect them from income loss due to yield reductions associated with implementing the conservation practices (compared to conventional production). Insurance indemnities were based on the countywide performance of cropping systems using conservation practices compared to conventional systems. Thus, insurance payouts would be made to farmers if the countywide average yield of conservation systems falls below the countywide average yield of conventional systems. Farmers then submitted a bid for the additional payment that they would require to adopt the BMP when provided with the green insurance free of cost.

In the tax credit auction, farmers submitted bids for the tax credit that they would request in exchange for adopting conservation practice(s). This auction was most similar to the direct payment auction, only with a different payment vehicle. Tax credits were offered at the state level to link regional environmental benefits and regional (state) incentives. Participants at the first auction site indicated that state tax liabilities for most farmers are less than the payment they would require to implement some conservation practices (e.g., cover crops on large acreage). With the latter three auction groups, I included an auction for federal tax credits in addition to the auction for state tax credits, as the level of federal taxes would be better able to fund conservation practices. Results between auctions for the two tax credits are the same; therefore, results are reported for state tax credits because this transaction was tested at all four auction sites.

A Becker-DeGroot-Marschak (BDM) mechanism was used to test farmers’ willingness to accept certification premiums. In the BDM procedure, farmers wrote down the price premium that they would require to implement the set of three in-field practices (cover crop, conservation tillage, and spring fertilizer application). Then, I randomly drew price premiums for corn and for soybeans from uniform distributions with known supports. Possible premiums ran from $0 to $1 for corn and $0 to $2 for soybeans in one-cent increments. If, for both crops, the price premium requested by farmers was less than the premium drawn, then participants' mock farms were enrolled in the stewardship certification program and they received the per bushel premium drawn.

1.4 Empirical Model

The theoretical framework presented in Section 1.2 showed that farmer preferences could cause conservation bids to differ by transaction type, thereby varying the cost-effectiveness of alternative conservation incentives. However, *a priori*, it is not known whether or how preferences will differ among the transaction types. In an experimental setting, I can test the impact of different transaction types on the bids submitted by farmers. Holding the level of conservation action constant, lower bids indicate that farmers are willing to adopt BMPs at a lower cost to the conservation agency. If the transaction type can lead to more cost-effective procurement of environmental benefits, then the conservation agency's problem, becomes an optimization over both the cutoff cost-benefit index, $\tilde{\beta}$, and the conservation program with transaction type j.

To identify relative differences in bids submitted for various incentives I analyze "net bids," which is the difference between the bid amount and the known cost of adopting one or more BMPs. As shown in the theoretical model, the net bid in discriminatory price auctions is impacted by expected changes in revenue from a yield effect, transaction costs of being involved with the conservation program, environmental attitudes and incentive type preferences, and the probability of bid acceptance.

Evaluating preferences among transactions involves comparing the relative net bids across transaction types. Therefore, it is important to acknowledge how bids may change between discriminatory price auctions and the BDM mechanism, unrelated to farmer preferences for a conservation incentive. Recall that the BDM mechanism induces truth telling and thus depends only on each farmer's willingness-to-accept for BMP adoption and not on the distribution of other farmer bids and corresponding environmental benefits. If transaction costs and expected changes in production and environmental values are the same among incentive types, one can expect a lower net bid for the certification premium because of the incentive compatibility principle. This outcome will be further explored in the empirical analysis.

Assuming a linear specification, the empirical model is presented in Eq. (1.7).

$$\begin{aligned} net\ bid_{nj} = \alpha_0 &+ \sum\nolimits_{j\in\{c,g,\tau,\phi\}} \delta_j \rho_j + \sum_{k\in\{cc,sf,ct\}} \xi_k a_{njk} + \gamma env_n \\ &+ \sum\nolimits_r \Psi_r C_{nr} + \sum\nolimits_l \varphi_l FARM_{nl} + \sum\nolimits_{m=1}^{4} \lambda_m exp_{nm} + \varepsilon_{nj} \end{aligned} \tag{1.7}$$

The type of transaction offered in each auction is modeled with binary variables that equal one when incentive program ρ_j is offered and zero otherwise. Recall that only one incentive is offered in each auction. Coefficient δ_j estimates how the bid will change when incentive ρ_j is offered compared to the baseline, which is the direct payment. I control for the type of BMPs (conservation actions) in each auction tender (a_{nj}), because they could impact farmer perceptions about the yield effect from adopting the suite of BMPs for which they submit a bid. A binary variable (env_n) equals one if the farmer is a member of an environmental organization and zero otherwise. Farmer characteristics are controlled for with continuous and binary variables (C_{nr}) as presented in

Table 1-5. Binary fixed effect variables control for the mock farm ($FARM_{nl}$) cluster to which each farmer was assigned (see Table 1-1) and the location of the experimental auction session (exp_{nm}) in which they participated.

This specification enables tests of the null hypotheses 1) that transaction type (δ_j) has no effect on bid amount, and 2) that environmental preference (as proxied by organizational membership) has no effect.

Table 1-5. Descriptive statistics of the characteristics of auction participants

	Paulding County	Henry County	Wood County	Hancock County	All
Number of participants	12	10	16	11	49
Participant characteristics					
Gender (% male)	100%	100%	100%	100%	100%
Average Age (yrs.)	61	62	44	64	56
Farming Experience (yrs.)	42	44	25	47	38
Education beyond high school (%)	42%	50%	69%	27%	49%
Off-farm income > $50,000 (%)	33%	50%	44%	55%	45%
Acres planted in 2012	1580	1076	1848	1190	1477
Member of environ. organization	17%	60%	25%	55%	37%
Recruitment					
SWCD	100%	44%	56%	72%	69%
Farm Bureau	0%	0%	44%	0%	15%
Input Supplier	0%	56%	0%	0%	10%
Tax Records	0%	0%	0%	27%	6%

1.5 Results

Outcomes from the experimental auctions are evaluated in two ways. First, farmer preferences among transactions are evaluated by comparing their “net bids” (i.e., the difference between their bid and assigned cost of BMP implementation). Next, the cost-effectiveness of the auctions is evaluated based on how much environmental benefit was acquired per dollar.

1.5.1 Overview and descriptive analysis

Fifty-one farmers participated in the experimental auctions, yielding 49 records that could be used in the analysis.[12] Auction participants included in this analysis were recruited using mailing lists from county Soil and Water Conservation Districts (69%), Ohio Farm Bureau (15%), an input supplier (10%), and property tax rolls (6%). Characteristics of participants at each auction location are presented in Table 1-5.

Participants were all male with a mean age of 56 years and mean farming experience of 38 years. Forty-nine percent of participants had continued their education beyond high school and 45% of farmers were from households earning $50,000 or more in off-farm income. Participants were row crop farmers following a corn and soybean rotation with some farmers growing wheat in the rotation. In 2012, the farmer participants planted an average of 1477 acres in corn or soybeans on land that they owned or rented. Thirty-eight percent reported being a member of an environmental organization.

[12] One participant was not a corn and soybean farmer and the other participant failed to complete the background questionnaire. I only report information and bidding results for the 49 participants included in the analysis.

1.5.2 Farmer preferences among transaction types

Farmer preferences among the four transactions types were evaluated by comparing net bids in each auction. The net bid was calculated for each farmer as the bid for that transaction minus the assigned cost of BMP implementation.[13] Recall that the cost of implementing each conservation practice was assigned among the mock farms using a main-effects orthogonal design with four cost levels, and all farm characteristics given to a participant were held constant across auctions. The only variable that differed among auctions was the type of incentive for which the farmers were bidding, thus changes in bidding behavior reveal farmer preferences among the four different incentive types.

Figure 1-3 summarizes the bidding behavior using a scatterplot of participant bids against their given implementation costs in four auctions. The 45-degree line connects points where bids equal monetary costs. Points above the line represent bids that exceed the cost of implementation. Bids below the line fall below implementation costs.

[13] If farmers bid on multiple practices, the net bid was calculated by subtracting the total cost of all practices from the total bid. In the econometric model, I controlled for the practices included in each bid.

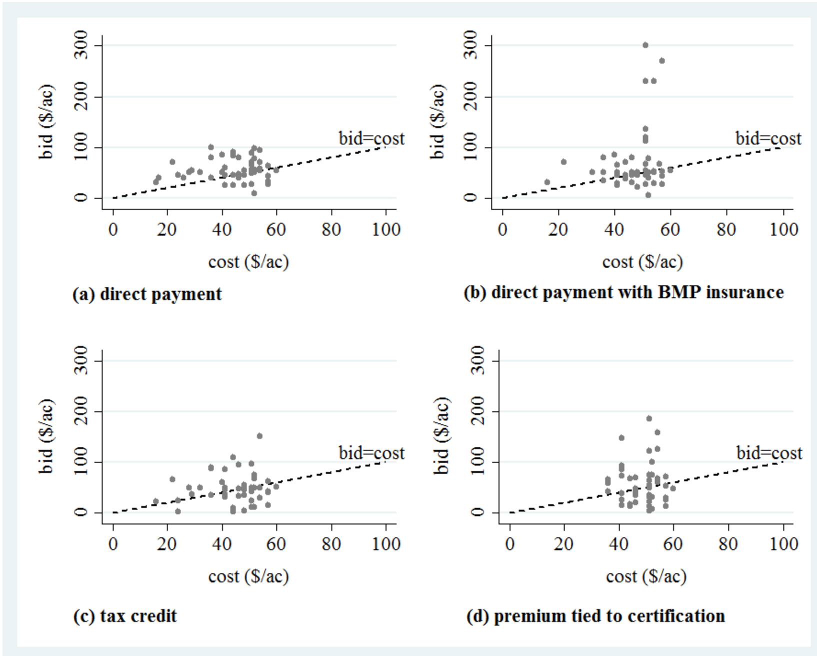


Figure 1-3. Scatterplots that compare producer bids and their costs to implement conservation practices show that producers bid both above and below their costs in all auctions.

Two important results are apparent. First, the variation among bids is smallest in the auction for direct payments and greatest in the one for direct payments with green insurance. Greater variation among bids mirrors the variation in farmer preferences. Some farmers were interested in green insurance to minimize perceived down-side yield risk associated with BMP adoption and thus required a lower payment when green insurance was provided free of cost. Other farmers showed strong aversion to green insurance by bidding for payments that far exceeded implementation costs.

Second, farmers bid both above and below their costs (Figure 1-3). Previous studies have concluded that bidding below one's cost is a mistake that inexperienced farmers make when bidding in conservation auctions in an attempt to increase their chances of winning (Cason, Gangadharan and Duke 2003). However, the frequency of bidding below costs that occurred in this study suggests that other factors may be influencing farmers' bidding decisions. As presented in the theoretical model, low bids may reveal farmers' environmental preferences or their expectations of private benefits from implementing the BMP(s). It is highly likely that farmers were considering their environmental preferences when submitting bids and this result is supported by the econometric analysis that follows. Participants took the experimental auctions seriously. During debriefing following the auction, farmers stated that they were willing to accept some of the costs associated with conservation practices on their own farm and did not always require payments equal to or above expected costs. In this way, farmers considered the payments more like a cost-share and bid accordingly.

Table 1-6 presents the summary statistics of net bids across the auctions and Figure 1-4 presents the frequency distributions. Mean net bids are highest in the auction for payments with green insurance, but the mean is pulled upward by several farmers with strong aversion to green insurance who bid significantly higher than they did in the payment auction. Net bids are lowest for the tax credit, but due to the high variance and relatively small sample size, the difference between net bids in the tax credit auction and the auction for direct payments is not statistically significant.

Table 1-6. Summary statistics of net bids (i.e., bid minus the cost of BMP implementation) for four transaction types.

Auction Transaction Type	n[a]	mean	std. dev.	min	median	max
a) Payment	49	11.0	22.7	-42.0	7.0	64.0
b) Payment with green insurance	47	24.0	61.8	-46.0	3.0	249.0
c) Tax credit	47	3.4	30.1	-43.0	-1.0	96.0
d) Certification price premium	47	8.7	40.3	-47.4	2.3	134.2

[a] All 49 participants submitted bids in the auction for a conservation payment; however, only 47 bids were submitted in the auctions for the alternative transactions. The participants who chose not to submit bids varied among the three auctions.

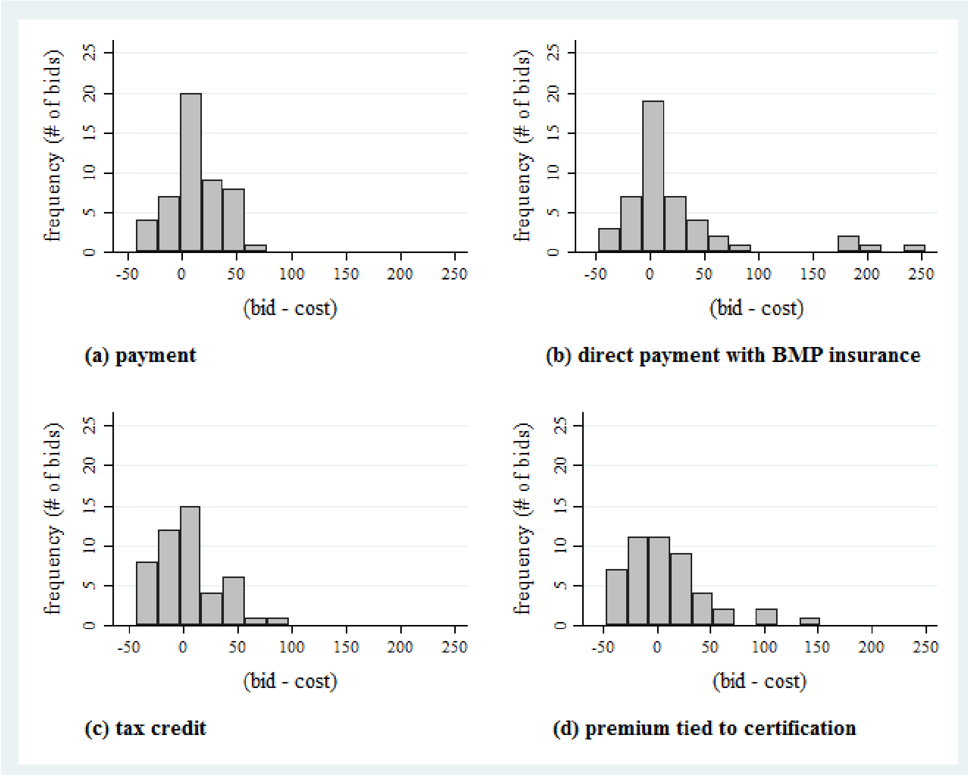


Figure 1-4. Histograms of net bids for each auction show that the variance of net bids is smallest in the auction for direct payments and largest among net bids for payments with green insurance.

A random effects regression model estimates Eq. (1.7), controlling for farm and farmer characteristics while testing for effects of environment preferences and differences in bidding behavior across transaction types. Relative to direct payment, the results reveal aversion to green insurance incentives, but no significant differences in preferences for tax credits or premiums tied to stewardship certification (Table 1-7). The continuous dependent variable is the net bid, the difference between the bid to adopt conservation practices and the assigned cost of adopting those practices. Independent variables include dummies for, 1) the treatment (transaction type), 2) the BMPs included in the bid, 3) the auction meeting site, 4) farmer characteristics, and 5) both continuous and binary variables for bidder characteristics (e.g. age, education, income, farming experience, acreage planted, and environmental organizations).

Table 1-7. Determinants of net bids (bid minus assigned costs of conservation practices) for 49 farmer participants in experimental auctions, random effects model

Variable	Coef.	Robust Std. Err.	p-value
Type of auction			
Green insurance	14.64*	8.84	0.10
State tax credit	-5.84	4.15	0.16
Certification premium	-5.00	6.11	0.41
BMPs included in bid			
Cover crop dummy	-6.56	6.18	0.29
Conserv. tillage dummy	-15.04	12.38	0.23
Spring fertilizer dummy	21.60***	5.56	0.00
Mock farm assignment			
Location A_2	-9.75	11.64	0.40
Location B_1	-7.09	10.76	0.51
Location B_2	-2.94	11.47	0.80
Location C_1	1.84	10.34	0.86
Location C_2	-36.16***	8.31	0.00
Location D_1	-6.82	13.02	0.60
Location D_2	-16.32	15.76	0.30
Auction meeting site			
Henry Co.	19.79***	6.17	0.00
Wood Co.	16.88*	9.19	0.07
Hancock Co.	39.32***	8.88	0.00
Farmer characteristics			
Age(years)	-1.11**	0.53	0.04
Educ. beyond high school (=1 if yes)	8.33	7.02	0.24
Farming experience (years)	0.68	0.63	0.28
Income (=1 if >$50,000 NFI)	-4.08	4.88	0.40
Acres planted in 2012	-0.001	-0.003	0.75
Environmental org. (=1 if a member)	-17.64***	6.68	0.01
Constant	47.65*	26.36	0.07

Relative to the auction in which farmers bid for a direct payment only, net bids were 14 dollars higher on average when green insurance (provided free to the farmer) was offered in addition to a direct payment. This result may seem counterintuitive if one expects required payments for BMP adoption to decrease with reduced risk, but debriefing after the auction revealed that many farmers were skeptical of green insurance and were uncertain about the administrative hurdles that the program may involve. Farmers stated that they lacked confidence that this type of green insurance program would pay indemnities in the event that yield loss on their farms from the adoption of conservation practices correlated poorly with county average effects. One farmer voiced his concern about how this type of insurance program would actually be administered and he asked, "[How well] would county level outcomes really represent my farm? There are many different soil types, operators, and weather variability." He stated that these factors made him less interested in green insurance.

Net bids did not differ significantly among the payment, tax credit, and certification premium auctions. When asked about preferences between payments and tax credits, one farmer explained, "You would need to make the tax credit the same value as the payment, but I don't have a real preference." Another farmer said, "I like the idea of a tax reductions, but it is a tricky thing to think about." This sentiment was shared by four other farmers who voiced concerns about how tax credits would be administered. Expressing his opinion about certification price premiums, a farmer said, "I like the certification idea. You can get certified and then your premium just jumps per bushel. That's so easy. You just have to get certified and show that you're doing these practices."

When comparing the net bid in the BDM mechanism for certification premium to the discriminatory price auction for payments, a lower bid for the premium is expected due to the incentive compatible properties of the BDM mechanism. However, even considering this impact, no significant differences are found among net bids. Therefore, one can conclude that the certification premium performs no better than a payment. Cost-effectiveness of payments and price premiums is further explored in the following section and additional support is found for the claim that certification premiums are not more cost-effective from the viewpoint of a single payer[14].

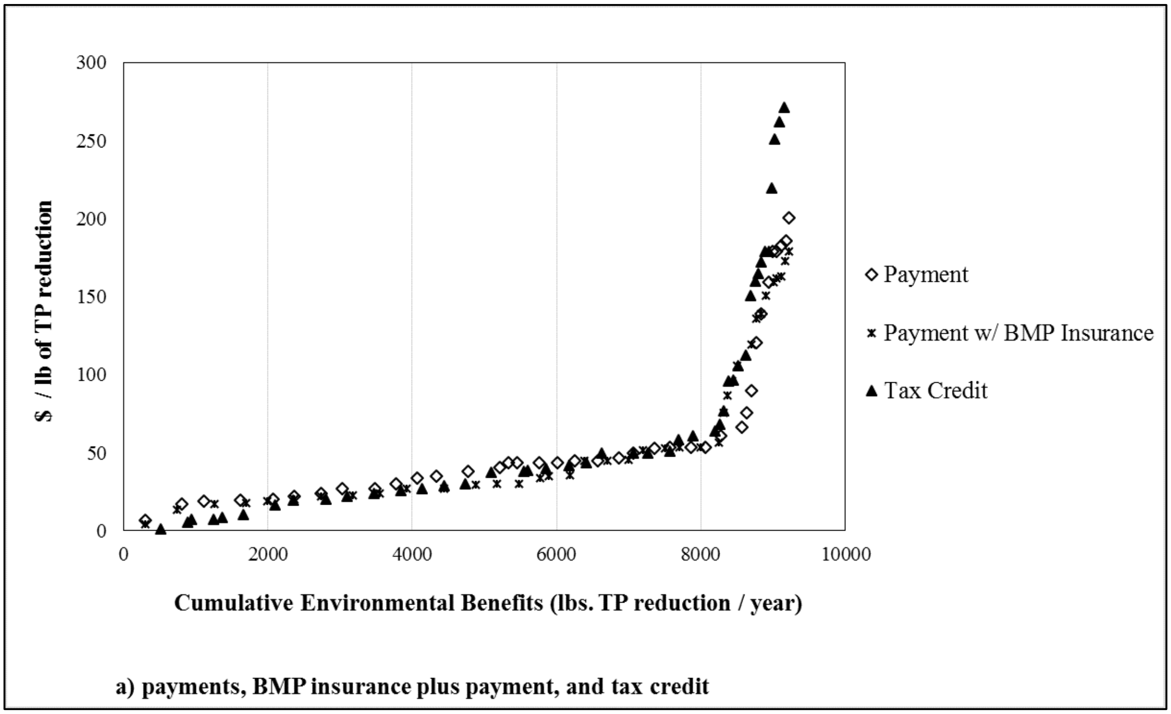
Among the three conservation practices, spring fertilizer application induced a large bid premium over costs. Average net bids increased by over 21 dollars when spring fertilization was included. Although changing the timing of fertilizer application may seem costless, farmers explained that spring fertilization requires extra time in an already short planting window and increases the risk of delayed planting that results in yield losses. They also reported that driving equipment over wet fields in the spring increases soil compaction in the heavy soils that dominate much of the landscape in the Maumee watershed. Soil compaction can interfere with planting and can also decrease crop yields.

Farmers that were members of environmental organizations placed net bids almost $18 lower per acre than nonmember farmers. If membership in an environmental organization is a valid proxy for environmental preferences, then the significance of this attribute supports rejecting the null hypothesis that environmental preferences have no effect on willingness to participate in conservation programs. Farmers who care about the environment are willing to accept lower financial incentives to adopt conservation practices that improve water quality.

[14] If the certification premiums were supported and financed by markets, cost-effectiveness may not be such a great concern. The topic of multi-stakeholder financing is outside the scope of this essay, but is an important consideration for future research.

1.5.3 Cost-effectiveness of different transactions

To evaluate the relative cost-effectiveness of each transaction type, contract supply curves are constructed to compare the cost to procure each unit of TP abatement across the different auctions in the experiment. It is important to recognize that these curves do not reflect the true contract supply curves because they are based on hypothetical costs; therefore, I do not estimating farmers' true willingness to accept. Instead, I compare the relative outcomes of the auctions depending on the type of incentive offered. Figure 1-5 presents contract curves that were created by ordering the bids from all four auctions by the cost per pound of reduced TP runoff and plotting the cost to reduce each pound of TP runoff against the cumulative reductions in TP runoff (i.e., cumulative environmental benefit). Figure 1-5(a) presents the contract curves for payments, green insurance, and tax credits, which overlap considerably and show no significant difference in cost-effectiveness of bids until the upper limit of the curve. Relative to PES programs that make direct payments to farmers, BMP insurance is administratively more demanding. Therefore, cost-effectiveness of BMP insurance would be further reduced when total costs of the program are considered.



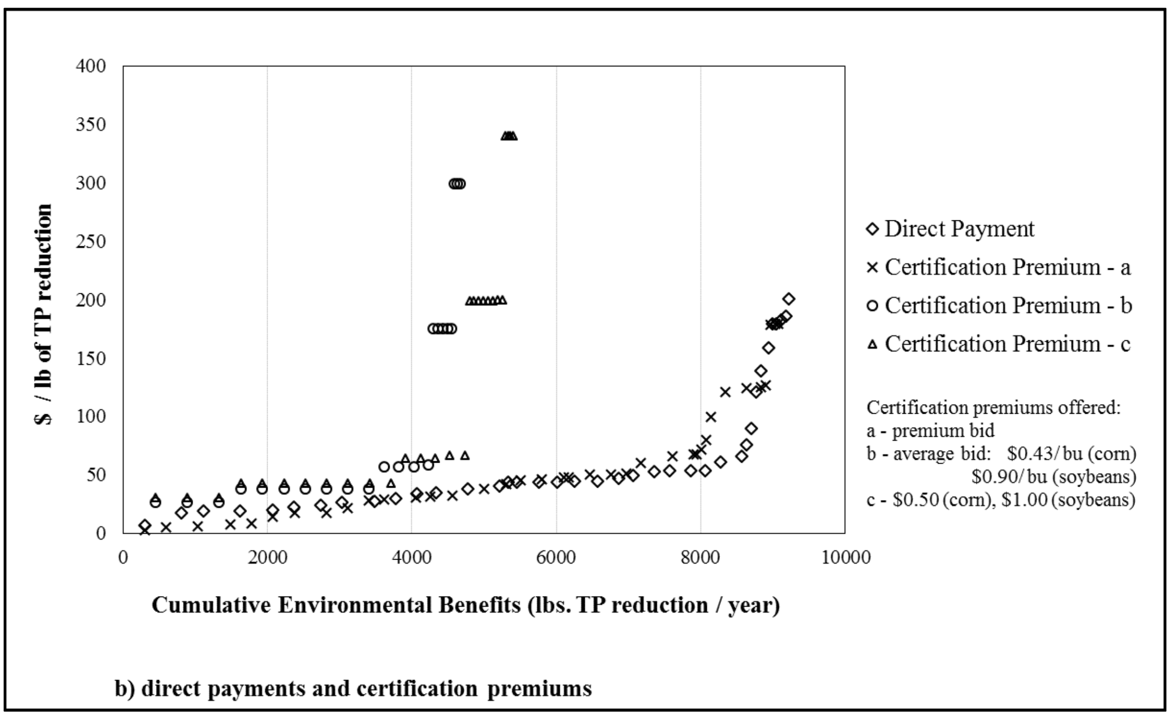


Figure 1-5. Contract supply curves for the reduction of total phosphorus runoff with different transactions in conservation auctions. Costs reflect the bids submitted in the four pilot auctions and do not account for the administrative costs involved with running a conservation program.

Figure 1-5(b) compares contract curves for three levels of certification premiums to the base curve constructed from bids for direct payments. Points on the curve "Certification premium – A" represent the cost per pound of TP reduction if farmers were paid price premiums for corn and soybeans equal to their bids. In this scenario, cost-effectiveness of bids for price premiums is no different than for bids to receive direct payments. However, an environmental stewardship certification program would not pay farmers unique price premiums based on their willingness to accept or the amount of environmental benefits that their conservation actions provide. Instead, a certification program would set a price premium and allow farmers to opt-in and adopt the required practices or decline to participate. This type of program is not targeted to environmentally vulnerable sites, so cost-effectiveness is reduced relative to targeted conservation payments.

Certification programs B and C (Figure 1-5 (a)) represent potential non-targeted incentive programs in which enrollment is determined by farmers' willingness to accept the established price premium. Price premiums for program B are set at $0.43 per bushel of corn and $0.90 per bushel of soybeans, which were the mean bids submitted for the respective premiums. The contract curve for program B increases sharply after land with high environmental benefits is enrolled. The program then begins paying the same price premium to farmers with limited ecological impact, thus decreasing the overall cost-effectiveness of the program. Relative to program A and the auction for direct payments, fewer benefits are procured at a greater cost per unit of benefit. By increasing the price premiums to $0.50 and $1.00 per bushel for corn and soybeans, respectively, certification program C has greater overall environmental impact than program B because more farmers are willing to enroll in the program for the higher price premium. If the premium is paid in the market, this transaction may be acceptable, but in the context of agencies with limited conservation funding, there are more cost-effective ways to allocate economic incentives by targeting funds to cost-effective conservation proposals.

1.6 Conclusion

Well-designed conservation incentives are critical to improve environmental outcomes across agricultural landscapes. This research highlights the importance of understanding farmer preferences for different conservation incentives in order to design cost-effective agri-environmental programs in which farmers are willing to participate. Using experimental procurement auctions, I compare farmer bids for four different incentive transactions, 1) direct payment, 2) payment coupled with green insurance, 3) tax credit, and 4) price premium tied to stewardship certification. Bidding behavior is evaluated across these auctions to identify transactions that generate the greatest ecological benefits per dollar of limited conservation funding. Rather than finding one transaction type to be most cost-effective, I find two traits that lead to less cost-effective transactions. First, when the transaction cannot spatially target conservation practices to vulnerable locations, environmental benefits (and hence cost-effectiveness) are reduced, as in the case of the certification price premium. Second, transactions that are perceived by bidders to have high transactions costs will elicit demand for high payments, as in the case of green insurance. By contrast, both direct payments and income tax credits were perceived to have relatively low transaction costs, and farmers were equally willing to accept these transactions in exchange for implementing conservation actions.

Crop yield insurance linked to conservation practices, also called “green insurance” or “BMP insurance,” has been proposed as a way to facilitate the adoption of environmentally sound production practices when farmers are risk averse and misperceive the downside risk of these practices on farm profitability (Mitchell 2004; American Farmland Trust 2012). However, results from the hypothetical auctions indicate that farmers often demand higher payments when coupled with green insurance (provided free to the farmer), leading me to reject the null hypothesis that farmers prefer green insurance. Comments during debriefing suggest that farmers were wary of uncertain transaction costs associated with obtaining and implementing the policy. Considering the added costs to the oversight organization of administering the green insurance policy, this is clearly a less cost-effective alternative to the direct payments alone[15].

Tax credits may be a worthwhile transaction for agricultural conservation, if designed correctly. Farmer bids for tax credits did not significantly differ from bids for payments, indicating farmers were indifferent between the two transactions. Farmers suggested that state tax credits would be insufficient to fund many conservation practices, but this form of incentive may be feasible for relatively inexpensive BMPs. The relative cost-effectiveness of the two contracts would depend on the administrative costs incurred by the government to manage the program. Two caveats not explored in this research are important to note. First, my analysis of tax credits assumes that the farmer also owns his land and would benefit from tax incentives. In much of the Corn Belt, producers rent a significant portion of the land they farm. In the sample of 49 farmers, many farmers (38%) rented-in twice as much land as they owned. When land is rented, benefits from tax incentives could be capitalized to rental rates, but may be difficult for

[15] For BMP insurance to be successful, it must be integrated into the current crop insurance market. However, past programs have found it difficult to generate support for green insurance in the private sector due to high transactions costs and uncertainty surrounding the new policy (Mitchell 2004; Campbell 2003). The Risk Management Agency's (RMA) pilot green insurance project ended in 2005 after enrolling only three farmers (Green et al. 2011). Another program, the American Farmland Trust's BMP Challenge®, offers a type of BMP insurance and successfully enrolled 18,000 corn acres between 2000 and 2012 to test nutrient and tillage BMPs without risk to income (American Farmland Trust 2012). On a small scale, this project has made a big impact, but scaling up is a challenge. Attempts to offer BMP insurance have failed due to the high transaction costs imposed on private insurance companies and low demand from farmers. Results suggest that BMP insurance is unlikely to promote widespread adoption of conservation practices and is even more unlikely to do so in a cost-effective manner.

the renter to take advantage of. Furthermore, there may be political resistance to a tax policy in which benefits are only available to owners of land with high environmental impact.

Programs that certify environmental stewardship provide signals about farmers' actions to promote ecosystem health and can induce conservation actions if farmers value benefits from the certification (e.g. price premiums, market access, social recognition, protection from future regulation). Enrollment in a certification program depends on the farmer's willingness to accept the premium offered. Auctions in which farmers bid the minimum price premium they would accept revealed that farmer willingness to enroll in conservation certification programs is high. But uniform price premiums would be paid to farmers for adoption of practices regardless of the environmental vulnerability of their cropland, resulting in more variable and less cost-effective outcomes relative to targeted PES or tax credit programs.[16]

Understanding farmer preferences for different types of conservation transactions is critical to design effective agri-environmental programs. This research begins to fill this gap by experimentally testing farmers' willingness to participate in conservation programs offering a variety of incentives for adoption of BMPs. Farmers prefer incentive programs with low transaction costs such as those offering payments or tax credits. Compared to non-targeted policies like environmental stewardship certification, agri-environmental programs that can successfully target conservation incentives to producers with environmentally sensitive cropland are more cost-effective.

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[16] Recent research analyzing the feasibility of certifying row crops that are grown in a manner that protects the environment found that certification is unrealistic at this time (Waldman and Kerr 2014). Consumer willingness to pay for sustainably produced foods is greatest for foods consumed directly, whereas most corn and soybeans are used to feed livestock or for other processed goods. Strong farmer willingness to participate in verification programs warrants additional research to identify ways to increase cost-effectiveness of stewardship certification. But if consumers are unwilling to pay a premium for these products, certification programs will be unsuccessful.

APPENDICES

APPENDIX 1-A AUCTION INTRODUCTION AND INSTRUCTIONS

Background:

During today's meeting imagine that you own and farm the piece of land described on your information card. You have the option to change your current corn-soybean cropping system by introducing various conservation practices, which are outlined in your conservation practices handout.

In this exercise, imagine that I work for a conservation agency and our goal is to improve water quality in the Western Lake Erie Basin (WLEB). Our organization is willing to pay some farmers to adopt certain conservation practices that reduce phosphorus runoff. We want to pay for practices that provide a lot of environmental benefit for a low price so that we can fund as many projects as possible with our limited budget.

To achieve this goal, I will conduct a conservation auction and ask you to submit bids for the annual payment that you want per acre to adopt one or more conservation practices. **The conservation contract is valid for 2 years and you will be paid annually**.

You will be able to submit a private bid for the amount of money you want to adopt a new practice (per acre). Then, we will determine the environmental benefit of each practice. I will select bids that provide the highest environmental benefit for the lowest price – the selected bidders will be the winners of the auction. The auctions are hypothetical and will not involve any additional commitment after this focus group.

How are environmental benefits determined?

We determine the environmental value of conservation practices by calculating the predicted reduction in phosphorus runoff into the local waterway. The environmental value of the conservation practices differs among farms because of differences in soil types and location of the farm. Producers will not know the exact amount of phosphorus that will be reduced by adopting a conservation practice.

What are the costs of the conservation practices?

The hypothetical cost of adopting a new conservation practice is written on your farm information card. The cost of adopting these practices differs among farmers.

What money will be used for bidding?

You will not use your own money to bid in the auctions. Instead you are bidding the amount of money you would want to adopt a certain practice (just in the game). Although the auctions are hypothetical, you can real win money depending on how you bid.

How will the auctions be structured?

You will be participating in multiple auctions, but the exact number of auctions is unknown. We will not announce any bids during the auctions, so your bids will remain private. We will tell you which auctions you won at the end of the meeting.

Decisions you make in one auction will not affect the outcome in another. Before each auction, we will read the instructions and answer any questions you may have.

What information will you be given?

You have information about your hypothetical farm and current cropping system on your information card. Information about the conservation practices has also been provided. Feel free to ask any questions before we begin or during the auction.

How will winners be selected?

After bids are submitted, I will review the bids and select the ones that will provide the most environmental benefit for the lowest cost.

I will accept bids until I run out of money.

How will payment work?

After each auction we will calculate your net earnings. If you win the auction, your net earnings will equal the difference in your farm profits before and after adopting the conservation practice(s). This difference will equal the auction payment minus the costs of the conservation practice(s) plus any changes in farm profits due to yield changes (these changes can be positive or negative). If you do not win the auction, your cropping system will not change and no payment will be made.

At the end of all of the auctions we will calculate your total winnings and make real payments to each participant based on a predetermined rate. Auction payments will result from the outcomes of the auctions, which are determined by your decisions and the decisions of the other participants.

Any game winnings will be in addition to the $50 participation payment you got when you entered. Payment will be distributed at the end of today's session.

Instructions for Auction 1 –

In this auction you are bidding the amount of money that you would need to be paid per acre each year to adopt one or more of the practices listed on the bidding sheet. If you win the auction, you will receive this payment and then you will also be responsible for the cost of the new practice.

Contracts will be awarded to bidders who offer to adopt practices that provide the most benefit for the lowest price to the buyer (me). I will accept bids until my budget runs out. The buyer's budget is unknown to all bidders.

In this auction, it is important to keep your costs and bids confidential, so we kindly request that participants do not talk during individual auctions.

Instructions for Auction 2 –

In this auction you are bidding the amount of money that you would need to be credited against your annual state income tax or annual federal income tax in exchange for adopting one or more of the practices listed on the bidding sheet. If you win the auction, you will get the tax credit that you requested in your bid. But you will be expected to pay the cost of adopting the new practice.

Contracts will be awarded to bidders with projects that provide the most benefit for the lowest price to the buyer (me). I will accept bids until my budget runs out. The buyer's budget is unknown to all bidders.

In this auction, it is important to keep your costs and bids confidential, so we kindly request that participants do not talk during individual auctions.

APPENDIX 1-B BID SHEETS

Auction 1 - Payment: ****Participant ID_______**

Individual Bid Sheet

Please **<u>indicate your bid</u>** to adopt the following conservation practice(s). **Your bid equals the annual per acre <u>payment</u> that you would require to adopt each conservation practice.**

You can bid any amount. If you do not wish to bid, please write "NA" in the space provided.

Bid Amount (annual payment per acre)	**Conservation Practice**
	cover crop – cereal rye after corn
	conservation tillage – leave at least 30% residue on the field
	no fertilizer application in the fall or winter – instead fertilize in the spring

In addition to your selection above, will you install filter strips? **No** **Yes**
(if yes, please write bid amount you would require) (***circle one***)

Bid Amount (annual payment for a 1 acre filter strip)	**Conservation Practice**
	filter strips

Green Insurance: ****Participant ID_______**

Think about the amount that you just bid to adopt one or more conservation practices. Would your bid change if you were also provided with a special type of insurance designed for conservation practices? We will call this type of insurance "green insurance."

What is green insurance and how does it work?

Green insurance is designed to protect producers against any yield losses that may occur due to using conservation practices (compared to conventional production). Farmers that agree to adopt cropping conservation practices (not filter strips) will receive green insurance coverage free of charge. This insurance is not a substitute for traditional multiple peril crop insurance (MPCI), which would need to be purchased separately.

Insurance payments are based on the countywide performance of cropping systems using conservation practices compared to conventional systems. We will record the yields reported from farmers using conservation practices and compare these to the yields reported from conventional cropping systems. Payments will be made to farmers if the countywide average yield of conservation systems falls below the countywide average yield of conventional systems.

Below, indicate what your bid would be if you were also provided with green insurance (free of charge).

Bid Amount (annual payment per acre)	**Conservation Practice**
	cover crop – cereal rye after corn
	conservation tillage – leave at least 30% residue on the field
	no fertilizer application in the fall or winter – instead fertilize in the spring

Auction 2a - State Tax Credit (Auction 2b - Federal Tax Credit):

Individual Bid Sheet ****Participant ID_______**

Please **indicate your bid** to adopt the following conservation practice(s). **Your bid equals the annual per acre state (federal) income tax credit that you would require to adopt each conservation practice.**

You can bid any amount. If you do not wish to bid, please write "NA" in the space provided.

Bid Amount (annual tax credit per acre)	**Conservation Practice**
	cover crop – cereal rye after corn
	conservation tillage – leave at least 30% residue on the field
	no fertilizer application in the fall or winter – instead fertilize in the spring

In addition to your selection above, will you install filter strips? **No** **Yes**
(if yes, please write bid amount you would require) (***circle one***)

Bid Amount (annual tax credit for a 1 acre filter strip)	**Conservation Practice**
	filter strips

Auction 3: Sustainable Certification **Participant ID_______**

Imagine that there is a new certification program that certifies corn and soybeans that are grown using production systems that protect water resources. **Certified corn and soybeans will receive a price premium at the elevator.**

There is no fee to become certified, but producers must adopt the following practices:
1. cover crops
2. conservation tillage
3. no fall or winter fertilizer applications

We would like to know what price premium you would accept to enroll in the program.

After you state you premium, we will randomly draw a price premium per bushel of corn and a price premium per bushel of soybeans. If you indicated that you would accept both of the price premiums drawn, then you are allowed to enroll in the certification by adopting the three practices listed above.

If you win the auction, your net earnings will equal the difference in your farm profits before and after adopting the conservation practice(s), which will not include the new price premium. If you do not win, you will not make or lose money.

What is the lowest price premium that you would accept to enroll in this certification program?

Remember that each year you plant 100 acres of soybeans and 100 acres of corn.

Price premium for corn: _______ (per bushel)

Price premium for soybeans: _______ (per bushel)

APPENDIX 1-C ANALYSIS OF BIDS

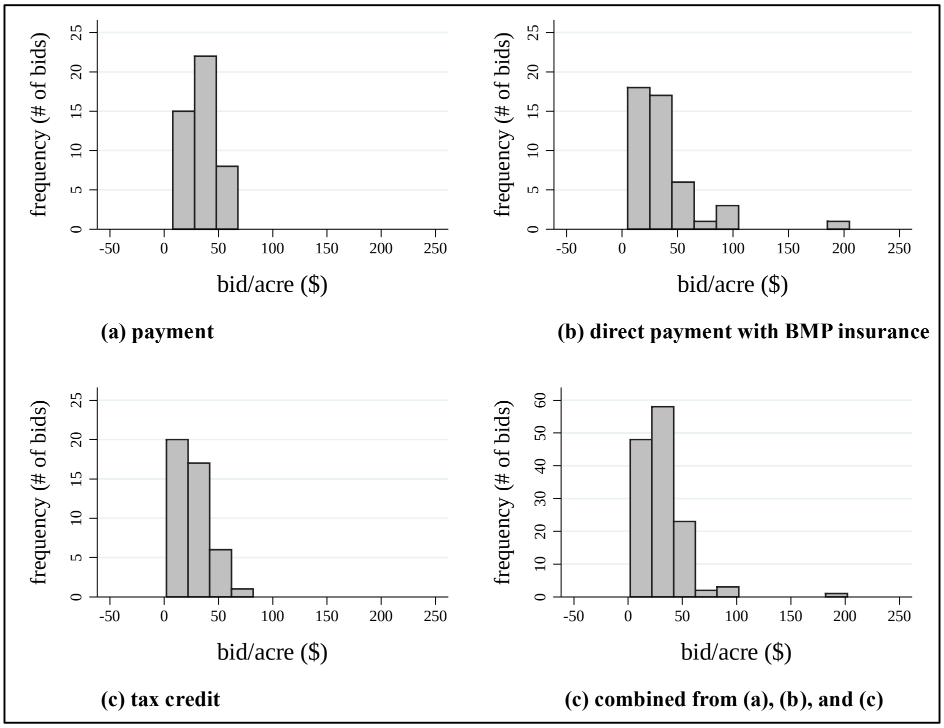

Figure A1-C-1. Histograms of per acre bids for cover crops in each auction show an outlier bid of $200/ac./yr.

Table A1-C-1. Determinants of net bids (bid minus assigned costs of conservation practices) in experimental auctions with 49 farmer participants, random effects model, n=186. Four outlier bids above $200/ac./yr. are removed (see Figure 1-3 (b)).

Variable	Coef.	Robust Std. Err.	p-value
Type of auction			
Green insurance	-1.72	3.53	0.63
State tax credit	-6.22	4.19	0.14
Certification price premium	-3.24	5.73	0.57
Other BMPs included in bid			
Cover crop dummy	-7.37	5.96	0.22
Conserv. tillage dummy	-29.55***	9.97	0.00
Spring fertilizer dummy	17.53***	5.88	0.00
Mock farm assignment			
Location A_2	-16.68*	9.97	0.09
Location B_1	-4.87	11.14	0.66
Location B_2	-5.83	11.48	0.61
Location C_1	-6.91	7.94	0.38
Location C_2	-30.70***	8.80	0.00
Location D_1	-3.68	13.53	0.79
Location D_2	-27.70**	10.85	0.01
Auction meeting site			
Henry Co.	18.79***	5.90	0.00
Wood Co.	7.03	6.22	0.26
Hancock Co.	27.94***	7.74	0.00
Farmer characteristics			
Age (years)	-0.88*	0.49	0.07
Education beyond high school (=1 if yes)	3.67	6.07	0.55
Farming experience (years)	0.30	0.56	0.59
Income (=1 if >$50,000 NFI)	1.95	4.48	0.66
Acres planted in 2012	0.00	0.00	0.63
Environmental org. (=1 if a member)	-14.03**	5.51	0.01
Constant	73.43***	20.90	0.00

Table A1-C-2. Determinants of net bids (bid minus assigned costs of conservation practices) for <u>cover crops</u> in experimental auctions with 49 farmer participants, random effects model, n=134. One outlier cover crop bid (bid=$200/ac./yr.) is dropped.

Variable	Coef.	Robust Std. Err.	p-value
Type of auction			
Green insurance	2.83	3.32	0.39
State tax credit	-6.07***	2.01	0.00
Other BMPs included in bid			
Conserv. tillage dummy	-8.71*	4.35	0.05
Spring fertilizer dummy	0.96	2.37	0.69
Mock farm assignment			
Location A_2	-6.57	4.62	0.16
Location B_1	7.56	4.72	0.11
Location B_2	2.13	4.39	0.63
Location C_1	4.06	3.90	0.30
Location C_2	-11.51***	3.84	0.00
Location D_1	-6.28	4.44	0.16
Location D_2	-6.77	5.59	0.23
Auction meeting site			
Henry Co.	10.26***	2.53	0.00
Wood Co.	13.98***	3.18	0.00
Hancock Co.	27.75***	3.53	0.00
Farmer characteristics			
Age (years)	-0.41**	0.19	0.03
Education beyond high school (=1 if yes)	5.04*	2.87	0.08
Farming experience (years)	0.22	0.21	0.29
Income (=1 if >$50,000 NFI)	-3.12	2.07	0.13
Acres planted in 2012	0.00	0.00	0.81
Environmental org. (=1 if a member)	-6.32**	2.52	0.01
Constant	17.26**	8.54	0.04

Table A1-C-3. Determinants of net bids (bid minus assigned costs of conservation practices) in experimental auctions when farmer participants submit bids for the level of direct payment required to adopt cover crops, linear regression model, n=45.

Variable	Coef.	Robust Std. Err.	p-value
Other BMPs included in bid			
Conserv. tillage dummy	-3.15	9.27	0.74
Spring fertilizer dummy	0.59***	4.74	0.90
Mock farm assignment			
Location A_2	-8.02	6.13	0.20
Location B_1	10.30	6.29	0.11
Location B_2	-1.83	6.47	0.78
Location C_1	1.41	7.43	0.85
Location C_2	-11.23**	5.95	0.07
Location D_1	-12.82*	7.51	0.10
Location D_2	-22.48***	6.73	0.00
Auction meeting site			
Henry Co.	7.01	4.17	0.11
Wood Co.	9.54*	5.19	0.08
Hancock Co.	26.05***	6.96	0.00
Farmer characteristics			
Age (years)	-0.36	0.28	0.20
Education beyond high school (=1 if yes)	5.24	3.92	0.19
Farming experience (years)	0.28	0.28	0.33
Income (=1 if >$50,000 NFI)	1.37	3.51	0.70
Acres planted in 2012	0.00	0.00	0.58
Environmental org. (=1 if a member)	-3.46	4.28	0.43
Constant	8.29	16.76	0.63

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ESSAY 2. PARTICIPATION AND COST-EFFECTIVENESS: INSIGHTS FROM A LAKE ERIE PAY-FOR-PERFORMANCE AUCTION[17]

2.1 Introduction

In the last decade, there has been growing interest in designing conservation programs that link payments to environmental performance instead of paying for practices. A concept that has become increasingly popular is to use reverse auctions to allocate conservation funds. Commonly called conservation auctions, they create a competitive market environment in which land managers compete for scarce payments to fund agricultural best management practices (BMPs). Through a bid selection process that accounts for both the payment required by an operator and the predicted environmental benefits, funding is allocated to the most cost-effective projects – i.e., projects that provide the most environmental benefit per dollar spent. Compared to uniform payment programs, conservation auctions have been shown to increase total environmental benefits procured with a limited conservation budget (Latacz-Lohmann and Schilizzi 2005; Juutinen, Mäntymaa and Ollikainen 2013; Selman et al. 2008; Reeson et al. 2008; Rolfe and Windle 2011a; Messer and Allen 2010; Horowitz, Lynch and Stocking 2009). However, cost-effectiveness of auctions relies on sufficient participation (Glebe 2013). If few people participate, there will be few projects to evaluate for funding, thus decreasing the likelihood of identifying a subset of projects with low cost-benefit (CB) ratios and reducing overall cost-effectiveness.

[17] Two papers have been submitted for publication from material in this chapter: 1) Palm-Forster, L.H., S.M. Swinton, F. Lupi, and R.S. Shupp. Too burdensome to bid: transaction costs and pay-for-performance conservation. In review, and 2) Palm-Forster, L.H., S.M. Swinton, T. Redder, J. DePinto and C. Boles. Cost-effectiveness of conservation auctions informed by environmental performance models to reduce agricultural nutrient flows into Lake Erie. In review.

Auctions differ from typical uniform payment-for-ecosystem-services (PES) programs. In an auction, land managers submit bids that indicate the payment that they require to adopt a specific BMP. In comparison to uniform payment programs that may accept applications on a continuous basis, auctions typically require bids be submitted during a specified time frame to ensure that the auctioneer has a large enough set of bids to evaluate. Cost-effectiveness is achieved by selecting bids with the lowest CB ratios until the budget is exhausted. Assuming heterogeneity of costs and benefits, more participation means there will be more bids with low CB scores and by funding these projects, an agency can increase the cost-effectiveness of its conservation program. If willingness to participate in a conservation auction is low, an agency may consider using a uniform payment program that will attract more participants.[18]

Participation in a conservation auction must be high enough to generate competition and to produce a set of bids that is large enough so that the auctioneer can select cost-effective projects to receive funding. But what level of participation and how many bids is "enough?" Not surprisingly, the answer to that question varies depending on the characteristics of the conservation program, the land managers, and the landscape. In this essay, I analyze the interactions among these characteristics and identify when auctions are preferred to alternative conservation policies.

There are three objectives for this essay. The first objective is to describe the Tiffin BMP auctions that were conducted in NW Ohio and report the outcomes of the auction program. The second objective is to identify barriers and deterrents that limited participation in the auction and test hypotheses about how these barriers affected farmers' willingness to submit a bid. Third, I

[18] Conservation auctions can be administratively burdensome, so another benefit of using a uniform payment program may be administrative cost savings. In this essay, I do not explore differences in administrative costs among alternative conservation programs, but this is an important consideration for conservation agencies.

use a simulation model to demonstrate how landscape and land manager characteristics affect cost-effectiveness among alternative conservation programs, including a conservation auction and two uniform payment programs.

2.2 Background

Environmental organizations and government agencies have shown increasing interest in contracting with private landowners to provide environmental services. However, heterogeneity among site characteristics and landowner attributes makes it difficult to determine efficient payment levels for various conservation actions (Shortle and Horan 2001). Conservation auctions have been touted as a cost-effective conservation tool that can overcome information asymmetries and pay for performance by allocating funds to the projects that will generate the most environmental benefit per dollar spent. A conservation procurement auction involves multiple sellers of environmental services (ES) (e.g. landowners) selling to one buyer (e.g. government or private organization). Bids implicitly reveal private information about the costs of providing ES. Bid acceptance, in turn, provides a mechanism to "purchase" ES. By coordinating ES supply and demand, auctions serve as a "quasi-market institution" to arrange the provision of public, environmental goods by private landowners (Latacz-Lohmann and Van der Hamsvoort, 1998).

Compared to uniform payment conservation payments, procurement auctions have several advantages that improve cost-effectiveness in theory, assuming that farmers are willing to participate. First, auctions address issues of asymmetric information between landowners and the ES buyer by creating a competitive environment in which landowners have an incentive to offer bids closer to their true opportunity costs, thus reducing rent seeking behavior (Latacz-Lohmann and Van der Hamsvoort, 1998; Rolfe et al., 2009). Assuming that farmers are willing to participate, Latacz-Lohmann and Van der Hamsvoort (1998) show that procurement auctions are more cost-effective than payment policies that don't base payments on *a priori* information regarding opportunity costs. Second, bid evaluation and ranking accounts for both the cost (bid) and benefit of the proposed project, thus the buyer can pay for performance rather than paying only for changes in inputs. In a study comparing the cost-effectiveness of a reverse auction in Pennsylvania to the USDA's Environmental Quality Incentives Program (EQIP), Selman and colleagues (2008) found that the procurement auction resulted in a seven-fold increase in the reduction of phosphorus runoff per dollar spent, compared to EQIP during the same period.

An increasing number of conservation auctions have been conducted over the past decade.[19] Most of these auctions have been implemented at a pilot scale, and limited participation is a common problem. Low participation in a conservation auction may occur for numerous reasons. Participation barriers may include a lack of awareness about the program or ineligibility for funding. Beyond these barriers, which apply to any type of conservation program, the auction mechanism itself may deter participation. For example, landowners may be unfamiliar with the bidding process or unsure about how much to bid.

Formulating a bid may sound like a straightforward process, but typically it requires additional information about the cost of implementing the BMP that may not be known to the land manager beforehand. The process of collecting and processing information required to make an informed bid can be costly both in terms of time and effort (Whitten et al. 2013). Additionally, bid acceptance is not guaranteed, and some land managers may be worried that their project will not receive funding, even after committing to sunk costs of bid preparation.

[19] See Appendix 2-G (Table A2-G-1) for a list of recent conservation auctions found in the literature.

Farmers have to weigh these transaction costs (TC) against their expected benefits of participating in a conservation auction to determine if participation is worthwhile.

Analyzing a conservation auction in Queensland, Australia, Comerford (2014) found that participation was greatest among a subset of landowners that were highly educated and possessed positive environmental attitudes and low opportunity costs of participation. Several participation barriers were identified, including a dislike of program requirements and unfamiliarity and confusion with the auction process.

Whitten and coauthors (2013) examined six case studies of auctions in Australia to identify barriers for participation and to establish a framework for improving participation in future auctions. In a contract design framework, they outlined distinct stages of auction participation for which they identified critical barriers faced by land managers. Using Whitten and coauthors' (2013) definition of participation, Figure 2-1 shows how barriers and deterrents limit participation at different stages.

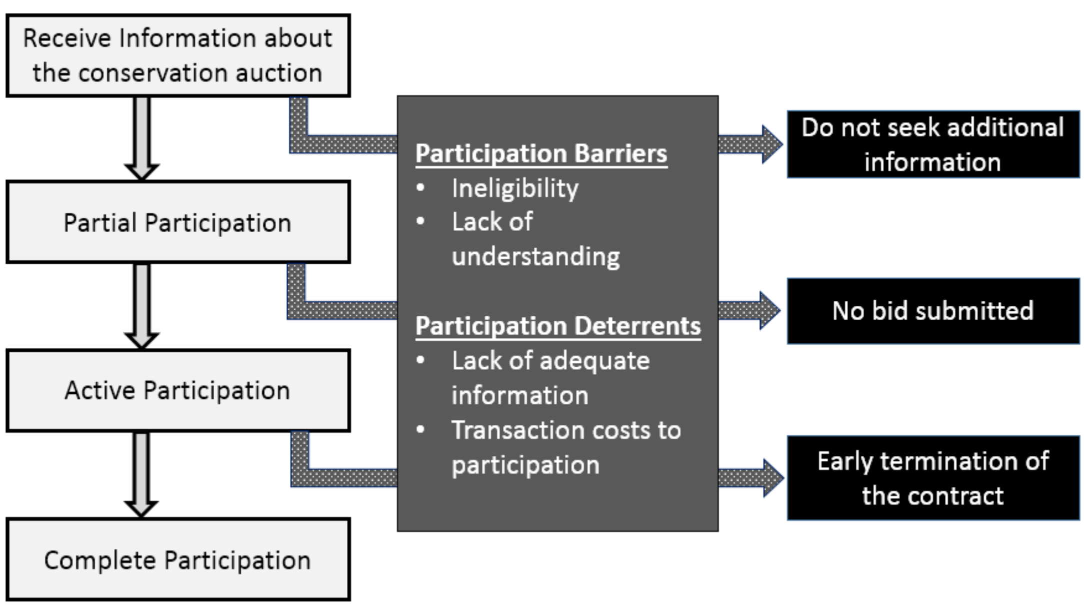

Figure 2-1. Flow chart of participation stages, associated barriers, and resulting outcomes, using Whitten and coauthors (2013) definitions of the stages of participation.

Three levels of participation occur after a land manager receives initial information about the auction program. First, "partial participation" refers to the state of collecting information required to submit a bid. Next, "active participation" is the process of calculating and formally submitting the bid. Finally, "complete participation" occurs when the land manager's contract is accepted, a payment is disbursed, and the BMP is implemented and verified.

2.3 Conceptual framework

In this section, I present a theoretical framework that links individual decisions about participation in conservation programs to the aggregate supply of environmental benefits available for procurement, and I show how this supply influences program cost-effectiveness. First, I show how individual land managers decide whether or not to participate in a conservation auction versus a uniform payment program. I present hypotheses about how the components of the behavioral model interact to influence participation. Then, I discuss how the aggregate decisions of many individuals generate a contract supply curve that represents the environmental benefits available for procurement through a conservation program. Additional hypotheses are presented about the biophysical and social characteristics that influence relative cost-effectiveness of auctions and uniform payment programs.

2.3.1 The participation decision

Land managers decide whether to participate in a conservation program by determining the expected utility of enrolling in the program and comparing it to their status quo utility. If their expected utility is higher than their current utility, they will participate in the conservation program. Otherwise, they will decline to participate. In the case of conservation auctions, this means that they will not submit a bid.

Assume a risk neutral land manager whose utility is derived from expected income π (including conservation payments θ) and stewardship satisfaction $v(a)$ that is gained from aligning management actions a with personal stewardship values. Disutility is derived from the transaction costs (TC) of applying for a program and complying with rules and regulations, $\psi(\boldsymbol{\rho})$. Assuming additive separability, the indirect utility of participating in conservation program j can be written as,

$$u(m, a_j, \theta_j, \rho_j) = m[\pi(a_j) + \theta_j] + v(a_j) - \psi(\rho_j) \tag{2.1}$$

where, m is the marginal utility of income, and $\boldsymbol{\rho_j}$ is the set of rules and regulations for program j. TC disutility is made up of two components: $\psi(\boldsymbol{\rho_j}) = \psi_1(\boldsymbol{\rho_j}) + \psi_2(\boldsymbol{\rho_j})$, where $\psi_1(\boldsymbol{\rho_j})$ is disutility associated with applying for the program, and $\psi_2(\boldsymbol{\rho_j})$ is the disutility from complying with rules and regulations once accepted into the program. Assuming $v(a_0) = 0$, status quo utility is $u_0 = m\,\pi(a_0)$.

Acceptance in a conservation program is not guaranteed, particularly when funding is allocated by reverse auction. But regardless of whether an application is successful, the applicant incurs TC disutility $\psi_1(\boldsymbol{\rho_j})$ in applying for the program. Let σ be the probability that the application is accepted and funding is awarded. Expected indirect utility from applying to undertake conservation action a_j can be written as,

$$E(u_1) = [m(\pi(a_j) + \theta_j) + v(a_j) - \psi_2(\boldsymbol{\rho_j})]\sigma + m\,\pi(a_0)[1-\sigma] - \psi_1(\boldsymbol{\rho_j}) \tag{2.2}$$

An individual will apply for funding from a conservation program if,

$$E(u_1) - u_0 \geq 0. \tag{2.3}$$

2.3.1.1 Participation in uniform payment programs

Deciding whether or not to participate in conservation auction j is, in essence, a similar decision but is slightly more complex because the land manager must choose his bid and determine the expected utility of participating based on his subjective beliefs about the probability that his bid will be accepted. To analyze the participation decision, it is important to distinguish between TC of bid preparation versus TC of compliance with regulations once enrolled in the program. Disutility from TC associated with bid preparation is denoted as $\psi_1(\rho_j)$ and disutility from TC associated with compliance is denoted as $\psi_2(\rho_j)$ such that $\psi_1(\rho_j) + \psi_2(\rho_j) = \psi(\rho_j)$. If the auctioneer requires information in addition to the bid itself (e.g., management details or records), then $\psi_1(\rho_j)$ will increase. Additional information, like details about baseline agricultural management, is often required in order to predict the benefits of new BMPs. Disutility from bid preparation is realized with certainty, but disutility from compliance is only experienced if the individual is accepted in the conservation auction program, thus expected disutility is,

$$\theta_j \geq WTA_j = \pi(a_0) - \pi(a_j) + \frac{\psi_1(\boldsymbol{\rho_j}) + \psi_2(\boldsymbol{\rho_j}) - v(a_j)}{m} \tag{2.4}$$

2.3.1.2 Participation in a reverse auction

Participation in a reverse auction involves submitting a bid (offer) to adopt one or more BMPs. When projects have heterogeneous environmental impacts, bids are evaluated and selected based on a scoring metric that accounts for both the payment requested (bid) and the level of environmental benefits targeted. The most cost-effective projects are selected for funding until the budget is exhausted. Numerous selection criteria have been proposed for auctions, including optimization algorithms and more simple metric-based ranking procedures (Messer and Allen III 2010). For this analysis, consider a cost-benefit ranking metric, $\beta = {}^{\theta}/_{e}$, where θ is the bid submitted and e is the predicted environmental benefit from the proposed project.

The land manager chooses a bid to maximize the difference between their expected utility and their status quo utility. Conservation auctions are typically discriminatory price auctions in which selected bidders are paid the amount of their bid (Hellerstein et al. 2015), thus bids are influenced by the probability of bid acceptance. Since bidder decisions can influence both the likelihood of bid acceptance and the level of payment, individuals have an incentive to bid strategically based on how they believe their bid and predicted level of environmental benefits will compare to others (Glebe 2013; Hellerstein et al. 2015; Cason et al. 2003; Jacobs, Thurman and Marra 2014).

In choosing a bid, the manager considers their perceived probability that the bid will be accepted. This perceived probability depends on beliefs about the predicted environmental benefits of BMPs on their land (often unknown) and beliefs regarding bids and benefits of competing projects. Payment (bid) caps are commonly used to prevent funding excessively high bids (Hellerstein et al. 2015). Caps may or may not be announced. Either way, individuals form a subjective belief about the range of βs (bid/benefit) that will be accepted.

Without specifying a functional form for the perceived probability of bid acceptance, the optimal bid (conditional on bidding) can be written as,

$$\theta_k^* = \pi(a_0) - \pi(a_k) + \frac{\psi_2(\rho_k) - v(a_k)}{m} - \frac{\ddot{\sigma}(\theta^*)}{{}^{\partial\ddot{\sigma}}/_{\partial\theta^*}}, \tag{2.5}$$

where, $\theta_k{}^* \geq 0$ since otherwise, the farmer would have adopted the BMP voluntarily without the presence of any incentive program. (The full derivation of the optimal bid is presented in Appendix 2-A.) The bid is influenced by 1) the change in expected profit reflected by the full cost of BMP adoption, 2) transaction costs of program compliance, 3) utility provided by environmental stewardship, and 4) the ratio between the probability of bid acceptance $\ddot{\sigma}(\theta^*)$ and the partial derivative of the probability of bid acceptance with respect to a change in one's bid $\partial\ddot{\sigma}/_{\partial\theta^*} \leq 0$. Notice that the bid θ_k^* looks similar to the individual's WTA for a uniform payment in Eq. (2.4), except that there is an extra quantity subtracted at the end $\left(\frac{\ddot{\sigma}(\theta^*)}{\partial\ddot{\sigma}/_{\partial\theta^*}}\right)$. As the probability of bid acceptance increases, the bid increases; therefore, if the individual thinks that their bid is particularly competitive, they will increase it in an attempt to extract information rents. Information rent is defined as the portion of the payment that exceeds the minimum payment necessary for the manager to participate – i.e., the portion of the payment that exceeds the minimum WTA.

Individuals submit an application only if $E[u_1(\theta_k^*, a_k, a_0, \rho_k, \ddot{\sigma})] \geq u_0(a_0)$, which accounts for the TC of application (see Eq. (2.2)). Since the TC of application, $\psi_1(\boldsymbol{\rho_j})$, is incurred regardless of bid acceptance, this cost does not influence the optimal bid amount; however, it does influence the participation decision. Additional information, like details about baseline agricultural practices or management records, is often required in order to predict the benefits of new BMPs, and these requirements increase $\psi_1(\rho_j)$.

2.3.2 Aggregate supply of benefits affects cost-effectiveness

In the previous section, a participation decision framework was presented for a single individual. In this section, I will use graphs to show how, at an aggregate level, these decisions can affect cost-effectiveness of two types of programs – a conservation auction and a uniform payment conservation program.[20] Consider a scenario in which there are multiple land managers in a watershed and imagine that the WTA and predicted environmental benefits are known for each manager and parcel. By dividing the individual's WTA by the predicted environmental benefits of the BMP, each individual has an associated CB ratio of their project. Imagine a case of full participation such that all managers are willing to participate if the payment offered is at least as great as their WTA. Figure 2-2 depicts the contract supply curve that would result from ranking all project by their CB ratio such that $CB = \frac{WTA}{e}$, where e is the environmental benefit generated by each BMP. The associated contract curve is represented by CB^1.

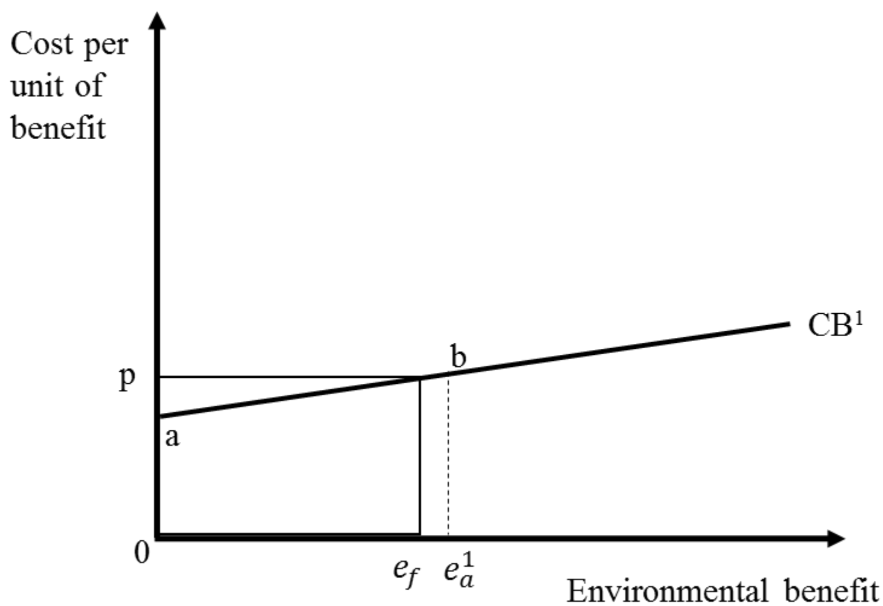

Figure 2-2. Environmental supply curve (contract curves) with full participation

[20] Uniform payment programs can be evaluated on a number of metrics to determine acceptance. In the simulation presented in Section 2.6, I consider an untargeted program that does not restrict enrollment and a targeted program that only enrolls parcels that are considered environmentally vulnerable. In this section, I do not differentiate between targeted and untargeted payment programs, but instead focus on how differences in the pool of participants can affect cost-effectiveness of auctions versus uniform payment programs.

A uniform payment program that offered price p would generate benefits e_f and make payments that total $p * e_f$. Holding the budget fixed, but using a conservation auction to allocate payments at the WTA of individual farmers, would result in an increase of benefit procured to e_a, and payments would equal the area $0,a,b,e_a$. Assuming that the pool of participants has the same CB contract curve, cost-effectiveness of the auction is greater than that of the uniform payment program because more benefits are generated from the same conservation budget.

But, as I showed in the previous section, the amount an individual will bid will differ from their minimum WTA. Thus the contract curves for the two programs will likely deviate. Deviations can be driven by differences in bids resulting from different TC or strategic bidding to extract information rents. Additionally, participation barriers such as a lack of knowledge about the program or ineligibility can affect the slope of the CB contract curve. Not all of the managers will be aware of the conservation programs, and some parcels will not be eligible because BMPs are already implemented on that field.[21] Targeted uniform payment programs may have additional eligibility requirements that will be discussed later.

The contract supply curve represents numerous individuals with heterogeneous costs and benefits. One can imagine a line of points that comprise the supply curve. The question becomes, which of these individuals are not going to participate because they lack the knowledge about the program, they are not eligible, or they simply do not want to adopt the target BMP?

Nonparticipants could be those with the lowest WTA, the highest WTA, or they may be scattered across the length of the supply curve. It is sensible to hypothesize that individuals with the lowest WTA may not be eligible for the program because they have already practice the

[21] Most programs ensure benefit "additionality" by paying only for new practices. I maintain this requirement.

BMP. One might postulate that these individuals receive utility from their stewardship actions because they believe farmers should protect water quality. Alternatively, they may have lower costs of BMP adoption that permits them to accept less payment for BMP adoption. Figure 2-3 show how the supply curve would shift if individuals with the lowest WTA did not participate in a new conservation program because they were already adopters of the practice(s) covered.

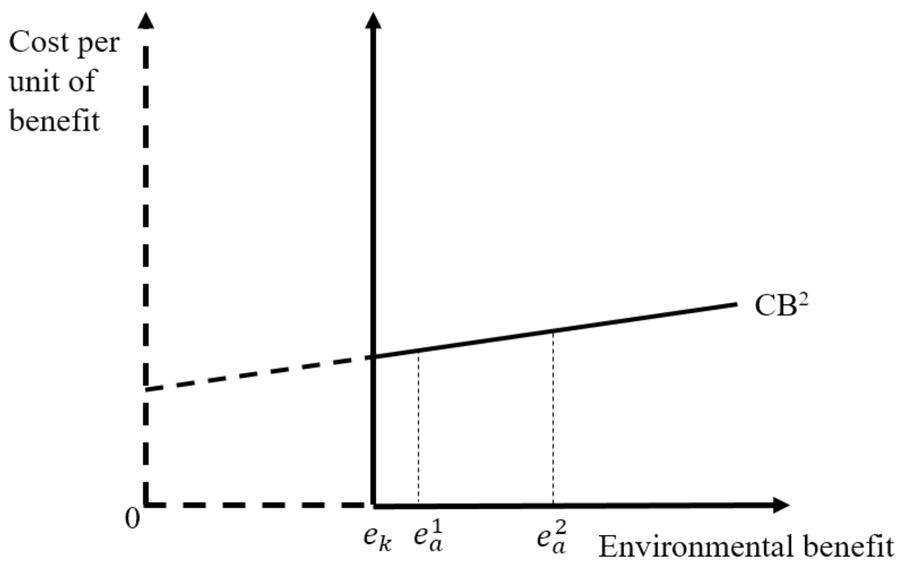

Figure 2-3. Environmental supply curves (contract curves) shift when a subset of individuals with low WTA do not participate

As illustrated in Figure 2-4, one can also imagine a scenario in which managers at many different points along the supply curve do not participate, as indicated by the hollow circles. The next question that emerges is, are there systematic differences in the supply curves between program types? The contract curve in an auction may be higher than the one generated for a uniform payment program if TC of bidding is high or strategic rent-seeking behavior is common. Additionally, TC of bid preparation may be exacerbated by concerns that a bid won't be accepted, thus jointly reducing participation. High TC and strategic bidding scenarios are analyzed using the simulation model described in Section 2.6.

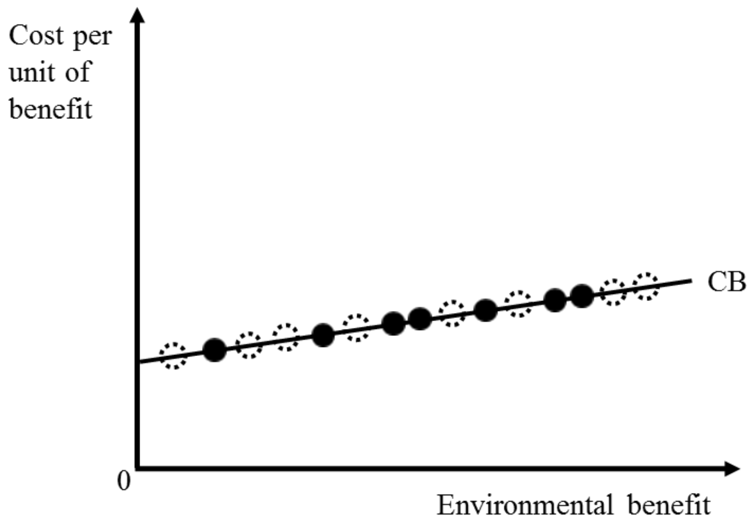

Figure 2-4. Participants and nonparticipants may be associated with BMP projects across a range of CB ratios. Hollow circles represent nonparticipants.

In Figure 2-5, I show a second contract curve represented by CB^2, which represents participants' contract curve in a conservation auction program. CB^2 can differ from CB^1 for two reasons. First, if the pool of participants is the same, individuals bidding in a conservation auction may inflate their bid if they think they have high value projects that are likely to be desirable even at higher payment levels. Second, the pool of participants may differ between those willing to engage in a conservation auction and those willing to participate in a uniform payment program. In a reverse auction for fishing license buybacks, DePiper (2015) found that individuals with low willingness-to-accept (WTA) participated in the auction at lower rates than other eligible individuals. If the contract curve is higher for the group willing to bid in the auction, cost-effectiveness will decline as environmental benefits procured using the same fixed budget declines from e_f to e_a.

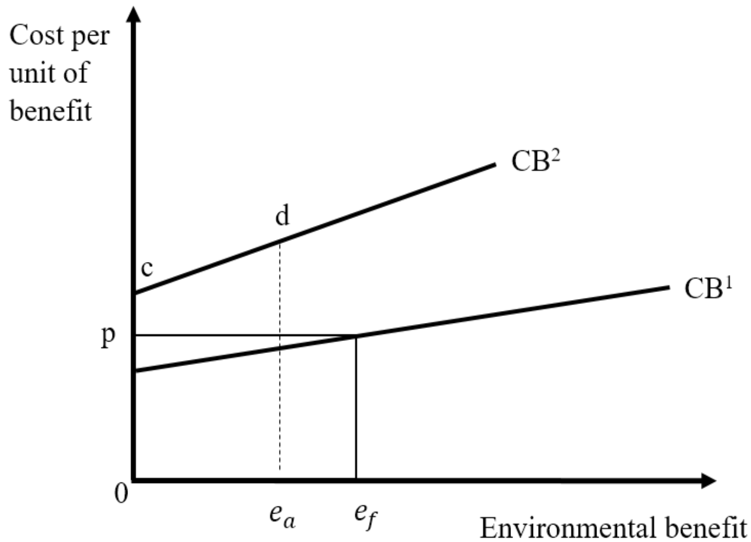

Figure 2-5. Contract curves for two different conservation programs may differ, thus affecting the benefits that can be procured with a given budget.

2.4 Data

Data used to analyze auction participation are drawn from two primary sources. First, I use data collected from the Tiffin BMP auctions that includes information on bids submitted, predicted environmental benefits, and site-specific nutrient runoff data for land parcels in two counties within the Tiffin watershed. Second, I use data from a follow-up survey that was sent to landowners who did not submit a bid in the Tiffin BMP auction. Responses to survey questions are used to identify barriers and deterrents to participation in conservation auctions. Additionally, survey data are coupled with parameters from the literature and used to calibrate a policy simulation model that is presented in Section 2.6.

2.4.1 BMP auction data

Two auctions were implemented in the Tiffin Watershed, a sub-watershed of the Maumee Watershed that feeds directly into the western basin of Lake Erie. Two counties – Fulton and

Defiance – were selected for the auctions (Figure 2-6). The auction was administered by Michigan State University with support from the Fulton Co. and Defiance Co. Soil and Water Conservation District (SWCD) offices. This section provides an overview of auction design and implementation. Additional details are provided in Appendix 2-B.

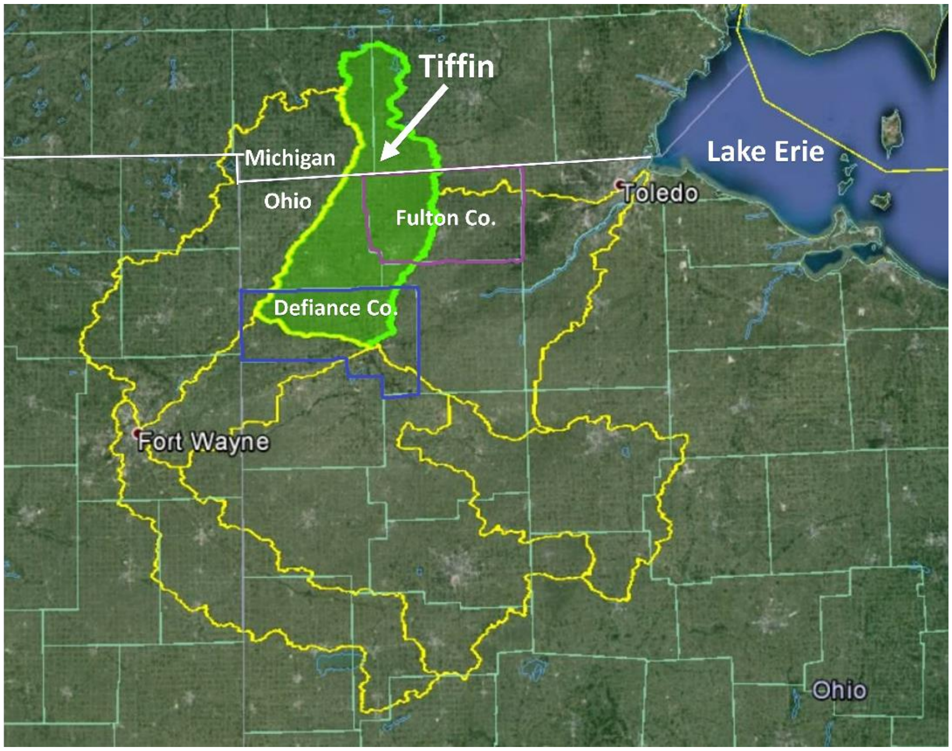

Figure 2-6. Location of Tiffin BMP Auctions in Defiance Co. and Fulton Co.

The auction was announced in June 26, 2014 and bids were accepted between July 21 and September 30, 2014. To generate awareness about the auction, notification letters were mailed to the owners of all eligible agricultural parcels ($n^{Defiance}$ = 507; n^{Fulton} = 578). These letters explained the purpose of the auction and directed landowners to a county-specific website for more information. With the letter, I also sent a postage paid postcard that landowners could return to receive a bidding packet by mail. Bid packets were also available at the local SWCD offices and on the auction websites.[22] An informational meeting was held in each county in mid-July. Informational fliers were posted at local grain elevators, and the auctions were announced in local newspapers, the SWCD newsletters, and Farm Service Agency (FSA) emails that were distributed in both counties. Reminder postcards were mailed a month prior to the bidding deadline.

Land managers were invited to submit bids to adopt three eligible BMPs – winter cover crops[23], filter strips, and drainage control structures. All funded BMPs would be implemented in the following year (2015). A separate bid packet was required for each field. In addition to the bid, participants were required to fill out a management questionnaire to establish their status quo management regime, which was necessary to determine the baseline amount of phosphorus emitted from their fields to then calculate how much runoff would be reduced by a BMP. Bids could be dropped off at the SWCD office or submitted via mail. All bids were private. In both counties, landowners were given the option to bid individually or jointly.

Landowners in Defiance County were given a signal about the environmental benefits (phosphorus reduction) that new conservation practices would have on their farm, relative to other farms in the county. Effects of the information treatment were not formally tested due to the small sample of bids submitted, but details about the information treatment are provided in Appendix 2-C.

All bids submitted prior to the deadline were evaluated using the Soil and Water Assessment Tool (SWAT) model that was implemented by LimnoTech in Ann Arbor, MI (LimnoTech 2013). SWAT is a watershed-scale hydrological model that computes sediment and

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[22] Additional information about implementing the BMP auctions is provided in Appendix 2-B. The bid packet is presented in Appendix 2-D.

[23] All cover crops were eligible.

nutrient flows from farmland to local waterways. It was originally developed for UDSA Agricultural Research Service (ARS) in 1998, but has since been adapted to numerous watersheds, including the Maumee and the Tiffin (Bosch et al. 2011; LimnoTech 2013). Figure 2-7 presents a conceptual diagram of the SWAT model, including the inputs required and the outputs generated. Using the SWAT model, nutrient runoff was simulated from 2000 to 2011 to account for variation in weather in order to predict the average annual reduction in phosphorus runoff into local waterways.[24]

Bioavailable phosphorus was the target pollutant because this portion of phosphorus drives algal production in Lake Erie (Baker, 2010). Soluble reactive phosphorus (SRP) is fully available for biological processes. Particulate phosphorus (PP) is tied to soil particles and makes up a large portion[25] of total phosphorus, but studies of northwestern Ohio rivers have shown that only about 30% of PP is bioavailable (DePinto et al., 1981). Bioavailable phosphorus (bio P) is calculated as,

$$bio\ P = SRP + (OP + PIP) * 0.30 \tag{2.6}$$

where, SRP is soluble reactive phosphorus, OP is organic phosphorus, and PIP is particulate inorganic phosphorus.

Responses from the management questionnaire were used to establish the baseline phosphorus runoff from each field. Bids were then evaluated to determine the amount of bioavailable phosphorus runoff that would be reduced as a result of the proposed BMP(s) included in the bid.

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[24] The Western Lake Erie Ecosystem Model (WLEEM) can be used to predict algal bloom size and intensity, but due to the size of the watershed, impacts cannot be predicted based on management changes for individual fields.
[25] PIP and OP combined comprised nearly 40% of the baseline phosphorus runoff for parcels evaluated in the auctions.

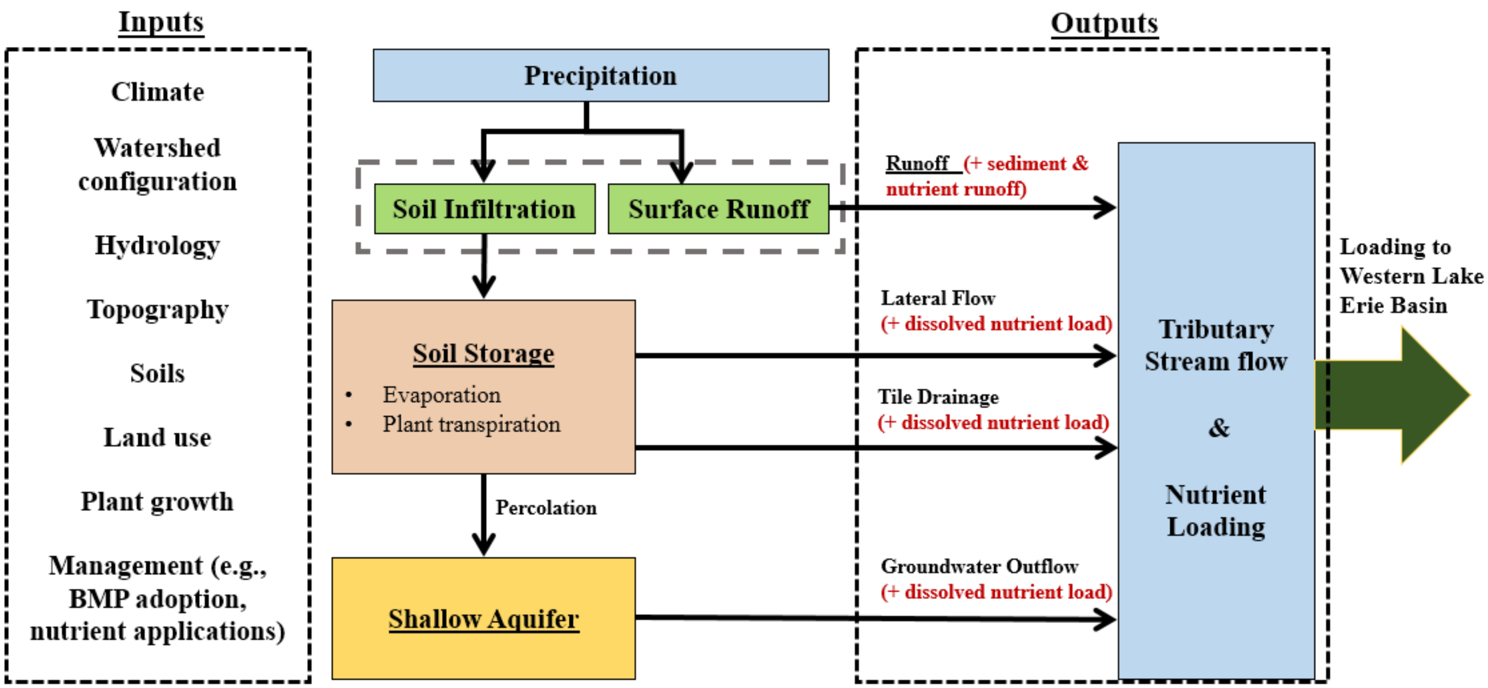

Figure 2-7. Conceptual diagram of the Maumee Soil and Water Assessment Tool (SWAT) model. Adapted from Redder (2014).

In each county, bids were ranked based on the cost per pound of bio P runoff reduction. Ranking the bids based on bio P enabled more weight to be placed on SRP reductions as SRP is considered the primary driver of HABs in Lake Erie. The most cost-effective bids (lowest cost per pound) were accepted in rank order until the budget for that county was exhausted ($25,000 per county).

Bidders were notified about bid acceptance in mid-November and winning bidders signed contracts prior to December 31, 2014. Land managers with accepted projects were paid 50% of the payment when the contract was signed and 50% upon BMP verification.

2.4.2 Follow-up questionnaire

A follow-up questionnaire that was mailed to the 1072 Defiance Co. and Fulton Co. landowners who were invited to participate in the Tiffin BMP Auctions, but who did not submit a bid[26]. The goals of the survey were 1) to identify participation barriers and deterrents, and 2) to test for previously hypothesized relationships among landowner characteristics and the barriers and deterrents that influenced nonparticipation. The questionnaire is provided in Appendix 2-E.

The questionnaire was designed based on questions, comments, and feedback received during the open bidding period of the BMP auctions. To maximize response rate, the questionnaire was limited in length to one, 2-sided page. Furthermore, most of the questions could be answered by simply checking a box indicating “yes” or “no.” The questionnaire had six sections that were designed to identify factors that influenced knowledge of the auction, eligibility to participate, and willingness to submit a bid. To gauge knowledge, the first section asked respondents to indicate the sources from which they had learned about the auction. In the

[26] After removing incorrect addresses and addresses for landowner that submitted bids, questionnaires were mailed to 572 landowners in Fulton Co. and 500 landowners in Defiance Co.

second section, respondents were asked if they had received a bid packet from a list of sources. Acquiring a bid packet indicated that the individual had made an active attempt to participate. The third section explored barriers and deterrents to participation by providing a list of potential reasons for not submitting a bid and asking respondents to indicate which reasons applied to them. Eligibility and willingness to adopt were also evaluated in section four in which respondents were asked to indicate which BMPs they currently use and the extent of their adoption. In the first four sections, space was available to write in an answer that was not included in the list. The fifth section of the questionnaire was a set of Likert scale questions about landowner attitudes toward the environment, stewardship, and conservation programs. The final set of questions asked about land ownership and rental as well as the percentage of household income that is earned from farm related activities.

Questionnaires were mailed using a three contact survey method, including 1) a cover letter with the questionnaire and one dollar incentive payment, 2) a post-card reminder, and 3) a replacement questionnaire.[27] Overall, 455 questionnaires out of 1072 were returned. Ten were returned blank. The response rate was 42% overall, with response rates[28] of 38% in Defiance Co and 45% in Fulton Co.

Double data entry was used to reduce entry error. Responses for each questionnaire were recorded in Excel spreadsheets by two undergraduate research assistants. After the double data entry was completed, the files were merged in Stata and compared for discrepancies. All discrepancies were manually checked and corrected by the main author of the study.

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[27] The first wave of questionnaires was mailed on February 2, 2015 and included a cover letter, postage paid return envelope, and a one dollar incentive payment. A reminder postcard was mailed on February 20. A second wave of questionnaires was mailed on March 3, 2015 to all addresses from which a questionnaire had not be received.

[28] Response rates were calculated by dividing the number of questionnaires returned that were at least partially completed by the total number of valid addresses to which the questionnaires were mailed.

2.5 Results

2.5.1 Auction outcomes

Only one percent of invited landowners submitted bids for the Tiffin BMP auctions. Ten landowners participated and submitted 36 bids in total. Low participation led to funding bids with high CB ratios at the margin. A major reason for high CB ratios was low levels of predicted runoff reduction. In this section, I present the results of the two auctions. The following section reports the reasons for low participation.

Six participants submitted bids in Fulton Co. and four participants bid in Defiance Co.[29] Table 2-1 presents a summary of bids submitted in each auction.

Table 2-1. Summary of bid submission in the Tiffin BMP Auctions

	Unit	Fulton	Defiance	Total
Land managers who submitted a bid	bidders	6	4	10
Total bids submitted	bids	24[a]	12[b]	36
Bids for cover crops	bids	19	8	27
Bids for drain control structures	bids	1	4	5
Bids for filter strips	bids	4	0	4
Acres treated	acres	998	510	1,508
Total funding requested	$	$35,926	$26,620	$62,546

[a] One bid was ineligible because it is located east of the Tiffin watershed.
[b] Three bids were withdrawn prior to bid evaluation.

In Defiance County, cover crop bid averages were $36/ac./yr. for cereal rye, $50/ac./yr. for an oat/radish mix, and $50/ac./yr. for annual ryegrass (weighted by acreage). Bids for

[29] This participation outcome is similar to an auction conducted in a Kansas watershed in which 12 landowners submitted 24 bids for BMPs (Smith, Nejadhashemi and Leatherman 2009).

drainage control structures averaged $1,700 per structure and each structure would treat an average of 23 acres. In Fulton County, cover crop bids averaged $34/ac./yr. for cereal rye, $35/ac./yr. for clover, and $50/ac./yr. for oats[30] (weighted by acreage). One bid of $1,200 was submitted for a drainage control structure that treated 8.4 acres. Four filter strip bids were submitted between $75 and $400 per location, which treated 5 to 53 acres per filter strip.

Prior to bid evaluation, one Defiance Co. landowner withdrew his bids because he decided to apply for another program. One of the bids in Fulton county was outside of the Tiffin subwatershed and thus ineligible for the program. Thirty-two bids were evaluated and ranked to determine which offered the most cost-effective reductions in bioavailable phosphorus runoff. Figure 2-8 shows the cost-benefit contract curves for bids submitted in each auction. As predicted reduction in bio P emission rises, costs per unit of bio P reduction increase slowly at first, but then rise sharply for the lowest ranked bids, creating a hockey stick shaped graph.

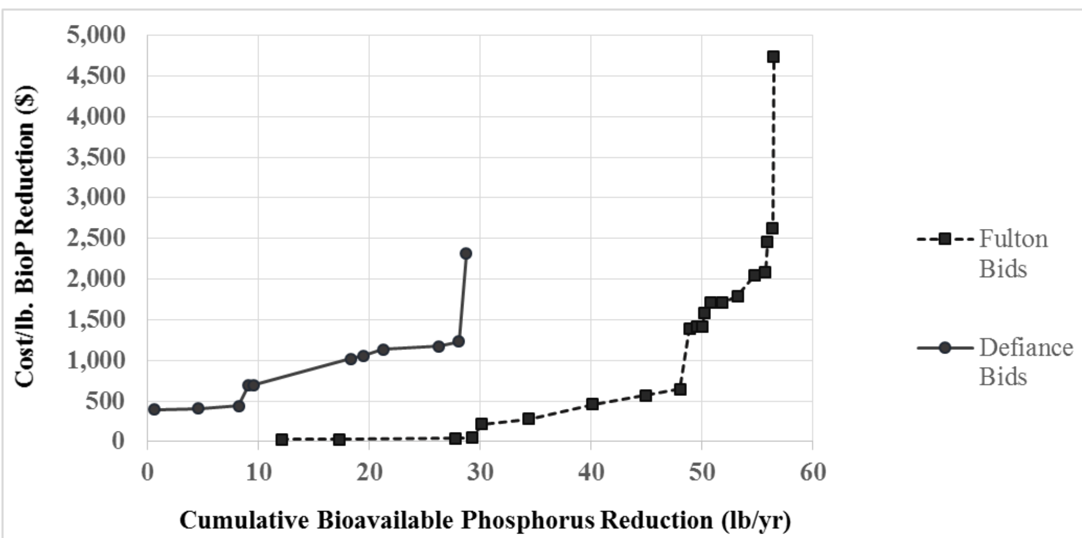

Figure 2-8. Cost-benefit (CB) contract curves reflects bids submitted in the Tiffin BMP auction

[30] Oats are not typically funded as a cover crop in most conservation programs; however, a SWAT analysis predicted substantial reductions in bio P runoff. Therefore, the bid was permitted.

Filter strips were the most cost-effective bid, with an average cost of runoff reduction of $31.53/lb of bio P.[31] The relative cost-effectiveness of cover crops and subsurface drainage control structures varied depending upon modeling assumptions about soluble reactive phosphorus (SRP) concentration in tile drain outflow.[32] While SRP concentrations have been reported in the literature, reported concentrations are highly variable, spanning from 1 μg/l to above 1,000 μg/l (Williams et al., 2015). An SRP concentration of 500μg/l in drain outflows is assumed. Under this assumption, costs to reduce bio P with cover crops ranged from $216/lb. to $4,739/lb. Costs to reduce bio P with drain control structures ranged from $406/lb. to $2,310/lb.

Table 2-2. Summary of bids accepted in the Tiffin BMP Auctions

	Units	Fulton	Defiance	Total
Total bids accepted	bids	20	9	29
Bids for cover crops	bids	15	5	20
Bids for drainage control structures	bids	1	4	5
Bids for filter strips	bids	4	0	4
Acres treated	acres	755	459	1,214
Bioavailable phosphorus reduction	lbs./yr	50	28	78
Total funding requested	$	$24,924	$25,651	$50,575

[31] In a reverse auction in the Conestoga Watershed in Pennsylvania, cost-effectiveness of grassed waterways ranged from $2.84/lb. to $54.41/lb. of reduced total phosphorus (Selman et al., 2008).

[32] The SWAT model was run with three different assumptions about the concentration of soluble reactive phosphorus (SRP) in subsurface drainage outflows. Assuming a high concentration (500μg/l), cost-effectiveness of drainage control structures was comparable to cover crops. However, under an assumption of low SRP concentration (35μg/l), controlled drainage *increased* runoff of bioavailable phosphorus. An SRP concentration of 500μg/l in drain outflows was assumed because reported concentrations range from 1μg/l to 1,000μg/l (Williams, King and Fausey 2015; LimnoTech 2013).

After bid evaluation, 29 bids were accepted into the program (20 in Fulton and 9 in Defiance). The funding agency awarded an additional $651 to Defiance County to fund all of the bids. Table 2-2 provides a summary of accepted bids. One farmer did not accept his approved contract for cover crops on five parcels because he decided he was not yet willing to try the new BMP. Overall predicted cost-effectiveness for each auction was $302/lb. bio P in Fulton Co. and $929/lb. bio P in Defiance Co.

2.5.2 Identifying barriers and deterrents to participation

The objective of the follow-up questionnaire was to identify participation barriers and deterrents for those landowners who did not submit a bid in the conservation auction. Figure 2-9 summarizes the questionnaire responses and shows how many people were affected by three different factors. First, people who lacked information or knowledge of the auction program were identified. Second, I identified respondents who did not think that they were eligible to submit a bid. Third, conditional on having knowledge about the auction and being eligible to participate, I identified the primary reasons that respondents stated as to why they chose not to submit a bid Chi-square tests of independence are used to test for relationships among farmer characteristics and the reported participation barriers and deterrents.

Of the 445 respondents who at least partially filled in the questionnaire, 309 (69%) had some knowledge about the BMP auction. The majority of respondents reported learning about the auction from the original letter that was mailed to them to describe the auction.

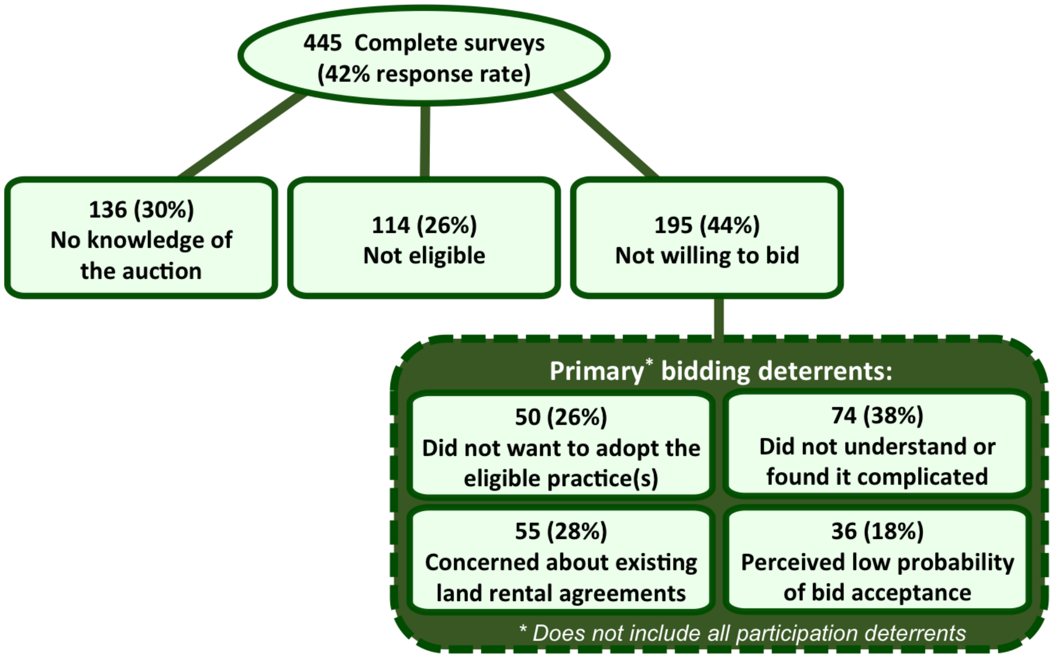

Figure 2-9. Of the 445 questionnaire respondents, 30% reported having no knowledge of the auction program, 26% were not eligible, and the remaining 44% has another reason for not participating in the auction program. Primary participation deterrents included, not wanting to adopt one of the eligible practices, feeling that the auction process was confusing or complicated, feeling that land rental agreements would make participation difficult, or perceiving a low probability of bid acceptance.

Figure 2-10 shows how many people reported receiving information from each source.[33] Landowners who reported being engaged with conservation agencies, were more likely to have knowledge about the auction,($\chi^2(1, \mathrm{N} = 369) = 5.17, \mathrm{p} < 0.05$). Some landowners attributed their lack of knowledge to not having to make agricultural management decisions because their land is rented. One respondent wrote, "I have a farmer that operates the acreage for me, so I do not keep up with all the current happenings." Another noted, "I knew nothing about this… I cash rent." A chi-square test confirmed a negative relationship between having knowledge about

[33] Question 2 was designed to determine how many people actively engaged the auction by requesting a bid packet; however, 36% of respondents reported receiving a bid packet by mail when there was no record of a packet being mailed to them. I assume that they confused the bid packet with the informational materials; therefore, this question is not used to identify "active participants."

the auction and renting out land, ($\chi^2(1, N = 388) = 8.62, p < 0.01$), which suggests that landowners who rent out land may be less aware of opportunities to fund conservation practices. There was a weakly positive correlation between having knowledge about the auction and renting in additional land, r=0.09, N=388, p<0.01.

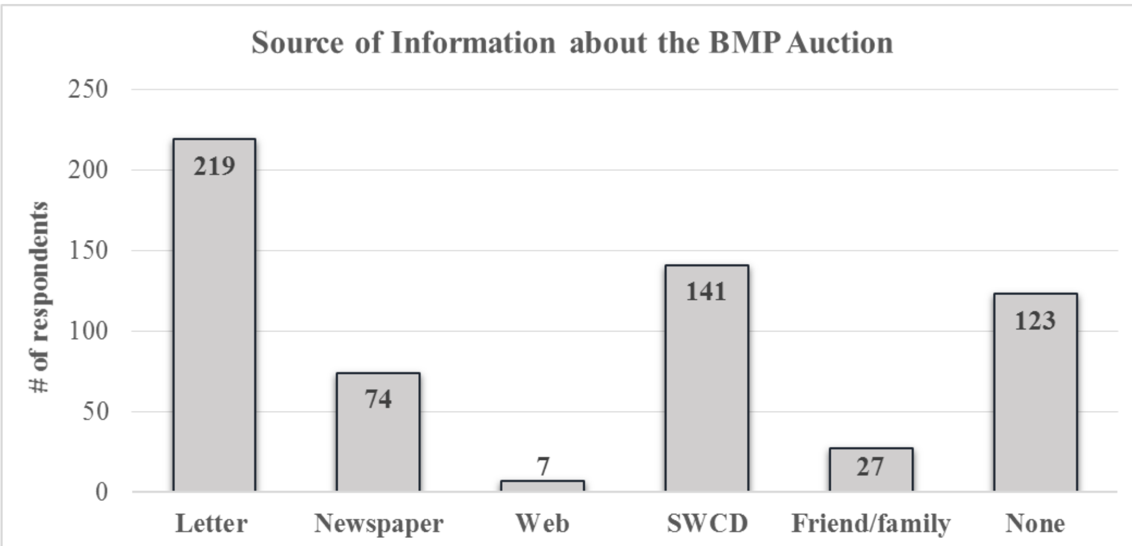

Figure 2-10. Reported sources of information about the BMP auction

Of the 309 respondents who knew about the auction, 195 were classified as eligible. Ineligible respondents included those who self-reported their ineligibility, stated that they already participated in another program for the three qualifying BMPs, or else stated that they did not own cropland. Nearly 45% of respondents who knew about the auction and were classified as ineligible, reported participating in another conservation program that pays them for these BMPs. To ensure additionality of benefits, land managers were only allowed to bid for new practices that are not currently implemented. Figure 2-11 shows how many respondents reported adopting the eligible BMPs on their land. I do not know if land managers received payments from other programs to implement these BMPs.

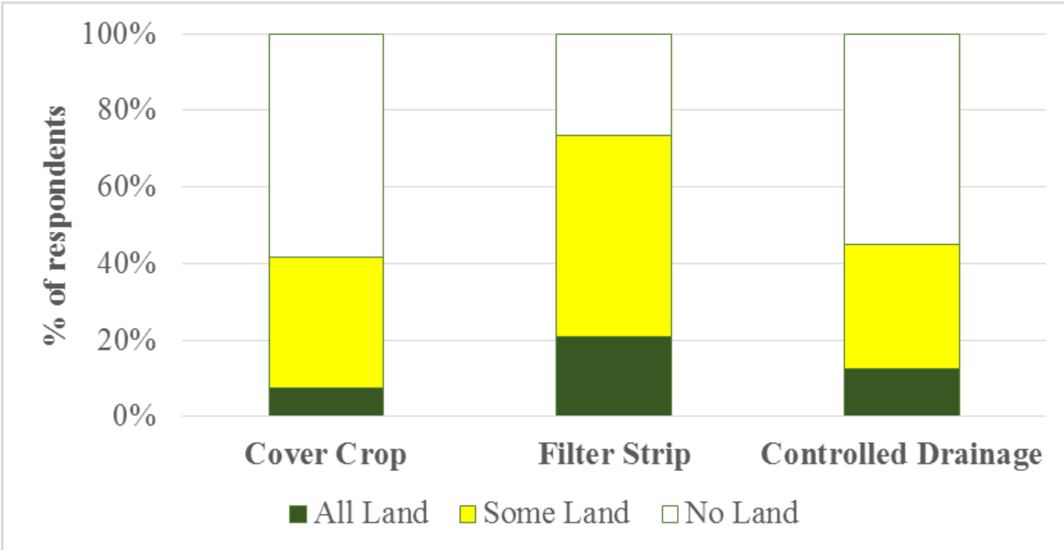

Figure 2-11. Current adoption of eligible BMPs

Consistent with previous research (Prokopy et al. 2008), there is a positive relationship between current participation in another program that pays for BMPs and 1) believing that farmers' choices affect water quality ($\chi^2(1, \mathrm{N} = 373) = 7.66, \mathrm{p} < 0.01$) as well as 2) believing that farmers have a responsibility to protect water quality ($\chi^2(1, \mathrm{N} = 373) = 5.50,\ \mathrm{p} < 0.05$). This result suggests that a subset of people who are aware of the impact of agriculture on water quality and have strong environmental stewardship attitudes did not participate in the auction because they were already engaged with programs that promote BMP adoption, such as USDA's Environmental Quality Incentives Program (EQIP).

Participation deterrents were identified by analyzing the responses of 195 individuals who indicated that they had knowledge about the auction and were eligible to submit a bid, but chose not to. Respondents could indicate multiple participation deterrents, so responses are not mutually exclusive. Seventy-four (38%) reported that the auction seemed complicated or time consuming or that they did not understand how to submit a bid. Fifty (26%) respondents stated that they did not want to adopt one of the three eligible BMPs. Fifty-five (28%) respondents reported that rental agreements made participation difficult and 36 (18%) indicated that they did not bid because they did not think their bid would be accepted. Twenty-seven (14%) respondents did not bid because the program was a “new research project” and 10 (5%) reported that they simply missed the deadline.

Of the 145 respondents who were knowledgeable about the auction, eligible to bid, and willing to adopt one of the eligible BMPs, respondents were less likely to think the auction was complicated if they reported working closely with conservation agencies ($\chi^2(1, \mathrm{N} = 99) = 3.99, \mathrm{p} < 0.05$). This result suggests that, in some capacity, working with conservation agencies reduced the likelihood that the individual was confused about the auction program. Individuals may have worked with conservation agency staff to clarify questions about the auction. Additionally, prior engagement with conservation agencies may have exposed them to similar programs or past experiences may have primed them to be more receptive to conservation programs. There was a moderately positive correlation between feeling that one’s bid would not be accepted and reporting that the auction was complicated or time consuming, r=0.23, N=145, p<0.01. A chi-squared test of independence confirmed the positive relationship between these two participation deterrents, $\chi^2(1, \mathrm{N} = 145) = 8.00, \mathrm{p} < 0.01$. There was also a positive relationship between having a concern about bid acceptance and a belief that auctions take more time than other conservation programs, $\chi^2(1, \mathrm{N} = 96) = 12.07, \mathrm{p} < 0.01$. These results suggest that potential participants may associate complexity of the program with a low likelihood of bid acceptance. These deterrents both reduce participation individually and they may reinforce each other. A full correlation matrix of participation deterrents is presented in Table A2-F-3 in Appendix 2-F.

Forty-five (23%) of potential participants stated that rental agreements made participation difficult; however, this statistic does not capture the full effect of land rental on auction participation. In total, 109 questionnaire respondents indicated that land rental was one of the factors deterring their participation. As discussed earlier, land rental may reduce awareness of conservation programs. Additionally, land rental may influence perceptions of eligibility and increase the costs of participation.

Some landowners allow renters to make all farm management decisions. Such respondents typically did not feel like they were in a position to participate or were not eligible to bid. One respondent noted, “I rent all my land out and they decide how to farm it. I think they do a good job with conservation.” Another wrote, “Our farm land is under our son's management - rented to him. Therefore I don't feel I'm eligible.” One respondent knew about the project and knew he was eligible to participate, but his land was co-owned and rented out and he did not want to consult with other decision makers about the auction. He wrote, “I am one of four family members who own. I did not want to take the time to consult with them on the project. We rent the acres to OH area farmer.”

2.6 Policy simulation

An important policy question is whether or not a reverse auction is more cost-effective than a uniform payment program when transaction costs limit participation in auctions. Although a statistical analysis of the questionnaire responses enabled identification of key barriers and deterrents to auction participation, the data could not be used to analyze the impact of these factors on program cost-effectiveness because the data do not reflect how participation and program outcomes would change if TC were different. Key findings from the landowner questionnaire and results from other studies in the literature were used to parameterize a simulation model to analyze how the identified participation barriers and deterrents could impact performance of conservation auctions relative to uniform payment programs. Auction outcomes are compared to results from targeted and untargeted uniform payment conservation programs that were simulated with the same data. To minimize the number of moving parts, cover crops are the only eligible BMP for each program.

2.6.1 Design and data

The simulation model is designed to analyze how outcomes might differ among reverse auctions and uniform payment conservation programs. I compare three incentive programs that pay farmers to adopt cover crops, 1) a reverse auction program, 2) an untargeted uniform payment program, and 3) a targeted uniform payment program. Simulated outcomes from the three programs are compared to a first-best scenario in which I assume that the administrator knows the true WTA for all decision-makers. Figure 2-12 illustrates the basic structure of the simulation model.

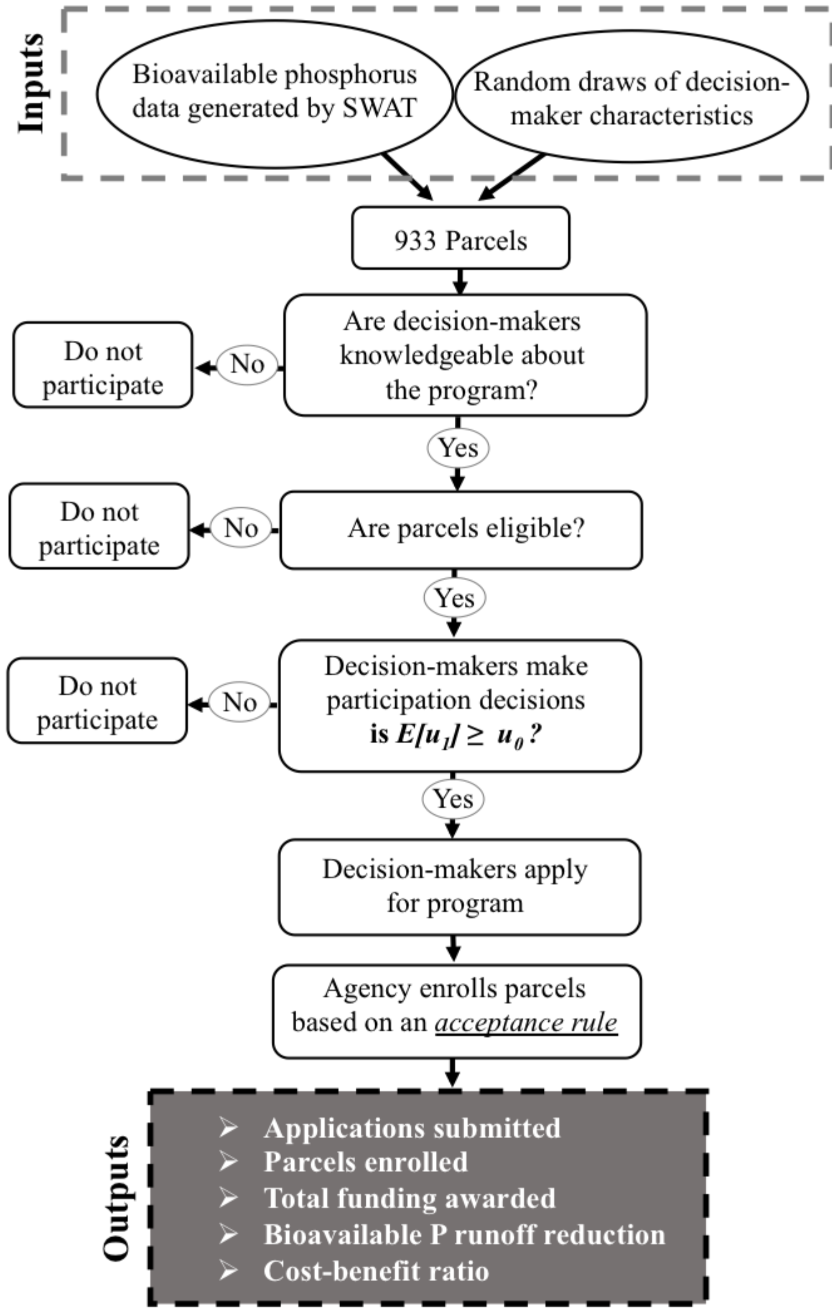

Figure 2-12. Policy simulation framework

Although many land management practices are possible, I focus on one in particular: winter cover crops that reduce soil erosion and associated P loss. Cover crop decisions are simulated for 933 agricultural parcels in Defiance County, Ohio, within the Tiffin River

Watershed (Figure 2-13). The Soil and Water Assessment Tool (SWAT) is used to predict the amount of bioavailable P runoff generated by 933 agricultural parcels in Defiance county that lie within the Tiffin watershed (LimnoTech, 2013). I assume that cover crops reduce per acre bioavailable P runoff by 6.9% for fields in the simulation. This assumption is based on the average predicted reduction of bioavailable P runoff generated by cover crop bids in the Tiffin Watershed BMP Auction Project.[34]

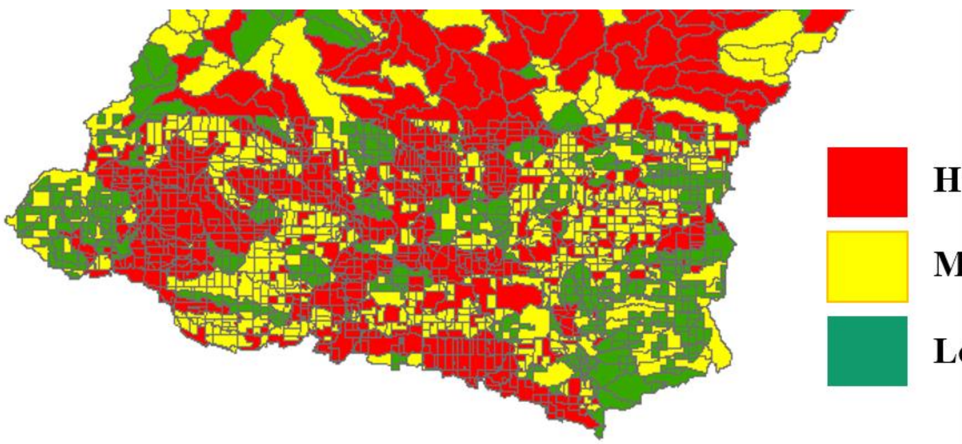

Figure 2-13. Map of the Tiffin Watershed and the three vulnerability areas for 933 parcels in Defiance County that were included in the simulation.

One decision-maker is assigned to each parcel and characteristics of that decision-maker are randomly generated for each simulation, including: 1) the cost of using cover crops, 2) TC of applying to the program, 3) stewardship attitude, 4) land rental agreement, 5) knowledge of the auction, and 6) eligibility based on current BMP usage. In the auction simulation, additional characteristics are 1) beliefs about phosphorus reduction from adopting cover crops on the

[34] This assumption removes the need to re-run the SWAT model for each parcel in the watershed, while still reflecting the heterogeneity of cropland by proportionally reducing baseline runoff calculated for each hydrologic response unit (HRU) within the landscape.

individual's land and 2) beliefs about the range of CB scores that will be accepted in the auction. Parameters and their associated ranges are presented in Table 2-3.

Table 2-3. Parameters used in the conservation policy simulation

Variable	Form/Value in Numerical Example	Description	Units	Source
c_j	U[20,60]	Cover crop costs	$	Essay 1 Table 1-4; NRCS, 2015
ρ_j[a]	U[4, 40]	Application time	hours	Peterson et al., 2014
τ[a]	35.5	Time cost	$/hr.	USDA-ERS, 2015
$pr(know = 1)$	0.30	Knowledge	prop.	Questionnaire Figure 2-9
$pr(eligible = 1)$	0.10	Eligibility	prop.	LimnoTech, 2013
$pr(rent = 1)$	0.33	33% are involved in a rent agreement	prop.	Author estimate.
v	$\begin{cases} pr(v = 6.32\ ) = 0.20 \\ pr(v = 0\ ) = 0.80 \end{cases}$	Intrinsic utility from taking actions that align with environmental attitudes/values,	$	Essay 1 Table A1-C-2
$\overline{\theta}$[b]	U[38,90], which is 1.5X the lowest ($25/ac./yr.) and highest ($60/ac./yr.) cost-share payments available from other programs.	Uniform distribution for beliefs about the highest bid that will be accepted in the auction.	$	Author estimate.
$\underline{e}$[b]	50th percentile of beliefs about one's own runoff reduction.	Belief about the lowest amount of bioavailable P runoff reduction accepted in the auction.	lbs. bio P	Author estimate.

[a] The transaction cost of application equals the application time required times the cost of time.

[b] $\overline{\theta}/\underline{e}$ equals the expected CB cutoff score, $\tilde{\beta}$.

To reflect the heterogeneity of farms, cover crop costs are independently drawn from a uniform distribution with a support of \$20 and \$60 per acre. This range of costs was selected based on interviews with farmers at the 2013 Michigan Ag Expo, and it aligns with cost-share payments available through government programs. For fiscal year 2015, the NRCS Environmental Quality Incentives Program (EQIP) offered Ohio farmers a 100% cost-share of \$44.24/ac./yr. for winter-kill cover crops and \$60.20/ac./yr. for cover crops that overwinter and are killed chemically or mechanically in spring (Natural Resources Conservation Service 2015).

Transaction costs involved with applying for a conservation program are distributed uniformly on the interval [142,1420], which represents a range of 4 to 40 hours of application time (following Peterson et al., 2014) with time valued at \$35.50/hr.[35] The TC associated with implementing the BMP and complying with program requirements are not expected to differ among program types, thus they would not differentially impact program performance. Without loss of generality, I do not incorporate these TC, but they could easily be included if data were available.

Assume that 20% of individuals gain utility from taking stewardship actions that align with their environmental attitudes. This assumption is motivated by results from the follow-up questionnaire in which 21% of respondents indicated that they *strongly agree* with the statement, “I feel good about using management practices that improve water quality.” For stewardship-minded individuals, I assume that WTA for cover crops is reduced by \$6.32/ac./yr. This value originates from experimental auctions held in 2013 in which farmers who were members of

[35] The cost of time is justified by assuming the 2014 median household income for farm operator households of \$71,000 per year (USDA-ERS 2015), which equates to about \$35.50/hr., assuming a 40 hour work week for 50 weeks per year.

environmental organizations (a proxy for stewardship attitudes) bid, on average, \$6.32/ac./yr. less to plant a cereal rye cover crop (See Table A1-C-2).

Assume that one-third of parcels are rented, thus the decision-maker would have to coordinate with another manager (owner or renter) to participate. Without data about TC and rental agreements, I assume that TC of application and bid preparation increase by 50% for rented land.

To participate in a conservation program, decision-makers must be both knowledgeable about the program and eligible to receive funding. Thirty-percent of survey respondents reported having no knowledge of the BMP auction, thus in the model I assume that 30% of decision-makers do not know about conservation programs and thus do not apply. Land is considered eligible if cover crops are not currently being grown. LimnoTech (2013) reports that stakeholders have estimated that cover crops are adopted on 5-10% of the agricultural acreage within the Tiffin watershed. Nearly 8% of questionnaire respondents reported using cover crops on all of their acreage, while 36% reported using cover crops on at least a portion of land that they manage. In the simulation of all conservation programs, I assume that 10% of parcels are ineligible because cover crops are already grown on those fields.

The behavior of land managers that are knowledgeable and eligible to participate in the conservation program is simulated based on a participation decision rule. The manager decides to apply for program j if expected utility from participating in the program exceeds baseline utility, which is assumed to be zero. In Eq. (2.1), utility from conservation is comprised of three components, 1) income that includes the BMP payment, 2) disutility from transactions cost associated with applying for and participating in the program, and 3) utility from aligning conservation actions with one's environmental stewardship ideals. In the simulation, all components of utility are converted to money metric units, assuming that farmers share the same marginal utility of income, m. Each program simulation is repeated 1000 times using new random draws for all decision-maker characteristics for each of the 933 parcels.

2.6.1.1 Conservation auction

Individuals will only participate in the auction if the expected utility of participating exceeds their status quo utility. To compute the expected utility of bidding, two additional decision-maker beliefs are required for the auction simulation. First, managers have a belief about how much their parcel's P runoff will be reduced by planting a cover crop. This belief is randomly drawn from a uniform distribution over the range of potential runoff reductions (predicted by SWAT) for the 933 parcels in the watershed. Second, each manager has a belief about the highest CB score (highest bid to benefit ratio, $\tilde{\beta}$) that will be accepted in the auction, depending on the expected bids and benefits of proposals submitted by other farmers. CB scores are assumed to be nonnegative, which requires that cover crops do not increase runoff and that bids are nonnegative. Individuals do not submit a bid if they believe their CB score exceeds the threshold. This belief may depend on the payments offered in existing programs. Current uniform payment programs in the Tiffin watershed offer land managers between \$25 and \$60 per acre, so I assume that beliefs about the highest acceptable bid will fall in this range. The denominator of the CB score (e.g., the runoff reduction associated with the largest bid) is set at 0.115 lb bio P/ac., which is the 50th percentile of beliefs about runoff reduction on one's own field. I conduct sensitivity analyses to test the robustness of these assumptions.

Assuming that each manager knows their costs to adopt a BMP, they formulate their bid using the optimal bidding strategy described in Appendix 2-A, which requires a distributional assumption regarding $\tilde{\beta}$. Conditional on bidding, the optimal bid from Eq. (2.5) and is solved for each decision-maker using the constrained non-linear maximization routine in MATLAB, assuming a uniform distribution for $F(\beta)$ (See Eq. (2A.15) for the optimal bid using this assumption). Next, the individual determines if that bid would generate positive net utility ($E[u_1] - u_0 \geq 0$) and if they think their CB score is below the maximum acceptable CB score, $\tilde{\beta}$. If both requirements hold, the individual submits a bid in the auction.

All submitted bids are evaluated to determine the cost per pound of reduced bioavailable P. Then, bids are ranked from lowest CB score (most cost-effective) to highest CB score (least cost-effective). Total payment required is calculated for each bid by multiplying the bid per acre by the total number of acres in that parcel. Bids are accepted in ranked order until the cumulative payment required exhausts the budget constraint, set at $100,000.[36]

2.6.1.2 Uniform payment conservation programs

In the uniform payment conservation program, individuals receive a payment of p per acre if they enroll in the program. If the payment offered by the program is at least as great as their minimum WTA, the individual will apply for the program.

Two types of uniform payment programs are simulated. The first targets environmentally vulnerable areas of the watershed, while the second is an untargeted program for which all parcels are eligible for payment. Participation in the targeted program is limited to individuals that manage highly vulnerable parcels while the untargeted program covers all parcels, regardless of vulnerability status.

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[36] The $100,000 budget constraint reflects funding earmarked for cover crops in two incentive programs that were implemented in Defiance and Fulton Counties in 2014, 1) the Lake Erie Nutrient Reduction Program (LE-NRP) that offered $25 per acre for cover crops on 1,000 acres county-wide, and 2) the NRCS Tri-State Western Lake Erie Basin Phosphorus Reduction Program that offered $50 per acre for cover crops on 1,500 acres county-wide.

Each of the 933 parcels is assigned a vulnerability index score, $I \in \{1,2,3\}$, by dividing the parcels into three equally sized groups based on the baseline amount of bioavailable P runoff (Figure 2-13). Parcels with predicted runoff less than 0.57 lbs./ac./yr. (the first tercile) are assigned a vulnerability score of I=1 (least vulnerable). Parcels are given a score of I=2 if predicted bioavailable P runoff is between 0.57 lbs./ac./yr. and 0.73 lbs./ac./yr. (the second tercile), and they are assigned a score of I=3 (most vulnerable) if predicted bioavailable P runoff is greater than 0.73 lbs./ac./yr. In the targeted program, only the most vulnerable parcels (I=3) are eligible for the program.

As in the auction, the budget for the uniform payment program is constrained to \$100,000. Participants are enrolled on a first-come, first-served basis depending on a randomly generated application order. The program is simulated for eight different per acre payment levels, $p \in \{\ \$25, \$30, \$35, \$40, \$45, \$50, \$55, \$60\}$. Other uniform payment programs have offered payments in this range, including the Lake Erie Nutrient Reduction Program (LE-NRP) that offers \$25/ac./yr. for cover crops and NRCS EQIP that pays \$60/ac./yr. for cover crop species that are killed chemically or mechanically (e.g. cereal rye) (Natural Resources Conservation Service 2015)

2.6.1.3 First-best program

To generate a best-case scenario reference point, a "first-best" conservation program is simulated in which land managers are paid exactly the amount that makes them indifferent between participating or not (i.e., they are paid their minimum WTA). This scenario assumes that the administrator knows all land manager costs and preferences and can exactly price discriminate and thus pay zero information rent. Using the same budget constraint and assumptions about the portion of knowledgeable and eligible participants, this scenario represents the most cost-effective outcome that would only be possible with perfect information.

2.6.1.4 Simulation experiments

Using the simulation model, I analyze the performance of reverse auctions compared to targeted and untargeted uniform payment programs. Transaction costs of bidding in a reverse auction are varied on a spectrum of equal to (1X), double (2X) and quadruple (4X) the cost of applying for the uniform payment programs. Five key conservation program outcomes are compared in each experiment: 1) number of applications submitted, 2) total funding awarded, 3) bioavailable P runoff reduction, 4) information rents extracted, and 5) cost-benefit ratio (cost per pound of bioavailable P runoff reduction). For each of the three TC levels, these five outcomes are compared among the reverse auction and targeted and untargeted uniform payment programs offering eight different levels of payments. In addition to the main experiment, I also examine the sensitivity of the results to variation in beliefs about the highest acceptable CB score.

2.6.2 Policy comparison

Results from the simulations illustrate how transaction costs reduce participation in reverse auctions and thereby undermine their cost-effectiveness compared to the uniform payment programs. The simulation also highlights how beliefs about the probability of bid acceptance can further erode the cost-effectiveness of auctions by reducing participation and promoting strategic bid inflation.

2.6.2.1 Equal transaction costs

In the first analysis, the TC of submitting a bid are equal to the TC of applying for a uniform payment program. Relative to the first-best policy, the auction scenario and uniform payment schemes all enroll fewer people and pay more for each unit of bioavailable P reduction. Figure 2-14 presents a comparison of the average cost-effectiveness (measured in $/lb. bioavailable P reduction) across 1000 simulations for 12 programs (first-best outcome, BMP auction at three TC levels, and untargeted and targeted uniform payment programs at four payment levels). Recall that the first-best outcome is achieved by price discriminating with perfect information. In the first-best scenario, cost-effectiveness averages $341/lb. reduction in bioavailable P annually, while allocating funds with an auction results in a cost per pound of bioavailable P reduction of $593/lb./ac./yr. (Fig. 2-14, columns 1 & 2).

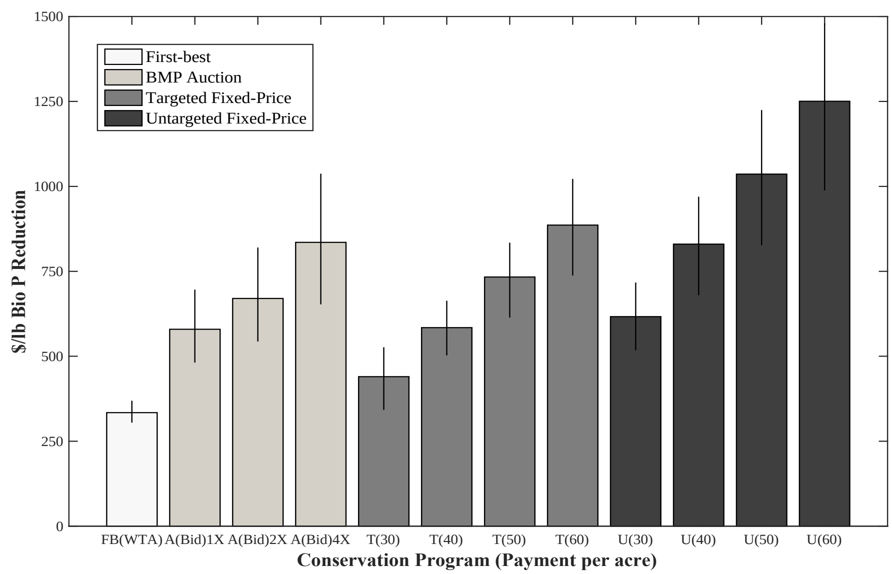


Figure 2-14. Simulated cost per pound of bioavailable phosphorus reduction for 11 conservation programs and the first-best outcome. Bars represent the average cost from 933 parcels over 1000 simulations; error bars show 95% confidence intervals.

Performance of the uniform payment programs varies by payment level (Table 2-4) and two patterns are evident. First, as expected, the untargeted payment program is less efficient than the targeted program at reducing P runoff at every payment level-- 41% more costly, on average. Second, in both uniform payment programs, the cost per pound of P abated decreases with lower uniform payment levels. But this benefit is partially offset by fewer applications submitted when lower payments are offered, which means fewer total benefits are procured. At the lowest payment levels, there are too few applications to exhaust the available program funds (Table 2-4).[37]

Table 2-4. Comparison of funding allocated, bioavailable P reduction and cost-benefit ratios among targeted and untargeted uniform payment programs at eight payment levels.

	Untargeted Uniform payment			**Targeted Uniform payment**		
Payment per acre	Funding Allocated ($)	Bio P Reduction (lbs./yr.)	Cost-Ben ($/lb. BioP)	Funding Allocated ($)	Bio P Reduction (lbs./yr.)	Cost-Ben ($/lb. BioP)
25	18,115	36	508	6,355	18	363
30	78,157	128	612	27,192	63	431
35	98,152	137	715	69,181	137	506
40	97,863	119	820	97,612	167	584
45	97,838	106	919	97,805	150	654
50	97,456	95	1027	97,549	134	727
55	97,303	86	1137	97,485	121	804
60	97,207	79	1238	97,208	111	874

Figure 2-15 shows the number of simulated land managers who were eligible and willing to enroll their land in each conservation program. At the highest uniform payment level analyzed ($p = 60$), 373 (40%) of land managers are willing to enroll their parcels in the uniform payment program relative to 249 (27%) who are willing to submit a bid in the auction when TC are equal between the two programs. As the offered payment declines, fewer people are willing to enroll

[37] As shown in Table 2-4, the $100,000 budget is never fully exhausted because funds were insufficient, on the margin, to pay for cover crops on all acres of the next highest ranking parcel. In this simulation, partial funding was not awarded to projects on the margin, but doing so would reduce the level of unutilized conservation funds.

in a uniform payment program, with only 10 and 35 people willing to enroll for $25/ac./yr. and $30/ac./yr., respectively. At these payment levels, so few people enroll in the two uniform payment programs that the conservation budgets are not fully utilized and runoff reduction is minimal.

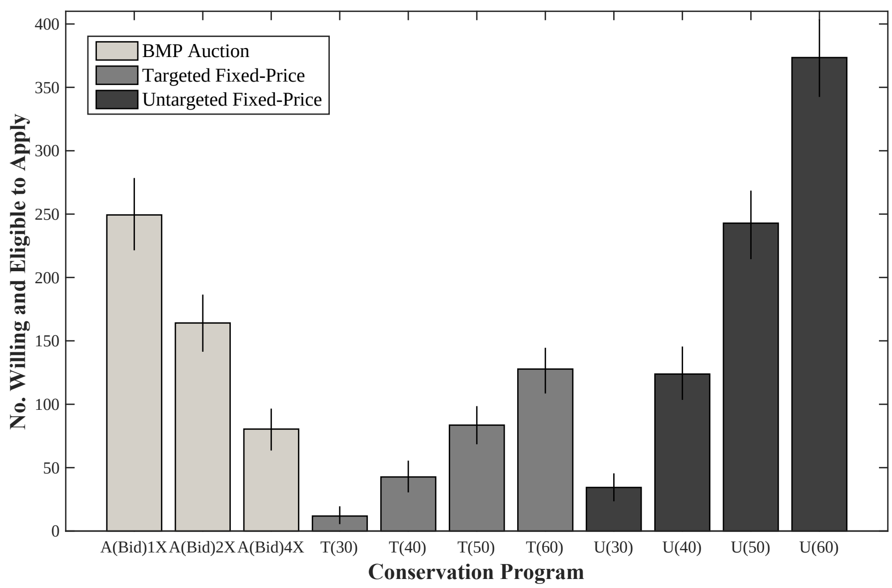


Figure 2-15. Simulated willingness to participate in 11 conservation programs. Bars represent the average number of people willing and eligible to participate from 933 parcels over 1000 simulations; error bars show 95% confidence intervals.

At higher fixed prices, cost-effectiveness of uniform payment programs is reduced because the benefit of greater participation is offset by the high information rents and lack of cost-benefit ranking of applicants. As shown in Table 2-5, high information rents are also paid in the auction program, but the ability to rank and select parcels makes auctions more cost-effective than both targeted and untargeted uniform payment programs paying above $40/ac./yr. and $30/ac./yr, respectively (Figure 2-14).

Table 2-5. Average information rents per acre extracted in auction and uniform payment programs. Zero information rents are extracted in the First-best scenario in which managers are offered a payment equal to their minimum willingness to accept.

Auction		Uniform Payment		
TC Level	Information Rent ($/ac./yr.)	Payment Level	Information Rent ($/ac./yr.)	
			Untargeted	Targeted
1X	11.4	30	3.8	3.8
2X	11.7	40	7.2	7.2
4X	12.2	50	11.1	11.2
--	--	60	15.5	15.5

2.6.2.2 Transaction costs vary by policy

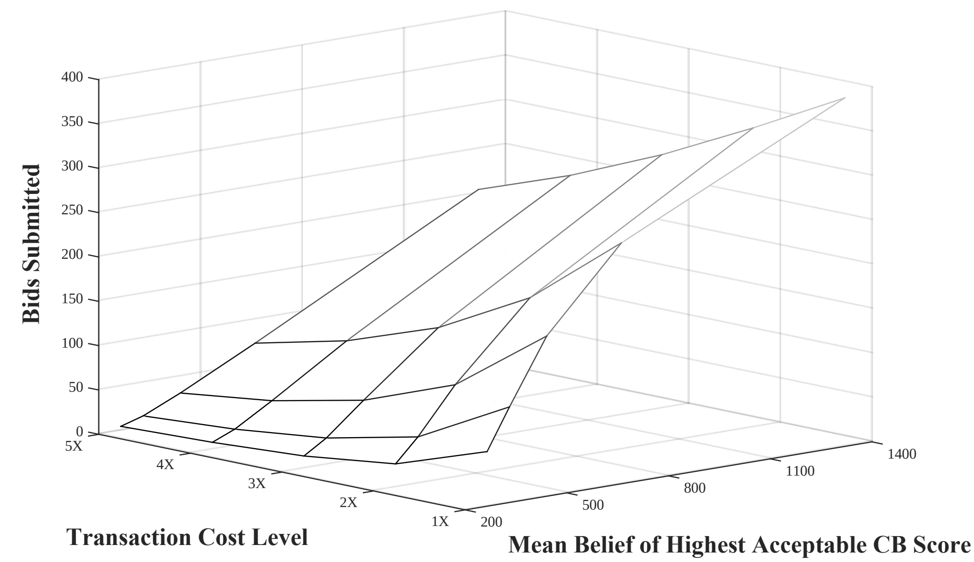
In the previous section, results were reported when TC of application are held constant across programs, but survey findings indicate that many farmer respondents perceived TC of submitting a bid to be daunting. In the follow-up questionnaire after the BMP auctions, 28% of respondents agreed with the statement that, "conservation auctions take more time to participate in than other conservation programs." Additionally, 34% of respondents who were aware of the auction reported not submitting a bid because "the auction seemed complicated or time consuming." These findings, along with the existing literature about transaction costs associated with conservation programs (Peterson et al. 2014) motivated experimental treatments that vary transaction costs of participation (measured in hours to submit a bid packet) by two (2X) and four (4X) times the participation cost of the uniform payment programs.

As the TC of auction participation increase, the number of people willing to submit a bid declines from 249 when TC are 1X greater to 164 when TC are 2X greater, and to 80 people when TC are 4X greater (Figure 2-15, bars 2 & 3). This decline in participation results in fewer high-impact bids being received, thus the average cost to reduce a pound of bioavailable P via reverse auctions increases from \$579/lb. to \$670/lb. when TC are double (2X), and \$835/lb. when TC are quadruple (4X) the baseline (Figure 2-14, bars 3 & 4). Even at the conservative estimate that TC participation costs are twice as high for an auction as for a uniform payment program, the reverse auction is less cost-effective and reduces P runoff less than targeted uniform payment programs offering \$40/ac./yr.

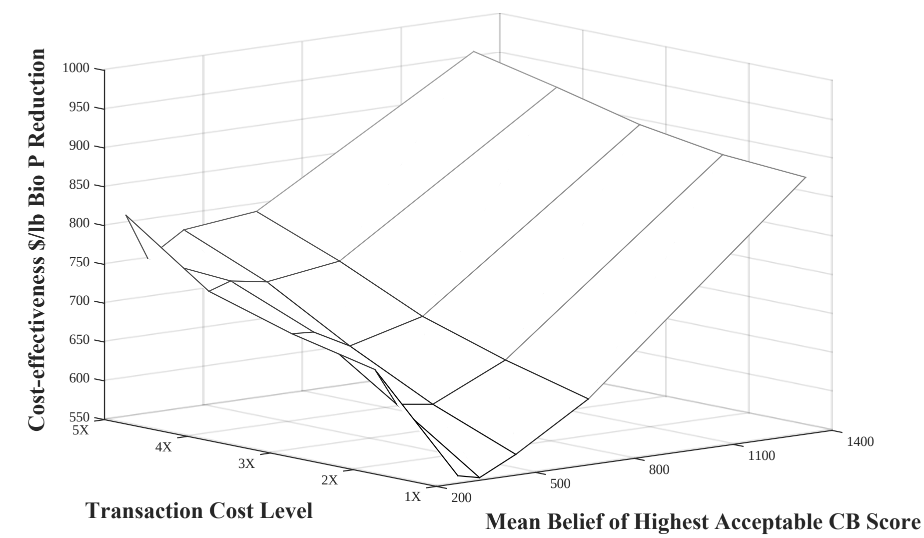
2.6.3 Sensitivity analysis

The general finding that reverse auctions are less cost-effective than some uniform payment programs when bidding is costly is robust to a wide range of parameter adjustments. However, bidder beliefs about the maximum acceptable CB score deserve additional attention as they impact the perceived probability of bid acceptance that can result in censoring participation and strategic bidding. Beliefs about the maximum CB score pivot on the perceived ratio of the maximum acceptable bid amount to the lowest associated level of environmental benefit. Sensitivity analyses were conducted by evaluating these parameters over a range of values.

In the baseline analysis, the belief about the maximum acceptable bid was randomly varied between \$38 and \$90/ac./yr., and the lowest associated level of runoff reduction was set at the 50th percentile of beliefs about one's own runoff reduction. Holding TC at the 2X level, a sensitivity analysis was conducted by varying the expected per acre maximum acceptable bids across four levels (\$25, \$40, \$60, and \$80/ac./yr.). Participation increased when the expected maximum was higher, but so too did strategic bidding to extract information rents. When the expected maximum bid was \$25, information rents were \$4/ac./yr., but only nine individuals submitted bids, on average. At \$80 /ac./yr., 230 bids were submitted, but information rents increased to \$15/ac./yr., on average. The most cost-effective outcome was achieved by setting beliefs about the maximum acceptable bid at $60/ac./yr., which resulted in 152 bids submitted, a cost of $659/lb. of bioavailable P abated, and $11/ac./yr. in information rents, on average.



a. Bids submitted with varying levels of TC and beliefs about acceptable CB scores.



b. Cost per pound of reduced bioavailable P with varying levels of TC and beliefs about acceptable CB scores.

Figure 2-16. Sensitivity analysis to analyze changes in the number of bids submitted (a) and the average cost per pound of bioavailable P reduction (b) in reverse auctions with varying levels of transaction costs of application (5 levels) and beliefs about the highest acceptable CB score (5 levels). Outcomes are simulated 1000 times for the 933 parcels in the watershed.

A similar finding exists when beliefs about the lowest environmental benefit accepted are adjusted. Figure 2-16 shows the how bids submitted (a) and cost per pound of bioavailable P reduction (b) change across five TC levels and five levels of beliefs about the maximum acceptable CB score. If bidders believe only low CB scores (e.g., low bids, high benefits) will be accepted, fewer bids are submitted, especially when TC are high. Although participation increases when people believe higher CB scores will be accepted, strategic rent seeking also occurs, which reduces cost-effectiveness.

2.7 Conclusion

Federal spending on conservation programs is projected to be $28.2 billion between 2014 and 2018, and an increasing proportion of funding is allocated to working lands programs (Lubben and Pease 2014). It is important to identify strategies to allocate funding cost-effectively among projects that provide environmental benefits. Conservation auctions have been identified as a key policy tool, but to be cost-effective they must attract a population of participants who are willing to submit bids. If participation is thin, projects may be funded with high costs per unit of environmental benefit procured. Two objectives of this essay were to identify barriers and deterrents to participating in conservation auctions and to analyze how these factors influence the relative cost-effectiveness of auctions compared to uniform payment conservation programs. These objectives were motivated by low participation experienced in two conservation auctions in two counties of NW Ohio during the summer of 2014. Only 1% of landowners who were invited to participate actually submitted a bid in the auction. Low participation led to less cost-effective outcomes as projects were funded with high costs per pound of reduced bioavailable phosphorus runoff.

A follow-up survey was conducted to determine the factors that deterred participation. Lack of knowledge about the auction restricted participation for 30% of respondents. Of the knowledgeable respondents, nearly 37% were ineligible because they either already adopted the BMP or they did not have cropland in the project area. Nearly 32% of respondents were classified as willing to participate but, for one reason or another, they did not. The respondents who were willing to participate reported three primary participation deterrents including, 1) they thought the auction was complicated or confusing, 2) they did not think their bid would be accepted, and 3) land rental agreements made participation difficult.

Finding the auction complicated or confusing was the primary reason for nonparticipation, despite the numerous resources for land managers to get additional information about the auction. The transaction costs involved with seeking out and processing information about the new project proved too great, at least for the first year of the program. Another important deterrent was a concern that a submitted bid would not be accepted. Results suggest that this deterrent is related to the concern about high transaction costs because it increases the chance of committing to submit a bid, but then not being admitted into the program. Potential participants are less willing to incur sunk costs for bid preparation if their subjective belief about the probability of bid acceptance is low.

Rental agreements also affected people's perceptions of the program. Many landowners indicated that their renters make all management decisions, including decisions about conservation, and thus they were not in a position to participate in the auction program. Additionally, some landowners did not know about the auction, likely because they are less aware of conservation programs because their renter makes all of the agricultural management decisions. Without surveying the farmers renting the land, one can only hypothesize the factors that deterred their participation in the auction, but renters may have less incentive to undertake expensive conservation practices on land that they do not own and are not guaranteed to manage in the future. Follow-up interviews with both landowners and renters would be necessary to fully understand the barriers for participating in conservation programs and adopting BMPs on rented land.[38]

Results from this research suggest that high transaction costs of bid submission limit participation and cost-effectiveness of conservation auctions. Lowering TC and reducing inflated perceptions of high TC involves familiarizing potential bidders with the auction process through straightforward advertising, information sessions, and working with leaders in the community to spread the word about the program. Whitten et al. (2013) propose a framework to help design conservation auctions to achieve greater participation that includes steps like building awareness, as well as educating and communicating with the eligible landowners. Streamlining the bidding process and reducing the time and effort required to participate may also reduce perceived TC and improve cost-effectiveness by increasing participation.

As participation increases, auctions become more attractive because the auctioneer can price discriminate among projects to select the most cost-effective ones. Auctions may also be preferred if land managers with high priority parcels have high costs of BMP implementation, thus requiring payments that exceed the levels offered in a uniform program. But for auctions to work efficiently in this case, managers must be educated about their ability to generate

[38] These results are in line with recent research that found land rental to be a significant barrier for conservation practice adoption and targeting. A study of farmers in Indiana reported that renters find that "the landowner's lack of interest in conservation [is] an impediment to using conservation practices that [they] would like to use on rented land" (Kalcic et al. 2014, p.805). In their research, discussions with landowners and farmers revealed that, in some cases, renters may wish to install conservation practices, like filter strips, but profit-oriented landowners may resist because they can make more money cash renting that acreage. Furthermore, renters are only likely to invest in conservation practices on land that is under a long-term contract.

environmental benefits using BMPs, and they must believe that submitting a bid is worth their time. However, previous research suggests that as bidders become more familiar with reverse auctions, they learn about the highest acceptable CB score or bid cap (if one exists) and can bid strategically to extract rents from the auctioneer (Kirwan, Lubowski and Roberts 2005). For example, bidders with high value projects in lab experiments have strategically inflated bids to extract information rents (Cason and Gangadharan 2005). Results suggest that a tradeoff exists between boosting participation levels and minimizing rent seeking in discriminatory reverse auctions.

In some circumstances, it may be more cost-effective for conservation PES programs to use a targeted uniform payment program in lieu of a reverse auction. More analysis is needed to identify preferred design parameters for targeted uniform payments and the associated conditions under which such a program is preferred to an auction, but results from the simulation model suggest that targeted uniform payment programs may perform better when high TC reduce auction participation. Given that conservation auctions can be administratively burdensome, administrative cost savings may be another benefit of using a uniform program. In this research, I do not explore differences in administrative costs among alternative conservation programs, but this is an important consideration for conservation agencies.

APPENDICES

APPENDIX 2-A OPTIMAL BIDDING

Expanding upon the pioneering conservation model developed by Latacz-Lohmann and Van der Hamsvoort (1997) and extensions proposed by Glebe (2013), to show how optimal bidding behavior changes when transaction costs increase.

When participating in a conservation auction, farmers submit a bid that represents the payment that they would require to adopt one or more BMPs. In most auction theory, game theoretic frameworks are used to solve the optimal bids for one or more identical objects. But economists have shown that modeling conservation contracts requires a different approach to handle the heterogeneous nature of farmer costs and benefits and the uncertainty about these distributions, as well as the multiple choices bidders can make regarding BMP selection and field enrollment (Latacz-Lohmann and Van der Hamsvoort, 1997; Glebe 2013).

As described in Chapter 1, assume that land managers maximize utility and utility is positively influenced by income, alignment of actions with environmental attitudes, and negatively affected by transaction costs of enrolling in a conservation program. Utility is defined as,

$$u(m, a_k, \theta_k, \boldsymbol{\rho_k}) = m[\pi(a_k) + \theta_k] + v(a_k) - \psi(\boldsymbol{\rho_k}) \tag{2A.1}$$

where, m is the marginal utility of income, a_k is the conservation action required to participate in conservation program k, θ_k is a conservation payment, and $\boldsymbol{\rho_k}$ a set of non-price attributes of the program. Agricultural income is $\pi(a_k)$, $v(a_k)$ is utility derived from aligning conservation actions with intrinsic environmental attitudes, and $\psi(\boldsymbol{\rho_k})$ represents disutility from enrolling in and complying with conservation program k. Recall from Chapter 2 that there are two components to disutility such that, $\psi_1(\boldsymbol{\rho_k}) + \psi_2(\boldsymbol{\rho_k}) = \psi(\boldsymbol{\rho_k})$, where $\psi_1(\boldsymbol{\rho_k})$ is the disutility from bid preparation and $\psi_2(\boldsymbol{\rho_k})$ is the disutility from complying with rules and regulations. Since $\psi_1(\boldsymbol{\rho_k})$ is associated with bid submission, it is experienced by all bidders with certainty, even if their bid is not accepted.

Land managers submit bids to maximize expected utility,

$$E(u) = u_k \, \sigma + \left(u_0 - \psi_1(\boldsymbol{\rho_k})\right)[1 - \sigma] \qquad (2A.2)$$

where, u_k is the utility received when one is enrolled in the conservation program k, u_0 is status quo utility when one is not enrolled in the program, and σ is the probability of contract acceptance. Unlike Chapter 1, where I assumed that there were no transaction costs (TC) of bid submission, here I consider these costs and how they influence participation and bid choice. Recall that $\psi_1(\boldsymbol{\rho_k})$ (disutility of TC from bid submission) is a component of $\psi(\boldsymbol{\rho_k})$ that is accounted for in the utility from the conservation program, u_k. It will also be experienced if the individual submits a bid but is not accepted in the program, which will occur with probability σ, as shown in Eq. (2A.2).

The probability that bid n is accepted depends on how bid n ranks among the other submitted bids. When projects have heterogeneous environmental impacts, bids are ranked and selected based on an environmental score that takes into account both the payment requested (bid) and the targeted environmental benefits. Thus expectations about bid acceptance depend on farmer expectations about their own environmental benefit (often unknown) and expectations regarding costs and benefits of competing project tenders.

Accounting for the two dimensional bid-scoring systems commonly used in conservation auctions, I expand upon and adapt the model proposed by Glebe (2013). The bid and predicted benefit level are used to determine the scoring index, $\beta = \theta/e$, which is simply the bid per unit of environmental benefit.

Individuals do not know the true probability of bid acceptance (σ), but instead develop their perceived probability of bid acceptance ($\ddot{\sigma}$). The perceived probability depends on farmer expectations about the distributions of payments requested (bids) $[\underline{\theta}, \overline{\theta}]$ and the predicted environmental benefits $[\underline{e}, \overline{e}]$ associated with bid submissions, which form the expected upper and lower limits of the scoring index, $[\underline{\beta}, \overline{\beta}]$. Subjective expectations about these distributions generate an expectation about $\tilde{\beta}$, which is the highest bid score (i.e., bid per unit of benefit) that will be accepted. Thus the perceived probability that a farmer's bid is accepted can be written as $\ddot{\sigma}(\ddot{\beta}_n, \ddot{\beta}_{-n})$, where $\ddot{\beta}_n$ is the subjective expectation of one's own score and $\ddot{\beta}_{-n}$ is the subjective expectation of the scores of other bids.

Let $f(\beta)$[39] be the expected density function of $\tilde{\beta}$, which characterizes farmers' expectations about the bid acceptance cutoff point. Given the predicted environmental benefits of the proposed conservation project, the expected probability that a bid is accepted is,

$$\ddot{\sigma} = P(\beta \leq \tilde{\beta}) = 1 - F(\beta) \tag{2A.3}$$

Bidders submit a bid (θ) such that the expected utility from participation is at least as great as the reservation utility when no conservation practices are adopted (i.e. *status quo* utility).

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[39] The probability density of the expected bid cap can be rewritten as the marginal impact of increasing one's bid on the probability that the bid is rejected (i.e., $f(\beta) = \partial F(\beta)/\partial\theta$). If a bidder increases his bid, ceteris paribus, the probability of bid acceptance declines and it becomes more likely that the bid will be rejected, thus $f(\beta) = \partial F(\beta)/\partial\theta > 0$. Therefore, the entire term $(1 - F(\beta))/f(\beta)$ is positive.

The *individual rationality* (IR) condition, requires that participants prefer or are at least indifferent between participation and non-participation,

$$u_k[1 - F(\beta)] + \big(u_0 - \psi_1(\boldsymbol{\rho_k})\big)F(\beta) \geq u_0 \tag{2A.4}$$

Substituting Eq. (2A.1) into Eq. (2A.4) results in,

$$\begin{gathered}\big(m[\pi(a_k) + \theta_k] + v(a_k) - \psi(\boldsymbol{\rho_k})\big)\,[1 - F(\beta)] + \big(m * \pi(a_0) - \psi_1(\boldsymbol{\rho_k})\big)F(\beta) \\ \geq m * \pi(a_0)\end{gathered} \tag{2A.5}$$

Rearranging Eq. (2A.5), it can be shown that,

$$\big(m[\pi(a_k) - \pi(a_0) + \theta_k] + v(a_k) - \psi_2(\boldsymbol{\rho_k})\big)\,[1 - F(\beta)] - \psi_1(\boldsymbol{\rho_k}) \geq 0 \tag{2A.6}$$

For simplicity of notation, let c_k represent the full cost (direct and opportunity) of taking conservation action a_k, such that $c_k = \pi(a_0) - \pi(a_k)$.

Farmers will choose a bid θ_k that maximizes expected net payoff in the program[40]. But farmers face a tradeoff when choosing their bid – a higher bid increases their potential payment, but it increases the agency's cost per unit of environmental benefit, thus decreasing the probability that the bid will be accepted. Assuming separability and linearity of the arguments in the utility function, maximizing Eq. (2A.6) with respect to θ_k yields the farmer's optimal bid, ${\theta_k}^*$. Recall that θ_k is an argument of u_k and $F(\beta)$, but not $\psi_1(\boldsymbol{\rho_k})$ or $\psi_2(\boldsymbol{\rho_k})$. For clarity, I show this derivation in four steps.

First, using the product rule I show,

$$m[1 - F(\beta)] + \big(m[-c_k + \theta_k] + v(a_k) - \psi_2(\boldsymbol{\rho_k})\big)\frac{\partial[1 - F(\beta)]}{\partial\, \theta_k} = 0 \tag{2A.7}$$

[40] I assume that non-farm income (NFI) is exogenous to the conservation policies or farmers' conservation actions.

Second, recall that $\beta = \frac{\theta_k{}^*}{e}$ so that I can use the chain rule to show that the derivative of $1 - F(\beta)$ with respect to θ_k is,

$$\frac{\partial[1 - F(\beta)]}{\partial\, \theta_k} = -\frac{\partial F(\beta)}{\partial \beta}\frac{\partial \beta}{\partial \theta_k} = -\frac{f(\beta)}{e} \tag{2A.8}$$

Third, I substitute Eq. (2A.8) into Eq. (2A.7),

$$m[1 - F(\beta)] = \big(m[-c_k + \theta_k] + v(a_k) - \psi_2(\boldsymbol{\rho_k})\big)\frac{f(\beta)}{e} \tag{2A.9}$$

Fourth, I rearrange Eq. (2A.9) to show that,

$$\theta_k{}^* = c_k + \frac{\psi_2(\boldsymbol{\rho_k}) - v(a_k)}{m} + \frac{[1-F(\beta)]e}{f(\beta)} \tag{2A.10}$$

To solve numerically, a functional form must be assigned to $F(\beta)$. It has become customary to assume a uniform distribution such that,

$$F(\beta) = (\beta - \underline{\beta})(\overline{\beta} - \underline{\beta})^{-1} \tag{2A.11}$$

where, $\overline{\beta}$ and $\underline{\beta}$ are the expected upper and lower limits of the scoring index, β.

Taking the derivative of $F(\beta)$ with respect to β yields,

$$f(\beta) = (\overline{\beta} - \underline{\beta})^{-1} \tag{2A.12}$$

Therefore, I show that

$$\frac{[1-F(\beta)]e}{f(\beta)} = \frac{\left[1-(\beta-\underline{\beta})(\overline{\beta}-\underline{\beta})^{-1}\right]e}{(\overline{\beta}-\underline{\beta})^{-1}} = \left(\overline{\beta} - \beta\right)e = \left(\overline{\beta} - \frac{\theta_k{}^*}{e}\right)e = \overline{\beta}e - \theta_k{}^* \tag{2A.13}$$

Then, by substituting (2A.13) into (2A.10), it can be shown that,

$$\theta_k{}^* = c_k + \frac{\psi_2(\boldsymbol{\rho_k}) - v(a_k)}{m} + \overline{\beta}e - \theta_k{}^* \tag{2A.14}$$

Finally, conditional on bidding, I can solve for the optimal bid,

$$\theta_k{}^* = \frac{E[e]\overline{\beta}m{*} + m\, c_k + \psi_2(\boldsymbol{\rho_k}) - v(a_k)}{(2m)}. \tag{2A.15}$$

where, the individual considers the expected environmental benefit ($E[e]$) since the true e is unknown to potential bidders.

APPENDIX 2-B IMPLEMENTING THE TIFFIN BMP AUCTION

Local partnerships and media – To ensure farmer trust in the auction program and increase the likelihood of bid submission, the auctions were conducted in collaboration with the local Soil and Water Conservation District (SWCD) offices in Fulton and Defiance counties. These offices partner with NRCS to help farmers adopt conservation practices with other incentive programs (e.g., EQIP), so farmers are familiar with the staff and services provided.

A website was developed for each county to educate landowners and farmers about the auction project and direct them to contacts from whom they could acquire additional information or assistance (Figure A2-B-1).

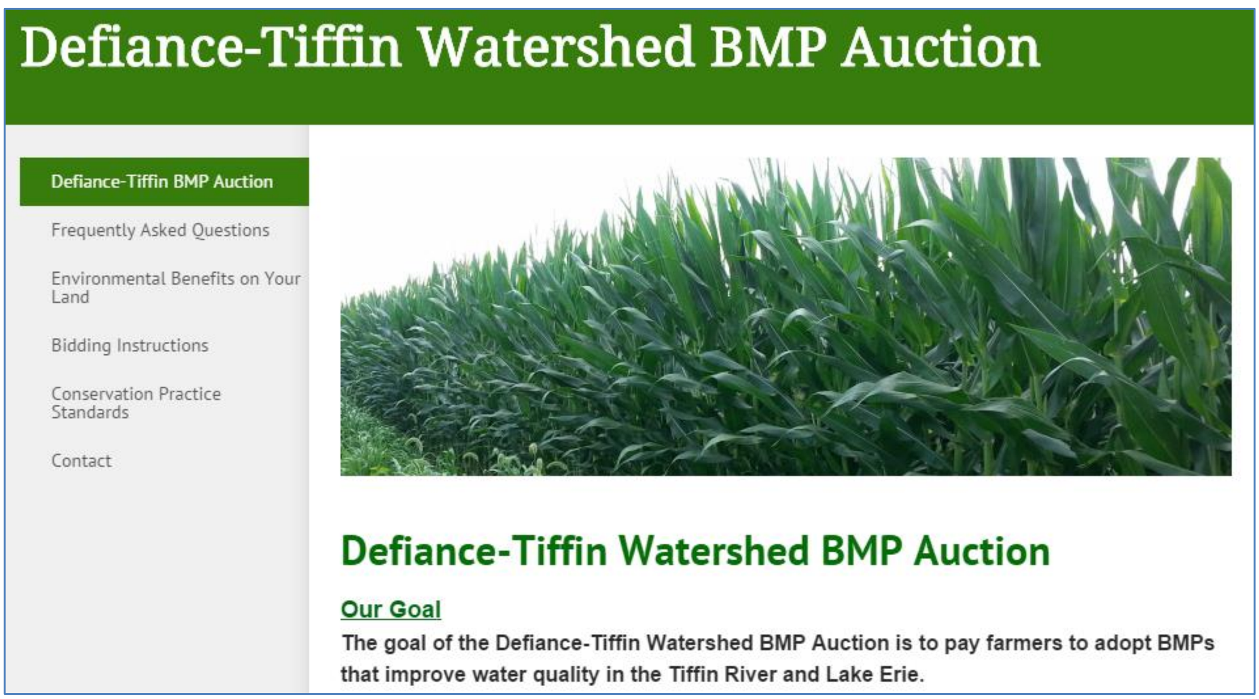


Figure A2-B-1. Screenshot of the Defiance-Tiffin BMP Auction Project website.

On July 24, 2014 an information session was held at each SWCD office to inform farmers about the auction and how to submit bids. Additionally, advertisements were posted in local newspapers to announce the auctions (Table A2-B-1; Figure A2-B-2).

Table A2-B-1. List of media attention for the conservation auctions in Fulton and Defiance Counties.

Fulton County		Defiance County	
Expositor News	June 26, 2014	Crescent News	July, 2014
Napoleon Radio	July, 2014	FSA Bulletin, Defiance	August 8, 2014
FSA Bulletin, Fulton	August 1, 2014	Farmland News	Sept 2, 2014
Farmland News	Sept 2, 2014	Crescent News	August 27, 2014

Figure A2-B-2. Announcement printed in the Farmland News, Sept 2, 2014.

Eligible practices – Three conservation management practices were eligible for funding, 1) cover crops, 2) drain water management structures, and 3) filter strips. These practices were chosen because they are particularly effective at reducing phosphorus loss, which is the main objective of this project and because they can be installed and verified before December 2015. Farmers could only bid to implement new conservation practices, not practices that they already use. Funding new practices ensures additionality, meaning that payments are procuring additional environmental benefits[41].

Bid ranking and acceptance – Bids were ranked based on the cost per unit of environmental benefit as measured by the annual reduction of bioavailable phosphorus loading (in pounds) into the local waterway. Phosphorus loading were estimated using the Soil and Water Assessment Tool (SWAT) managed by LimnoTech. Bids were accepted in order from most cost-effective to least cost-effective until the budget is exhausted. Each auction has a budget of $25,000, which is unknown to bidders.

Contract agreement – Farmers were asked to sign two agreements. First, when bids were submitted, farmers signed an agreement acknowledging their willingness to participate in the conservation program if their bid is accepted. After bid selection, accepted farmers signed a second contract that stated the amount they would be paid and detailed description of the practice(s) to be implemented (type, location, timing, etc.).

Verification – Practices will be implemented and visually verified prior to December 2015 by staff at The Nature Conservancy.

Contract noncompliance – Farmers with accepted contracts are expected to implement the practices for which they submitted the original bid prior to December 2015. Farmers who chose not to implement their contract will not receive their payment, but will not be subject to further penalty. There is a small chance of BMP failure with the cover crop due to factors out of the control of the farmer (e.g., an early freeze). If the farmer can show receipts verifying that the

[41] Farmers could stack funds from multiple payers to finance a new practice that would provide additional environmental benefits. In this auction we were unable to verify the level of payment that may be provided by other payers, so to ensure additionality we required farmers to only bid on practices that they were not currently using. Furthermore, farmers are asked not to bid on practices that they plan to implement with financial assistance from other organizations.

cover crop was planted within the agreed upon time and at the correct rate, that farmer will receive payment regardless of cover crop performance.

The auction timeline proceeded as follows:

Mar. – May – Developed connections with SWCDs staff

May – Finalized BMPs with LimnoTech team

June – Developed website and media materials

June 26 – Mailed letters to farmers that notify them about the open bidding period. Include postage paid postcard that farmers can return to have a bid sheet mailed to them.

June 26 – Websites went live: www.FultonTiffinBMPAuction.org; www.DefianceTiffinBMPAuction.org

July 1 – Bid sheets posted on website

July 21- Sept. 30 – Bidding period opened

July/Aug./Sept. –Advertisements in local newspapers announcing the auctions and answer farmer questions

July 24 – Information sessions at Fulton and Defiance SWCD Offices

Sept. 2 – Mailed follow up postcards to remind farmers to bid by Sept 30

Oct. 1st– **Nov. 14** – Evaluated bids using the SWAT model; Ranked bids; Selected projects to fund

Nov. 17 -21 – Notified winners of bid acceptance

Dec. 2015 – Accepted bidders reviewed and signed contracts.

Mar. 2015 – MSU mailed checks with first 50% of payment

Apr. 2015 – Nov. 2015 – TNC disbursed final 50% of payment upon verification that the practice was implemented.

APPENDIX 2-C INFORMATION TREATMENT

Overview

When the Tiffin BMP Auction Project was first designed, one of the research objectives was to experimentally test the impact of providing information about environmental information on the cost-effectiveness of conservation auctions. To achieve this objective, information signals were provided to landowners in Defiance Co., but withheld this information from Fulton Co. landowners. I proposed to test for differences in participation and bid levels among individuals who were provided with environmental information and individuals who were not. Low participation in the auctions limited my ability to test for effects of the information treatment, but this section provides motivation for the original auction design. An important direction for future research would be to examine the impact of information provision on participation and cost-effectiveness.

Background

Scholars agree that bids for conservation practices are affected by farmers' perceptions of the environmental value of their offer[42] (Latacz-Lohmann and Schilizzi 2005; Cason et al. 2003; Glebe 2013; Ferraro 2008), but recent research suggests that participation may also be influenced by environmental information. There are three likely impacts of information revelation on bidding strategy, 1) bids increase as farmers attempt to extract additional rents, 2) increased participation raises competition among farmers resulting in lower bids, and 3) increased participation provides the auctioneer a more favorable pool of bids.

[42] Past research has shown that individuals with high value project inflate their bids to extract additional rents (Cason, Gangadharan and Duke 2003).

In an experimental study, bids increased with higher environmental scores, suggesting that cost-effectiveness decreases when environmental information is disclosed (Cason, Gangadharan and Duke 2003). Examining bids in the Conservation Reserve Program (CRP), Jacobs and coauthors (2014) found that landowners bid strategically when they receive environmental information in the form of exogenous Environmental Benefit Index (EBI) points awarded to parcels in environmentally vulnerable regions.

Participation may also be influenced by provision of environmental information. If participation increases when information is provided, the impact will raise competition among bidders and may decrease bids. If farmers sense higher competition, their perceived probability of bid acceptance may decline. In response, farmers will reduce bids to increase the probability of bid acceptance. In a budget constrained auction, lower per unit bids result in greater procurement of desired environmental benefits. Even if individual farmers don't adjust bids, the increase in participation creates a larger pool from which bids can be selected. From the standpoint of a conservation agency, more project choices increases the chance of funding a favorable subset of bids (Glebe 2013).

Experimental Design

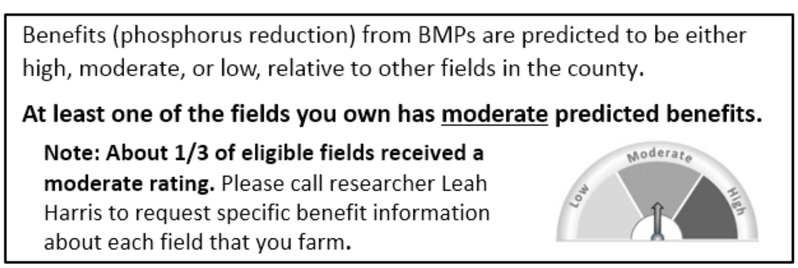
In the letter to landowners that announced the BMP auctions, Defiance Co. landowners were given a signal regarding the potential environmental benefits (low, moderate, or high) from adopting conservation practices on their land, relative to other parcels. Signals were created using the Soil and Water Assessment Tool (SWAT) model to predict the annual pounds of bioavailable phosphorus runoff from each of the 933 parcels located in Defiance Co. within the boundaries of the Tiffin watershed. Parcels were then divided equally into three bins that represented the low, mid, and high runoff loads. The 933 parcels were owned by 507 unique landowners. Farmers that had multiple parcels with different signals received the signal for the highest priority parcel they owned. Of the 507 unique landowners, 187, 165, and 155, received the high, moderate, and low information signals, respectively. Specifically, the letter provided the following information:

"Based on the soil type and location of one of your agricultural parcels, we estimate that the potential environmental benefits from BMPs on that land are (**high**, **moderate**, **low**), relative to other farms in the area. If you own more than one land parcel or farm land owned by someone else, you may request environmental benefit information for specific parcels by contacting Michigan State researcher Leah Harris at (804) 357-8510."

In the notification letter famers were also shown an image of their signal to draw attention to the information treatment.

Figure A2-C-1 Images for low, moderate, and high environmental benefit information signals

The information signals were reinforced in the reminder postcards with the statement in Figure A2-C-2. Except for the information treatment, the auctions in Fulton Co. and Defiance Co. were managed in the same manner.



Benefits (phosphorus reduction) from BMPs are predicted to be either high, moderate, or low, relative to other fields in the county.

At least one of the fields you own has moderate predicted benefits.

Note: About 1/3 of eligible fields received a moderate rating. Please call researcher Leah Harris to request specific benefit information about each field that you farm.

Figure A2-C-2. Information signal provided to farmers in the reminder postcards

APPENDIX 2-D BID PACKET

July 1, 2014

Dear Defiance County Landowner,

A new project is studying how auctions in northwest Ohio can be used to pay corn and soybean producers for adopting agricultural best management practices (BMPs) that improve water quality. As part of this research project, we will host the **Defiance-Tiffin Watershed BMP Auction**. Through the auction, we will pay producers in Defiance County to adopt BMPs that reduce the amount of phosphorus that enters the Tiffin River and flows into Lake Erie. Reducing excess phosphorus improves our water quality and limits the frequency and size of algal blooms.

<u>You are eligible to participate</u> in the auction if your land is located in Defiance County within the Tiffin River Watershed (see attached map). Participation is voluntary, but if you grow corn or soybeans, you can submit a bid to adopt one or more of the following practices: **1) cover crops, 2) subsurface drainage control structures,** and **3) filter strips**. You may bid the amount of money you would require to adopt one or more of these BMPs. **Bids may be submitted individually or jointly with other producers/landowners.** Bids will be confidential and can be submitted to the Defiance Soil & Water Conservation District (SWCD) Office between **July 21 and Sept. 30, 2014**. Project researchers will evaluate bids and select projects that reduce the most phosphorus runoff per dollar until our budget runs out. Farmers with selected projects will be notified by November 21, after which contracts will be offered for payment to implement the BMPs in 2015.

The project intends to fund practices that provide the most environmental benefits (reduced phosphorus runoff) per dollar. Based on the soil type and location of your parcel, project researchers can estimate that the potential environmental benefits from new BMPs on your land relative to other farms in the area. You may request environmental benefit information for your cropland by contacting Michigan State researcher Leah Harris at (804) 357-8510.

The bid packet is attached. To submit a bid, please read the instructions and fill out a bid sheet and management questionnaire for each field included in your bid. The attached flyer answers some commonly asked questions. For more information and to print additional bid packets, please visit our website at www.DefianceTiffinBMPAuction.org.

We will also host an information meeting on Thursday, July 24th from 7-8pm at the Defiance SWCD Office Building located at 06879 Evansport Road, Defiance 43512. Refreshments will be provided. Please let us know if you plan to attend by calling the SWCD Office at (419) 782-1794.

Sincerely,

Jason Roehrig, District Administrator
Defiance Soil & Water Conservation District
06879 Evansport Road, Suite C
Defiance, Ohio 43512
Phone: (419) 782-8751
Email: jasonroehrig@defiance-county.com

Scott M. Swinton, Professor
Agricultural, Food, & Resource Economics
Michigan State University
East Lansing, MI 48824-1039
Phone: 517-353-7218
Email: swintons@msu.edu

FREQUENTLY ASKED QUESTIONS

What is this BMP Auction?
This BMP auction is a "reverse auction" in which farmers submit bids to implement best management practices (BMPs) to the Tiffin Watershed Best Management Practice (BMP) Auction Project. Farmers compete to be the low bidder in terms of the cost per pound of predicted reduction in phosphorus entering the Tiffin River. The phosphorus reduction will be predicted using a model called the Soil and Water Analysis Tool (SWAT).

Who is eligible to bid?
Producers who currently grow corn or soybeans on land in Defiance County within the Tiffin River Watershed are eligible to submit a bid for new practices (not practices already in use). Bids can be submitted individually or jointly with another producer or landowner. A map of eligible land is attached. Farmers who rent land must have landowner permission to enroll land in this program.

Should I submit a bid individually or jointly?
We welcome both individual and joint bids. Joint bidding provides an opportunity to bid with neighbors on conservation practices that may be less costly or more effective at a group level. Any bids can be submitted jointly, even if the fields are not next to one another. If you are submitting a joint bid, please submit all bidding sheets in the same envelope. If you submit a joint bid, you may check a box to request that the component bids be evaluated individually; that way, even if the entire joint bid is not approved, one or more component bids could be approved.

Which practices are eligible?
In this auction, you can submit a bid to **use one or more** of the following practices:
1) cover crops 2) subsurface drainage control structures 3) filter strips

Can I bid on a practice that I already use?
No. You may only bid on a new practice.

How much should I bid?
Bid the amount of money that you would require to adopt the BMP(s). If you are not sure, talk with folks at the Soil and Water Conservation District Office or ask a friend who uses the practice.

Note: Lower bids increase your chance of being accepted, because they reduce the cost to the Tiffin Watershed BMP Project. But lower bids also reduce the amount of money you will be paid if your bid is selected. A good bidding strategy is to bid the lowest amount of money you will accept to adopt the BMP. This gives you the best chance of being selected while making sure you will be paid enough to make the BMP worthwhile.

How do I submit my bid in the Tiffin River Watershed BMP Auction?
Follow the instructions on the bidding sheet. Complete your bidding sheet and return it to the Defiance SWCD Office at, **06879 Evansport Road, Suite C, Defiance, OH 43512.**

When is the bidding deadline?
September 30, 2014.

When will I find out if I won the auction?
We will notify farmers about bid acceptance by November 21, 2014.

If I win, when do I have to implement the BMP?
Producers with accepted bids will implement the BMP before November 1, 2015.

Defiance-Tiffin Watershed BMP Auction Eligibility Areas

Corn and soybean acreage in Defiance County within the Tiffin Watershed is eligible for the Defiance-Tiffin BMP Auction. The eligible area is shaded in the map below.

If you are not sure if your land is eligible call or email MSU researcher Leah Harris
Phone: (804) 357-8510; Email: leahmh@msu.edu

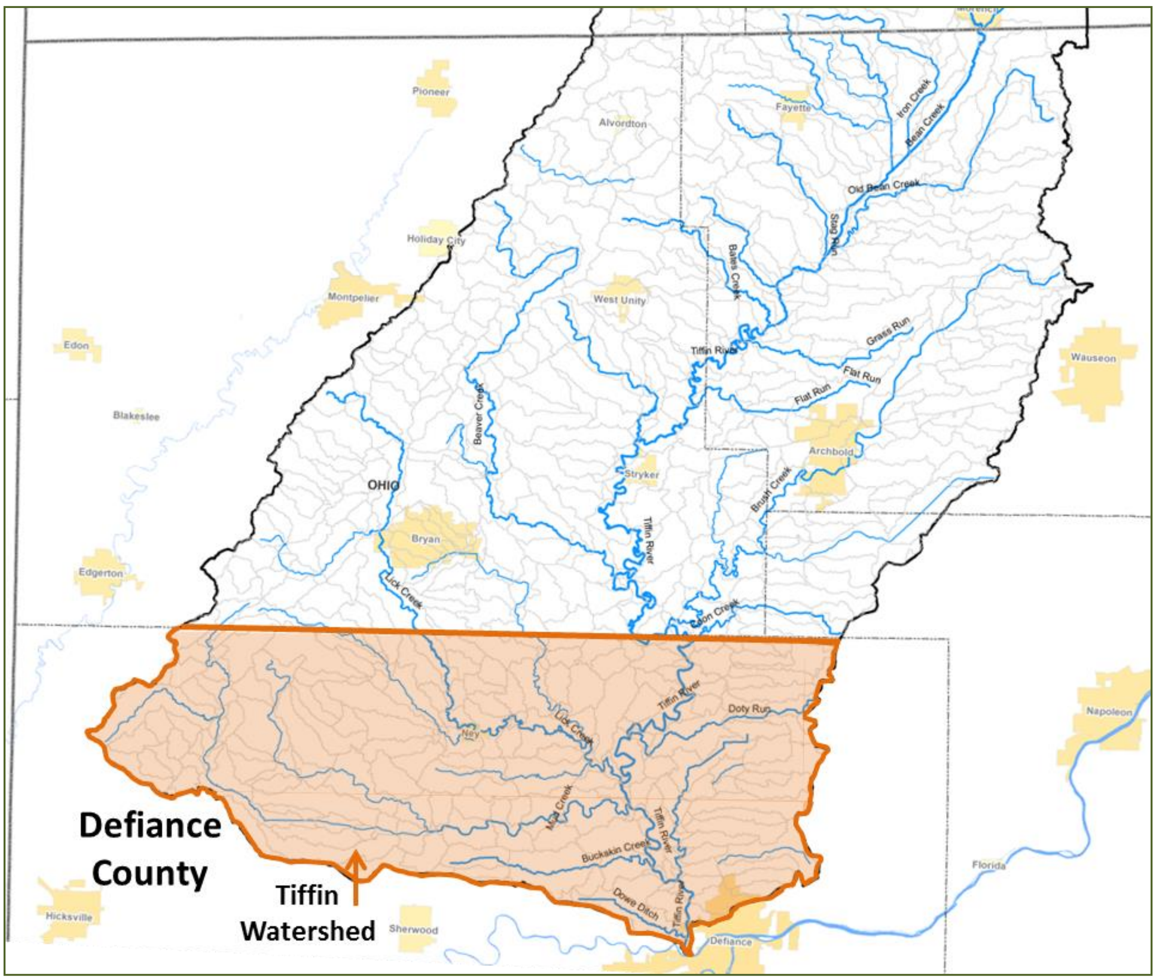


Figure A2-C-3. Eligibility area for the Defiance-Tiffin Watershed BMP Auction

Defiance-Tiffin Watershed BMP Auction
~Summer 2014~

<u>Bid Summary</u>

Please include this page as the cover page when you submit your bids.

Fill out a separate bid sheet for each field included in your bid. Extra bid sheets can be downloaded and printed from our website www.DefianceTiffinBMPAuction.org or picked up at the Defiance SWCD office.

Date:________________

Which type of bid you wish to submit? (check one)

☐ **Individual bid (<u>single</u> landowner/producer)**

An individual bidder may submit bids for multiple fields.

☐ **Joint bid (<u>multiple</u> landowners/producers)**

Joint bids are evaluated together. If we cannot accept the entire bid, we can also evaluate the bids individually. How you would like your joint bid to be reviewed? (check one)

- ☐ Only evaluate the joint bid together and do not evaluate the bids separately.
- ☐ Evaluate the joint bid first, but also evaluate the component bids individually.

Please provide information about each bid included in your bid packet.

Field #	Name of bidder	Bid Total ($)
Field 1		
Field 2		
Field 3		
Field 4		
Field 5		

** If you are submitting bids for more than 5 fields, please write down all of the bidder names and bid totals on a separate sheet of paper and attach it to this page.

BIDDING INSTRUCTIONS

- Cropland dedicated to corn and soybeans is eligible if it is located in Defiance County within the Tiffin River Watershed. *See attached map.*
- The conservation practices eligible for payments under the Tiffin River BMP Auction are defined in the U.S. Department of Agriculture, Natural Resources Conservation Service (NRCS), Conservation Practice Standards. Standards for each practice are available on our website: www.DefianceTiffinBMPAuction.org. You may also contact the Defiance Soil and Water Conservation District (SWCD) office with questions regarding the practices.
- Submit a bid to request funding to implement a new BMP on cropland you manage. <u>Funds are only available for new BMPs, not for BMPs that are already in use.</u>
- Bids may be submitted individually or jointly by multiple farmers.
- Please submit a separate bid for each field. Producers may submit bids for multiple fields and practices. Include a map of each field, which is available free of charge from the Defiance SWCD.
- Please complete the attached management sheet to indicate your current and planned management for each field that you are bidding on for new BMPs.
- The project team reserves the right to cap the amount that a single landowner/producer can receive to $10,000.

BMP Definitions for 2014 Tiffin Watershed BMP Auction Project:

- **Cover Crop (1 year contract):** Grasses or legumes grown during the off-season when cash crops are not being produced. Cover crops reduce erosion from wind and water, improve soil health, manage excess nutrients, conserve soil moisture, and increase biodiversity.

  Plant species, seedbed preparation, seeding rates, seeding dates, seeding depths, and planting methods will be consistent with approved local criteria and site conditions (See Ohio Conservation Practice Standard #340). *Examples of cover crops include: cereal rye, wheat, oats, annual ryegrass, clovers, oilseed radish, winter peas, cow peas, turnips, and hairy vetch.*
- **Filter strip (2 year contract):** A grass strip in a cropland field seeded to appropriate seeding mixtures to filter sediment, nutrients, pathogens and pesticides from getting into surface drains or waterways. See Ohio Conservation Practice Standard #393 for more details.

  Indicate how many acres will be treated with this filter strip. *Ex. If a 300 ft. long, 30 ft. wide filter strip treats runoff from 25 acres of the field, then enter 25 treated field acres.*
- **Subsurface drainage control structure (2 year maintenance contract):** A structure in a water management (drainage) system that controls the rate of flow and maintains a desired water surface elevation. Please contact Jason Roehrig at the Defiance SWCD Office to determine how many acres would be treated by your proposed control structure. A drainage engineer must approve the installation of the control structure before funds are disbursed. See Ohio Conservation Practice Standard #554 for more details.

Next Steps:
Bids received during the bid submission period (below) will be evaluated to determine the environmental benefits of the proposed BMPs by calculating the reduction in total phosphorus runoff from each proposal. Bids will be ranked by how much total phosphorus runoff is reduced per dollar. The bid that provides the highest reduction in phosphorus runoff at the lowest cost will be contracted first. Then, the next "best" bids will be accepted until funds run out.

Important Dates:
Bids must be received **by September 30, 2014.**
You will be notified about bid acceptance **by November 21, 2014.**

~Bid Sheet – Field #1~

Important: Please submit a separate bid sheet for each field you wish to enroll.

Bidder name: ____ Date:______________

Home Address: ____

Phone: _________________________________ Email: ___________________________

Field Location___________________________ Field Size:_______ acres

***Please attach an aerial map of this field – available at the Defiance SWCD office.*

✓	BMP – see next page for definitions	Treated Field Acres	Bid per acre	Total Bid
☐	**Cover Crop:** Type________________________________ Planting method: ☐ Broadcast ☐ Drill ☐ Aerial (fly on) Planned planting date: Will you harvest the cover crop? ☐ Yes ☐ No Will you use a chemical herbicide to kill the cover crop? ☐ Yes ☐ No Planned kill date: __________ Will you till after the cover crop? ☐ Yes ☐ No		*$_____ per acre of cover crops.*	$
☐ ☐ ☐ ☐	**Filter strip** (please select one) *Attach a map that shows the location of the filter strip* 30 ft. wide – Cool Season Grasses; Length ________ ft. 30 ft. wide – Warm Season Grasses; Length ________ ft. _____ ft. wide –Cool Season Grasses; Length ________ ft. _____ ft. wide –Warm Season Grasses; Length ________ ft.			$
☐	**Subsurface Drainage Control Structure** *Attach a map that shows the location of the control structure and how many acres are treated.*			$
	BID TOTAL (add bids for all BMPs)			$

By signing this bid you agree to participate in the 2014 Defiance-Tiffin Watershed BMP Auction. You will not be able to revise or change this bid. Submission of a bid does not guarantee funding. Before funding is awarded, individuals with accepted bids will be asked to sign a contract to commit to adopting the BMP(s) listed in the bid above.

Signatures (need both producer and landowner signatures for rented land):

Producer ____ Date________________

Landowner ____ Date________________

<u>Questionnaire for Field #1</u>: Please fill out a separate questionnaire for each field.

Please tell us about your management practices **<u>for the field that you will implement the BMP(s) on if your bid is selected</u>**. *Staple this sheet to your bid sheet.*

1. **What crop rotation do you use?** (*Ex: Corn-Corn-Soybean*)

____

2. **How would you describe the most common soil textures in this field?** *(check all that apply)*

☐ Sand ☐ Clay
☐ Silt ☐ Other (please specify_________________
☐ Loam

3. **Do you have filter strips, buffers, or grassed waterways that filter runoff from this field? Yes No**

If yes, how big is the filter/buffer and what proportion of water flowing through this field flows through it?

The filter strip / buffer is _______ feet wide, ______ feet long, and ______% of the field drains into this area.

4. **Is the field tile drained? Yes No If 'yes' please answer the questions below.**

What is the most common spacing of drainage pipes?	☐ less than 20 feet ☐ 36 – 50 feet ☐ 20 – 35 feet
The average depth of the drainage pipes?	☐ less than 3 feet ☐ 3-4 feet ☐ more than 4 feet
What is the diameter of the pipes?	☐ 8 inches or less ☐ more than 8 inches
Is drainage controlled by subsurface drainage control structure(s)? If yes, how many acres are controlled by the drainage control structure?	☐ Yes, _________acres controlled ☐ No

2013 Management: Please tell us about how you managed this field <u>last year</u>

i. **2013 Crop**_____________________________________

Approximate planting date _______________ Approximate harvest date_________________

ii. **Did you use a cover crop after your 2013 crop? Yes No**

If yes, which cover crop or mix ____

Approximate date of planting __________________ Approximate date of harvest/kill____________________

iii. **Please tell us about your nutrient/fertilizer applications in 2013.**

	Type/Source	Application Rate (average)	Application Method
Application before or at time of planting		lbs./acre ☐ Uniform rate ☐ Variable rate	☐ Surface applied ☐ Incorporated
Side dress application		lbs./acre ☐ Uniform rate ☐ Variable rate	☐ Surface applied ☐ Incorporated
Post-harvest fertilizer application		lbs./acre ☐ Uniform rate ☐ Variable rate	☐ Surface applied ☐ Incorporated

Please complete the back of the form →

iv. **What type of tillage did you use in 2013?** (*check applicable boxes*)

Description of Tillage Operation	**Approx. date**
☐ **No-till**………………………………………	________________
☐ **Reduced (conservation tillage)** Depth: _____ inches; Residue left: _______%	________________
☐ **Moldboard plow or deep tillage** Depth: _____ inches; Residue left: _______%	________________
☐ **Other; Type:** _____________ Depth: _____ inches; Residue left: _______%	________________

2014 Management: Please tell us about how you are managing this field this year

i. **2014 Crop**___________________________________

Approximate planting date ______________ Approx. planned harvest date_________________

ii. **Do you plan to use a cover crop after your 2014 crop? Yes No**

If yes, which cover crop or mix ____

Planned planting date (approx.) ____________ Planned harvest/kill date (approx.) _____________

iii. **Please tell us about the nutrient/fertilizer applications in 2014, including planned applications.**

	Type/Source	Application Rate (average) (lbs /acre)	Application Method
Application before or at time of planting		lbs./acre ☐ Uniform rate ☐ Variable rate	☐ Surface applied ☐ Incorporated
Side dress application		lbs./acre ☐ Uniform rate ☐ Variable rate	☐ Surface applied ☐ Incorporated
Post-harvest fertilizer application		lbs./acre ☐ Uniform rate ☐ Variable rate	☐ Surface applied ☐ Incorporated

iv. **What type of tillage have you used or do you plan to use in 2014?** (*check applicable boxes*)

Description of Tillage Operation	**Approx. date**
☐ **No-till**………………………………………	________________
☐ **Reduced (conservation tillage)** Depth: _____ inches; Residue left: _______%	________________
☐ **Moldboard plow or deep tillage** Depth: _____ inches; Residue left: _______%	________________
☐ **Other; Type:** _____________ Depth: _____ inches; Residue left: _______%	________________

APPENDIX 2-E FOLLOW-UP QUESTIONNAIRE

MICHIGAN STATE UNIVERSITY

A Few Questions about the Defiance-Tiffin BMP (Best Management Practice) Auction of 2014

1 **Please tell us if you heard about the Defiance-Tiffin BMP Auction from any of these sources. Check either "Yes" or "No" for each option.**

	Yes	No
A letter or postcard in the mail.	☐	☐
A newspaper article	☐	☐
The auction website: www.DefianceTiffinBMPauction.org	☐	☐
The Defiance Soil & Water Conservation District (SWCD) Office	☐	☐
A friend or family member	☐	☐
Other: (please specify)____		

2 **Did you get a BMP Auction bid packet in any of these ways? Check either "Yes" or "No" for each option.**

	Yes	No
In the mail	☐	☐
From the auction website: www.DefianceTiffinBMPauction.org	☐	☐
From the Defiance SWCD office.	☐	☐
I got a bid packet from somewhere else (*Please specify*): ________________________________		

3 **We did not receive a bid from you and we would like to understand why. <u>Do these reasons for not bidding apply to you? (Check "Yes" or "No")</u>**

	Yes, this applies to me	No, this does not apply
I did not hear about the BMP auction.	☐	☐
I did not think I was eligible to bid.	☐	☐
I meant to submit a bid, but I missed the deadline.	☐	☐
I do not own or manage cropland within the Tiffin Watershed	☐	☐
I already participate in another program that pays me for these BMPs	☐	☐
I did not want to adopt any of the three eligible practices.	☐	☐
I did not understand how to submit a bid.	☐	☐
The auction seemed complicated or time consuming.	☐	☐
I did not think my bid would be accepted.	☐	☐
My land rental agreements would make participation difficult.	☐	☐
I did not bid because the BMP Auction was a new research project.	☐	☐
Other reason for not bidding: (*please explain*)____		

Please continue to <u>Question 4</u> on the back of the questionnaire

4 **Do you currently use any of these management practices on your cropland?**

	Yes, on **all** of my land	Yes, on **some** of my land	**No**
Cover crops during the winter (ex: rye, radish, clover, etc.)	☐	☐	☐
Filter strips, riparian buffers, or grassed waterways	☐	☐	☐
Conservation tillage or no-till	☐	☐	☐
Subsurface drain water control structures	☐	☐	☐
Nutrient management plan (ex. 4R nutrient stewardship)	☐	☐	☐
Other practices: (*please specify*)____________________	☐	☐	

5 **How strongly do you agree or disagree with these statements?**

	Strongly agree	**Agree**	**Neutral**	**Disagree**	**Strongly disagree**
By their choice of management practices, crop farmers can affect water quality.	☐	☐	☐	☐	☐
Farmers have a responsibility to manage cropland in a way that protects water quality.	☐	☐	☐	☐	☐
I feel good about using management practices that improve water quality.	☐	☐	☐	☐	☐
Environmental stewardship only makes sense on my farm if it also contributes to income.	☐	☐	☐	☐	☐
Conservation auctions take more time to participate in than other conservation programs	☐	☐	☐	☐	☐
I work closely with conservation agencies like the SWCD, NRCS, or other groups.	☐	☐	☐	☐	☐

6 **How much total acreage in corn, soybeans, or wheat did you own, rent in, and rent out in 2014?**

Owned: __________ **acres**

Rented in: __________ **acres**

Rented out: __________ **acres**

7 **What percentage of your total household income is from farm related activities?** ________**%**

8 **May we have your email in case we have follow-up questions?** **Email:** ______________________

Thank you for completing our questionnaire! <QID>

APPENDIX 2-F DESCRIPTIVE STATISTICS FROM QUESTIONNAIRE

Table A2-F-1. Summary statistics for cropland ownership, rental, and farm income of questionnaire respondents.

Variable	Unit	N = no. of responses	Mean	Std. Dev.	Min	Max
Cropland owned	acres	389	222	321	0	2500
Rented In [a,c]	acres	389	148	415	0	3500
Rented Out [b,c]	acres	389	659	118	0	1300
Income from farming (%)	%	351	42	35	0	100

[a] 35% of respondents reported renting in land
[b] 46% of respondents reported renting out land
[c] 77% of respondent reported either renting in or renting out land.

Table A2-F-2. Summary of responses to Likert scale attitudinal questions on follow-up questionnaire (Question #5)

Variable	N	Mean	Strongly Agree = 5	Agree=4	Neutral = 3	Disagree = 2	Strongly Disagree = 1
Farmers can affect water quality.	390	1.9	96 (25%)	241 (62%)	42 (11%)	9 (5%)	2 (1%)
Farmers have a responsibility to manage for water quality.	390	1.9	93 (24%)	253 (65%)	37 (09%)	6 (2%)	1 (<1%)
I feel good about using practices that promote water quality.	382	2.0	92 (24%)	217 (57%)	69 (18%)	4 (1%)	0 (0%)
Stewardship only makes sense if it generates income.	380	2.7	45 (12%)	129 (34%)	120 (32%)	75 (20%)	11 (3%)
Conservation auctions take more time than other programs.	356	2.7	21 (06%)	79 (22%)	239 (67%)	12 (3%)	5 (1%)
I work closely with conservation agencies.	369	2.7	34 (09%)	100 (27%)	189 (51%)	36 (10%)	10 (3%)

Table A2-F-3. Correlation matrix for reported participation deterrents of all respondents

	Did not know about it	Not eligible	Missed the deadline	Do not own cropland	Paid by another program	Do not want to adopt BMPs	Do not understand how to bid	It seems complicated	Do not think my bid will be accepted	Rental agreements	It is a new research program
Did not know about it	1.00										
Not eligible	-0.04	1.00									
Missed the deadline	-0.06	0.06	1.00								
Do not own cropland	0.01	0.55	0.05	1.00							
Paid by another program	-0.15	0.08	0.07	0.03	1.00						
Do not want to adopt BMPs	-0.16	-0.02	0.03	0.03	0.00	1.00					
Do not understand how to bid	0.01	0.26	0.15	0.21	-0.03	0.03	1.00				
It seems complicated	-0.17	0.10	0.13	0.06	0.09	0.17	0.45	1.00			
Do not think my bid will be accepted	-0.18	0.13	0.24	0.03	0.15	0.16	0.19	0.43	1.00		
Rental agreements	-0.05	0.10	0.02	0.22	-0.06	0.07	0.07	0.05	0.09	1.00	
It is a new research program	-0.09	0.17	0.18	0.11	0.07	0.21	0.30	0.34	0.27	0.09	1.00

Table A2-F-4. Correlation matrix for reported participation deterrents of respondents who were knowledgeable about the auction, eligible to bid, and willing to adopt one of the three eligible BMPs, n=145.

	Did not understand how to bid	Auction seemed complicated	Did not think my bid would be accepted	It was a new program
Did not understand how to bid	1			
Auction seemed complicated	0.38	1		
Did not think my bid would be accepted	0.04	0.23	1	
It was a new program	-0.02	0.07	0.35	1

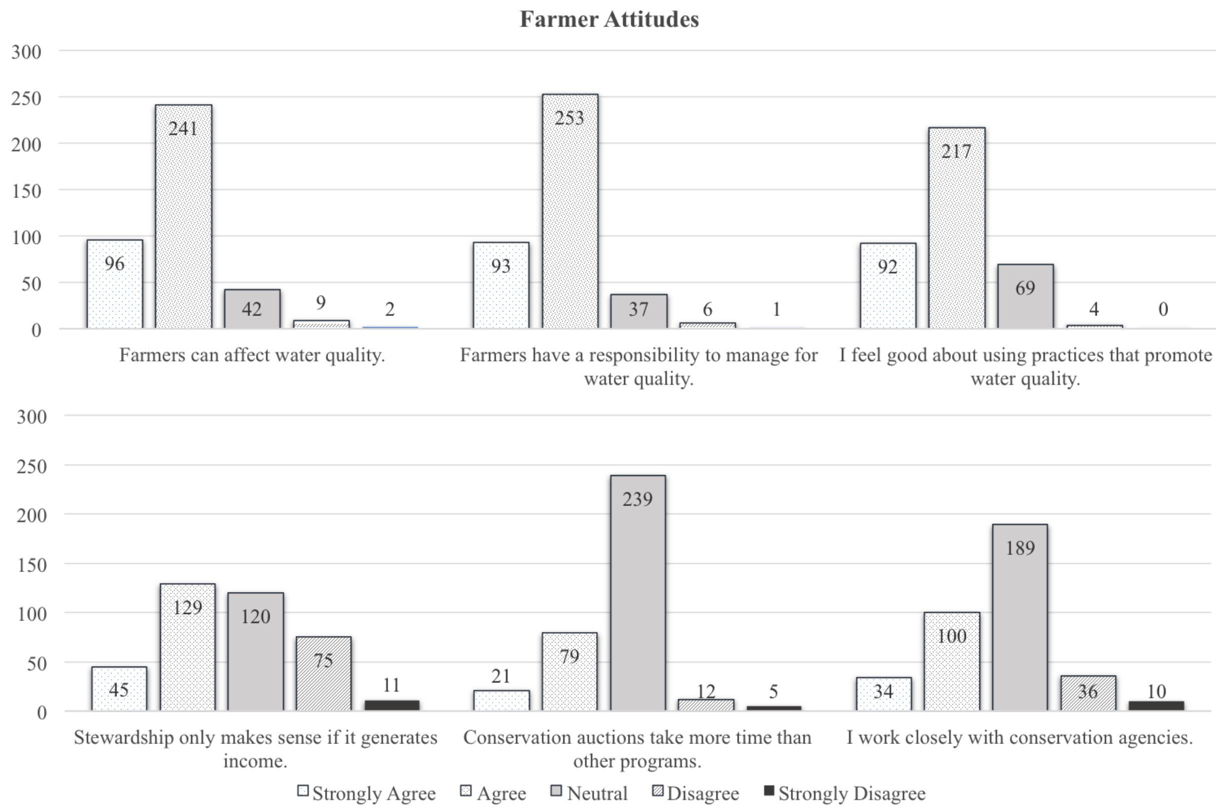


Figure A2-F-1. Responses to Likert scale attitudinal questions (Question #5)

APPENDIX 2-G OTHER CONSERVATION PROCUREMENT AUCTIONS

Table A2-G-1. Overview of conservation procurement auctions that have been conducted from 2000 – 2012.

Auction Name	Reference	Goal	# of rounds	Bid Submission	Pricing Mechanism	Ranking	Information feedback	Bid acceptance	Contract length
ICRAF Pilot Auction for Erosion Mitigation (Indonesia)	Ajayi et al., 2012	erosion mitigation	seven non-binding and one binding round	sealed bid	uniform, nth price that equaled the price of the lowest rejected	ranked on bid amount	price information withheld	no reserve	one year
Conservation Easement Auctions (Canada)	Brown et al., 2011	land conservation using easements	single	mailed in a bid booklet	uniform, nth price that equaled the price of the lowest rejected bid	bids were converted to the percentage of assessed value of the land	reserve price withheld	hidden reserve price	multi-year conservati on easement
Catchment Care (Australia)	Connor et al., 2008	watercourse and riparian restoration	single	sealed bid	discriminatory, first price	bids ranked based on cost-effectiveness i.e. EBI score divided by bid price	information withheld	no reserve, bids accepted until budget constraint	-
EcoTender	Eigenraam et al., 2005	multiple objectives	single	sealed bid	discriminatory, first price	multiple outcome index of cost-effectiveness based on the Catchment Modeling Framework (CMF)	revealed information about ranking metrics	no reserve, bids accepted until budget constraint	five or ten years

Table A2-G-1. (cont'd)

Auction Name	Reference	Goal	# of rounds	Bid Submission	Pricing Mechanism	Ranking	Information feedback	Bid acceptance	Contract length
Assiniboine River Watershed (Saskatchewan, Canada)	Hill et al., 2011	wetland restoration	two	sealed bid via phone	discriminatory, first price	bids ranked based on price and an EBI	benefits withheld, feedback about provisional bid acceptance after first round	bids rejected for exceeded the fair market value; bids accepted until budget constraint was met	12 year
Conestoga Watershed Reverse Auction (Pennsylvania, USA)	Selman et al, 2008	improved water quality in the Conestoga Watershed	single	sealed bid	discriminatory, first price	ranked based on price per pound of reduced phosphorus runoff	-	no reserve, bids accepted until budget constraint	varied
Pomona Lake Watershed (Kansas, USA)	Smith et al., 2009	improved water quality in Pomona Lake	single	sealed bid	discriminatory, first price	ranked by the tons of predicted sediment reduction (at Pomona Lake) per dollar	no feedback provided	no reserve, bids accepted until budget constraint	varied
Victoria's BushTender Trial (Australia)	Stoneham et al., 2003	increase biodiversity	single	sealed bid	discriminatory, first price	bids ranked based on Biodiversity Benefits Index (BBI) divided by bid	benefits score withheld	no reserve, bids accepted until budget constraint	multi-year

Table A2-G-1. (cont'd)

Auction Name	Reference	Goal	# of rounds	Bid Submission	Pricing Mechanism	Ranking	Information feedback	Bid acceptance	Contract length
Great Barrier Reef Auctions (Australia)	Rolfe and Windle, 2011b	water quality improvements in the Great Barrier Reef	multiple	sealed bid	discriminatory, first price	bids ranked on price and EBI	reserve price withheld	hidden reserve price	one year
Lenawee County Conservation Auctions (Michigan, USA)	Personal commun-ication and Sommerlot et al., 2013	reduced sediment flow and erosion	two - some bids accepted in first round	sealed bid	discriminatory, first price	bids ranked on tons of sediment reduction per dollar	no feedback provided	no reserve, bids accepted until budget constraint	one year

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ESSAY 3. BENEFIT TRANSFER TO ESTIMATE WELFARE LOSS FROM LAKE ERIE BEACH CLOSURES AT MULTIPLE SCALES[43]

3.1 Introduction

Up-to-date and timely information about how resource management decisions influence the value of ecosystem services is necessary to make informed policy decisions. However, well-executed nonmarket valuation studies are time consuming and costly to implement. Benefit transfer – a method that uses nonmarket values of a resource calculated in a primary study to evaluate a proposed or observed change to a similar resource in a different setting – is especially useful to answer urgent policy questions when constraints on time or money inhibit primary data collection (Freeman, Herriges and Kling 2014).

In this essay, a benefit transfer is used to estimate how the recreational value of Lake Erie beaches is affected by harmful algal blooms (HABs)[44]. To conduct the transfer, I use welfare estimates and welfare functions from an original study of Michigan beaches (i.e., the "study site") to estimate welfare losses from closures of Lake Erie beaches (i.e., the "policy site.") This research is particularly relevant because, in the last decade, the Western Lake Erie Basin (WLEB) has experienced frequent and intense HABs spurred primarily by agricultural phosphorus runoff. Policymakers and stakeholders want timely information about the causes and impacts of HABs. Benefit transfer methods are especially useful in this case because researchers can quickly respond to requests for value estimates when primary data are unavailable.

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[43] A version of this chapter has been submitted for publication: Palm-Forster, L.H., F. Lupi, and M. Chen. Valuing the impact of harmful algal blooms on Lake Erie beaches: Is it worth it? *In review*.
[44] HABs generate numerous negative impacts that can result in welfare losses, but this study estimates only the welfare losses from beach closures. I acknowledge that the magnitude of total welfare loss from HABs may be far greater. This study is an example of how a benefit transfer can be used to estimate welfare losses due to HABs. Future studies that estimate other welfare losses are needed.

The goals of this essay are two-fold. First, I use two benefit transfer methods (value transfer and function transfer) to estimate the value of Lake Erie beaches and the welfare loss from hypothetical beach closures due to HABs. Second, I analyze how the relative merit of function transfers and value transfers differs depending on the availability of behavioral and economic data in the policy setting and the scale of environmental damage being assessed (in this case, it is the number of beach sites that are closed due to HABs).

The methodological contribution of this essay is motivated by the fact that there are several benefit transfer methods that can be used to estimate resource values in a policy site, each with its own advantages and disadvantages. When selecting the appropriate method, researchers face a tradeoff between simplicity and the ability to more accurately represent the unique characteristics of the policy site and population that would be affected.

The simplest transfer method involves transferring a single, point estimate of value from the study site to the policy site. This method is quick and straightforward, but it does not account for differences between the study site and policy site and assumes that the conditions of the study site, in which the point value was estimated, are also representative of conditions of the policy site. When valuing recreational sites, a value transfer does not capture how the choice sets differ between the study site and policy site. Accounting for the availability of site alternatives is important because fewer site alternatives limits the substitutes available when a site closes and can lead to substantial welfare losses.

A benefit function transfer is a more complex approach and refers to the process of using an estimated value function from one or more original studies to value a resource at a policy site (Boyle et al. 2010). Broadly speaking, the literature tends to favor function transfers over value transfers because they are more flexible and can account for heterogeneous population characteristics and amenity attributes between the study site and policy site (Kaul et al. 2013; Boyle et al. 2010; Johnston and Rosenberger 2010; Brouwer and Spaninks 1999). However, function transfers are more time consuming and require additional data from the policy site to calibrate the value function. When planning to conduct a benefit transfer study, researchers are faced with a question, “Is a function transfer worth it?”

McConnell (1992) emphasizes that benefit transfer estimates rely, at least in part, on the judgment of the researcher. Therefore, it is up to the researcher to critically evaluate original studies to determine the appropriateness of transferring values or model results. Past research has aimed to answer the question, “When is it appropriate to use benefit transfer in estimating values for policy analysis and when would we expect there to be positive returns to conducting original research?” (Allen and Loomis 2008, p.4). In a similar spirit, this essay provides insight about conditions under which function transfer is preferred to value transfer.

To evaluate the merit of employing a more complicated transfer method, I compare welfare losses from HABs when losses are obtained from a value transfer versus a benefit function transfer. Losses are estimated for single beach closures as well as “regional” closures (i.e., closures of groups of beaches). I determine how estimated losses differ depending upon the transfer method used and the number of beach sites affected in the hypothetical closure scenarios.

In the context of transferring values from travel cost models, this research found that benefit function transfer was essential to estimate beach demand (trips) and demand elasticity (change in trips), but yielded results very similar to a simple value transfer if changes in trip demand were known[45] and closures only occurred a single beach. Deviations between estimates from the two transfer approaches increased exponentially as more beaches closed due to HABs. When environmental conditions considerably change the choice set of beaches, a benefit function transfer approach that more fully accounts for site substitution effects and price elasticity of trip demand is preferred. If benefit function transfer is infeasible, identifying a study site with a comparable scale of beach closures to that of the policy site will facilitate a more applicable value transfer.

3.2 Benefit transfer approaches, best practices, and applications

3.2.1 An overview

In the United States and Europe, benefit-cost analyses are frequently required by governments to evaluate the potential impacts of proposed policies or management plans (Boyle et al. 2010; Johnston and Rosenberger 2010). Constraints on time and funding limit the ability to use primary valuation studies to inform these analyses; therefore, benefit transfers are often the only feasible option. Application of benefit transfer dates back to the 1960s, but an increasing demand for reliable benefit transfer methods spurred researchers to develop more sophisticated approaches and to identify best practices.

In the 1990s, a significant amount of research was conducted to formalize the procedures and protocols of benefit transfer, including research presented in a special section of *Water Resources Research* (1992, Vol. 28, 3) (Brookshire and Neill 1992) and a book that elucidated

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[45] Ex post, I do not know the number of trips that are displaced by beach closures for all of the Lake Erie sites analyzed. Instead, the participation model from Chen (2013) is used to estimate the number of trips taken to each site. I then conduct a value transfer using point estimates from Chen (2013) assuming that the estimated number of displaced trips is accurate.

methodological advancements (Desvousges, Johnson and Banzhaf 1998). Fourteen years later, advancements of the approach were highlighted in a special issue of *Ecological Economics* (2006, Vol. 60, 2) (Wilson and Hoehn 2006) and in two edited books (Rolfe and Bennett 2006; Navrud and Ready 2007). In the past five years, two excellent review papers have summarized challenges and opportunities for using benefit transfer (Boyle et al. 2010; Johnston and Rosenberger 2010) and a new handbook provides guidance for researchers and practitioners using transfers (Johnston et al. 2015). This rich research history is highlighted to emphasize the ongoing relevance of benefit transfer approaches and the need for continuous refinement of our methods and protocols.

Benefit transfers allow researchers to use valuation estimates from a "study site" to estimate values of a similar resource in another "policy site." Values can be transferred from original studies using a variety of nonmarket valuation approaches, including revealed-preference methods (e.g., travel cost, hedonic models) and stated-preference methods (e.g., contingent valuation). Methods include value transfers, function transfers, and meta-analytic approaches that can utilize both value and function transfer techniques. Value transfer is the simplest method and involves using a single summary statistic (e.g., mean willingness-to-pay) from an original study to estimate value at a policy site. A meta-analytic approach to value transfers uses the mean or median of values at multiple study sites to estimate resource value at a policy site. This has been referred to as a measure of central tendency transfer (Rosenberger and Loomis 2003). Function transfers, on the other hand, involve the transfer of a statistical model that estimates the value of a resource while accounting for unique characteristics of the policy site. Function transfers allow the value to vary because of heterogeneity between the study site and policy site, whereas point value transfer cannot account for differences between these sites.

Function transfers can be divided into two categories: 1) reduced-form meta-analysis and 2) structural transfers[46] (Boyle et al. 2010).

3.2.2 Best practices

Controversy surrounding benefit transfer "best practices" has led to a significant body of research that aims to identify an agreed upon set of protocols for benefit transfer. Boyle and coauthors (2010) synthesize this body of research and they present a unifying framework for implementing benefit transfers. Much of the research has focused on how to reduce transfer error – the difference between the true valuation and the valuation estimated using benefit transfer. There is general consensus on two principles: 1) to reduce transfer error, the study site and policy site should be as similar as possible – including similarity among populations, resources, markets, and site attributes, and 2) benefit function transfers are more accurate than value transfers. Boyle and coauthors (2010) note that these two principles are related because the equations used in function transfers are used to calibrate for differences between the study and policy site, thus reducing the emphasis on similarity requirements.

Values of recreational amenities can differ between the study site and policy site because of differences in supply-side factors and/or demand-side factors (Freeman et al. 2014). Supply-side factors include amenity characteristics, like on-site parking and beach length. Demand-side factors refer to characteristics of the population that values the resource, including preferences and socio-economic characteristics. The preference for function transfers is largely attributed to

[46] Structural transfers can include both preference function transfers and preference calibration. Preference transfers use the estimated parameters from an original study to transfer a utility function to the policy site, as I do in this essay. Preference calibration uses estimated nonmarket values from an original study to calibrate the parameters of a utility function built by the researcher. Boyle et al. (2010) and Johnston and Rosenberger (2010) present good overviews of these methods.

the flexibility this method provides to account for heterogeneity in amenities and population characteristics, thus reducing transfer error when estimating values in a new policy site (Kaul et al., 2013). Rosenberger and others (2003) present validity tests for 13 benefit transfer studies and report that function transfers are generally more accurate than value transfers, though the range of errors are considerable for both approaches (Rosenberger and Loomis 2003, p.458). The superior performance of function transfers is attributed to the researcher's ability to tailor the function to better reflect attributes of the policy site, thus increasing precision and reducing transfer error (Rosenberger and Loomis 2003). It should be noted, however, that this method relies on the assumption that the statistical relationships between the independent and dependent variables used to model the study site are the same in the policy site, making results only as accurate as this assumption (Rosenberger and Loomis 2003). A drawback of function transfers is that this approach is time consuming to implement and some literature suggests that function transfers do not outperform value transfers in all circumstances (Barton 2002).

Researchers have agreed that error is minimized in benefit transfer studies when certain conditions hold. By expanding on conditions for benefit transfers first identified by Boyle and Bergstrom (1992), Loomis and Rosenberger (2006) describe three criteria that affect reliability and validity of benefit transfer estimates, 1) commodity consistency, 2) market consistency, and 3) welfare measure consistency. The first two conditions imply that the nonmarket commodity being valued and the affected populations in the original study site and the new policy site should be similar. The third condition implies that the assignment of property rights at each site should lead to the same welfare measure. Boyle and coauthors (2010) develop a conceptual framework of benefit function transfers around four "***S***-conditions", 1) separability (utility must be separable at both the original study site and policy application site), 2) specification (the study-site and policy-site models must be correctly specified), 3) sorting (unobserved preferences do not systematically vary between subjects at the study site), and 4) selection (data on the characteristics of subjects in the study and their choices must be free of selection problems).

3.2.3 Relevant applications in literature

Applications of benefit transfer are plentiful as they are frequently used to facilitate benefit-cost analysis and other policy-driven valuation needs. For example, the USDA uses function transfers to estimate water quality and wildlife habitat provided by agricultural best management practices (BMPs) subsidized by the Conservation Reserve Program and the Environmental Quality Incentives Program (Boyle et al. 2010, Natural Resources Conservation Service 2005). Examples of benefit transfer are also found in the academic literature, but these studies tend to focus more on the methodology of benefit transfer rather than being conducted solely for the purpose of resource valuation. Instead of summarizing the scope of the benefit transfer literature[47], three studies are highlighted that employ benefit transfer to value recreational access. These studies highlight the challenges associated with transfers for recreational sites and they discuss the data required to obtain reliable estimates. Additionally, I discuss an original travel cost study that estimates losses due to hypothetical beach closures at various scales.

Previous benefit transfer studies have shown that acquiring information about trip demand can improve accuracy of benefit estimates, but obtaining necessary data can be challenging. Deacon and Kolstad (2000) discuss methods that can be used to estimate welfare losses from environmental disasters that harm beach recreation sites. Due to the scale of impact,

[47] Excellent summaries of the literature are provided by Boyle et al. (2010) and Johnston and Rosenberger (2010).

regional beach closures due to HABs are similar to widespread closures from environmental disasters such as oil spills or bacterial contamination from storm runoff. A paramount step in their analysis is systematically estimating how many beach visits would have occurred absent the disaster. In other words, the researcher must know how many trips would be displaced at each affected site. The authors emphasize that estimating status quo attendance requires data on reported beach visitation that is difficult to obtain. When beaches have entry fees or controlled access through entrance booths, estimating attendance may be fairly straightforward. However, beaches often have numerous access points making it difficult to accurately estimate visitation. The authors stress the importance of accounting for substitute sites in any beach valuation analysis.

Parsons and Kealy (1994) tested the accuracy of three benefit transfer approaches by estimating the "true" values of lake recreation in Wisconsin and then comparing the values to estimates from a value transfer, model (function) transfer, and an updated model (Bayesian transfer). Results showed that the function transfer estimated recreation values within 4% of the true values, whereas simple value transfers had an error of 34%. Some improvement was gained by updating the model with behavioral information about current trip demand, but improvements were slight relative to the substantial gain in accuracy of the function transfer alone.

Zandersen and coauthors (2007) test the accuracy of benefit function transfers over a 20-year time period using random utility models to value day trips to forest recreation sites in Denmark. They estimate the value of recreational access in Northern Zealand with two function transfers using a random utility maximization (RUM) model estimated with data from 1977 and then they compare the results to the "true" access values estimated with a RUM model using 1997 data. The two function transfers differ in that the first determines the margin of error from transferring preferences through time, but updating trip demand, whereas the second transfer determines the margin of error from transferring both preferences and trip demand through time. Updating trip demand in the first model reduces transfer error 282%, on average, compared to using the second model in which trip demand is not updated. When trip demand is updated, benefit transfer errors are considered “acceptable” for 39 of the 52 sites, meaning that the error is lower than the cost of undertaking a new on-site study. However, only seven of the 52 transfers pass this standard when demand is not updated.

Although not a benefit transfer study, research by Parsons and coauthors (2009) is particularly relevant to this study as they estimate economic losses from hypothetical beach closures on Padre Island National Seashore, the longest stretch of undeveloped barrier island in the world. Using a travel cost RUM model, they estimate welfare losses due to lost single-day trips when closures affect a single beach, groups of beaches, or all of the Padre Island beaches. They estimate value losses from a single site closure between $25 and $34, while losses from group closures range from $32 to $98. They estimate a loss-to-trip ratio of $179 when all Padre Beach sites are closed. Their study is applicable to this research because Parsons and coauthors (2009) show how welfare loss per trip increases as more beaches are simultaneously closed, reflecting the impact of restricting the choice set of available substitutes. Practitioners using benefit transfers must be cognizant of the impact choice set restrictions have on valuations because value (point-estimate) transfers are not able to reflect these effects.

3.3 Lake Erie beaches and HABs

Harmful algal blooms (HABs) produce a toxin called microcystin that harms ecosystem health, contaminates drinking water supplies, and reduces the value of fisheries, lake front property, and recreation sites. In 2011, the largest HAB ever recorded in Lake Erie drew international media attention. In the following two years HABs were smaller yet persistent, leading up to another expansive bloom in 2014 that contaminated drinking water sources for half a million people and triggered a state of emergency declaration for three counties in the Toledo area.

In previous decades, point source polluters (e.g. factories, water treatment plants) were the primary contributors of impaired water quality in Lake Erie, but recent eutrophication is a result of nutrient runoff emitted from nonpoint sources (e.g. agriculture, lawns) (International Joint Commission 2014). Limiting the occurrence and intensity of HABs requires implementing non-point source policies that abate nutrient runoff. However, these policies would involve thousands of potential polluters (farmers and homeowners) making them expensive and administratively challenging, thus it is important to understand both the costs and benefits of HAB reduction to determine if policy implementation is worthwhile. In 2014, $2 million in new federal emergency funding was appropriated to reduce runoff in the Western Lake Erie Basin (WLEB) through agricultural conservation programs that limit phosphorus loss. The influx of state, federal, and private spending has spurred stakeholders to demand timely information about the value of benefits generated by HAB mitigation programs. Few studies have estimated beach recreation values in Lake Erie, but understanding this value is essential to accurately estimate the economic impact of HABs on recreational value.

Conducted in the mid-1990s, the only published economic estimates of recreational value for Lake Erie beaches to date examined 15 beach locations along the Ohio coastline (Murray et al. 1999; Sohngen, Lichtkoppler and Bielen 1999). Researchers estimated that single day visitors invest $20 million in local communities when visiting this set of beaches. In a closer examination of two popular Lake Erie beaches – Maumee Bay State Park and Headlands Beach State Park –

Sohngen et al. (1999) estimated average values of single day trips between $15.50 (Headlands Beach) and $25.50 (Maumee Bay Beach), in 1998 dollars. Using the same dataset, Murray and coauthors (2001) examined the impact of beach advisories on welfare. They found that the average seasonal benefit of reducing one advisory was $28 per visitor or $3.2 million per year for the 15 beaches combined. Beyond this research, no other studies have been published that formally value Lake Erie beaches. Yet these studies have shown that Lake Erie beaches have considerable value that should be acknowledged when discussing the costs and benefits of policies to reduce eutrophication and improve overall water quality.

3.4 Benefit transfer using a travel cost model

Benefit transfer enables estimation of welfare losses from hypothetical beach closures resulting from HABs in the policy site – the western and central basins of Lake Erie. In this essay, I transfer beach values and an estimated benefit function from a study by Chen (2013) that values Great Lakes beaches using a random utility maximization (RUM) framework. Chen's model explains Michigan residents' choices to visit beaches along the Michigan coast, including beaches on Lakes Michigan, Huron, St. Clair, and Erie. The value transfer is conducted by multiplying Chen's estimated per trip value and my prediction of the number of displaced trips to estimate welfare loss from beach closures in my policy site. Using the repeated nested logit model (see Figure 3-1) estimated by Chen, I conduct a function transfer that accounts for heterogeneity in my policy site by updating Chen's model with Lake Erie beach amenity data as well as census tract data that characterizes the potential visitors from Michigan, Ohio, and Indiana. I later discuss how the welfare values from the two transfer approaches differ depending on the scale of the beach closure scenario.

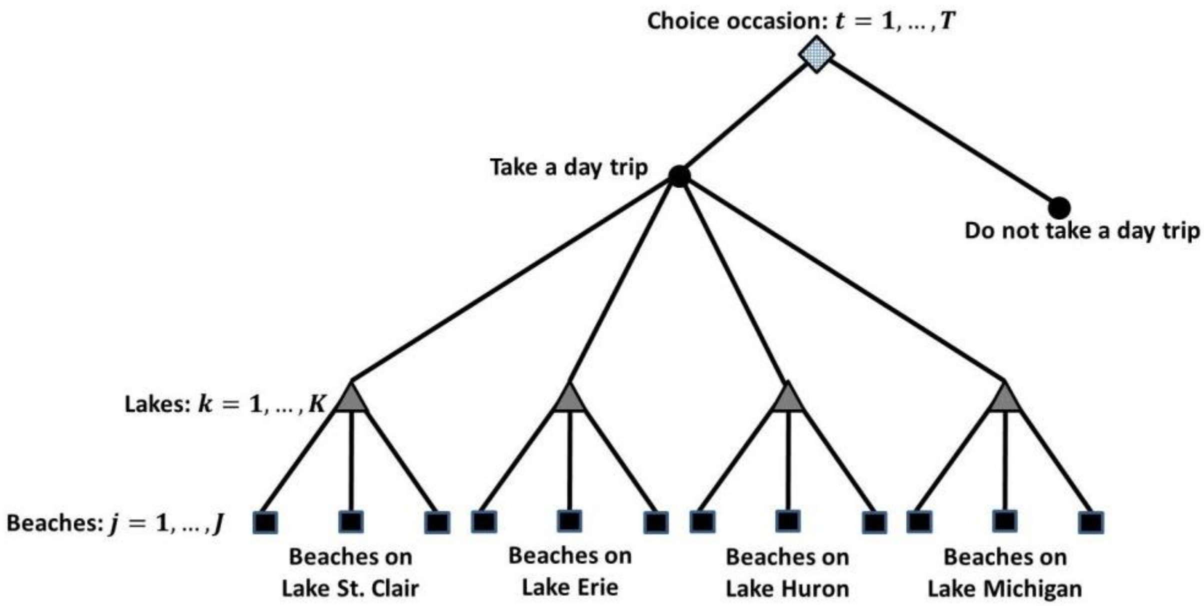

Figure 3-1. Repeated nested logit model

Value transfer and benefit function transfers require estimates of trip demand and demand elasticity, but current data on beach use are unavailable for the majority of Lake Erie beaches. I use Chen's model to generate predictions about the number of trips taken to each Lake Erie beach. Her repeated random utility model is able to predict trip demand because it captures both site choice and participation decisions. Since the model was estimated for the full adult population of Michigan, it can be used to generate trip predictions for the population of the policy site.

Chen's (2013) model is amenable to function transfer using census data for the population of the policy site. Using coefficients from the repeated nested logit model, the functions were transferred to estimate the demand for single day trips to Lake Erie beaches using population weighted demographic data of potential beach users. Demographic data were collected from the 2012 American Community Survey (ACS) 5-year Estimates (U.S. Census Bureau 2014). The study area includes 2,936 census tracts in Ohio, 1,702 census tracts in

Michigan, and 102 census tracts in Indiana. The universal choice set of beaches includes 424 beaches in Michigan and Ohio. The average choice set consists of 162 beaches.

I consider how the transferability requirements and ***S***-conditions previously described in Section 2.2 apply to this study to highlight the suitability of the benefit transfer approach. First, the commodity (Great Lakes beaches) and markets (mid-West residents) are the same in both the original study by Chen (2013) and my policy study. Furthermore, property rights are allocated the same way in both studies – i.e. individuals are free to choose among a set of publicly accessible beaches. The first of the four ***S***-conditions implies that an individual's valuation of the nonmarket commodity should depend on observed characteristics (*separability*), not variables that cannot be observed at the original site or policy study site. In both studies, I assume that beach values are determined by the attributes of beaches. These characteristics include both observable and unobservable attributes, but there is no reason to think that they differ between the study and policy sites.

The probability of taking a trip to a beach is determined by characteristics of individual people. The individual-specific characteristics measured by Chen (2013) are also observed for the population in the policy study, with the exception of retirement status, which is not directly measured in this study. Instead I use the percentage of the population over 65 years old as a variable to approximate retirement. The *specification* of the recreation choice model in Chen (2013) (i.e., a repeated nested logit model) is theoretically consistent and has been used in numerous other studies when participation and site choice decisions are important (Lew and Larson 2008; English 2008; Morey, Rowe and Watson 1993). Systematic *sorting* between the study and policy sites is unlikely as there is no reason to believe that the Michigan sample used in Chen (2013) is systematically different from the Ohio, Michigan, and Indiana sample in this study. Although one can never guarantee that the *selection* condition is fulfilled, appropriate actions were taken to avoid selection bias in conducting the original study, including surveying a representative sample of Michigan residents to understand beach recreation demand and following best practices[48] for survey design and implementation. This study aligns with the four ***S***-conditions indicating that it is an appropriate application of benefit function transfer.

3.4.1 A review of the random utility maximization (RUM) model

It is evident that people derive utility from visiting a beach because they are willing to trade time, money, and other opportunities to take a trip to the beach. Along a coastline there are typically multiple beach sites that someone could visit. Individuals select among beaches to visit the one that provides the most utility in any given choice occasion, t. In other words, in a choice set with J beaches, person n will choose to visit beach j in choice occasion t if and only if that beach provides the individual with higher utility than all other choice alternatives, i (other beaches).

$$U_{njt} > U_{nit}, \quad \forall \ i \neq j \tag{3.1}$$

The random utility model (RUM) model is commonly used to analyze individual preferences for amenities, like beaches. As depicted in Eq. (3.2), the RUM consists of two parts, 1) a deterministic portion of utility, V_{njt}, that depends on observable characteristics of each amenity – including the "price" of the amenity and 2) a random portion of utility, ε_{njt}, that is impacted by individual preferences and is unobserved by the researcher.

[48] Three waves of survey packages were mailed and reminder phone calls were used to improve response rate for the screener survey. Four waves of contact (letters and postcards) and small incentive payments were used to encourage participation in the web survey. Response rates were 37% for the screener survey and 58% for the online survey (Chen, 2013).

$$U_{njt} = V_{njt} + \varepsilon_{njt} \tag{3.2}$$

where, $V_{njt} = \beta X_{njt} + \alpha Q_{jt}$.

X_{njt} is a vector of characteristics that vary across beach sites and individuals. Variables may include travel cost and interactions between site attributes and attributes of the beach users. Q_{jt} is a vector of site-specific characteristics that are unique to each beach.

Under the assumption that ε_{njt} is independently and identically distributed as Type I extreme value, the probability that individual *n* chooses beach *j* in time *t* is,

$$P_{nt}(j) = \frac{e^{V_{njt}}}{\sum_{i=1}^{J} e^{V_{njt}}} \tag{3.3}$$

The model in Eq. (3.3) is known as a conditional logit model. A problem with the conditional logit model is that the relative probability of choosing between two sites is independent of the other alternatives introduced in the choice set – this principle is known as the independence of irrelevant alternatives (IIA) (Haab and McConnell 2002). In other words, the IIA property implies that the relative probability of choosing among sites would remain the same, even if another site was introduced that was a perfect substitute for one of the existing sites. In many cases, IIA is not a valid assumption because underlying characteristics of some beaches make them more similar and thus more likely to be chosen as alternatives. Therefore, a more general model of site choice known as the nested logit (NL) model takes into account the commonalities that make beaches more or less similar to one another (see Figure 3-1).

The NL model partially relaxes the IIA assumption by grouping similar beaches in "nests". If beach l in nest k is no longer available, individuals are more likely to choose a substitute from nest k because these beaches are most similar to beach l. In this model, each nest includes all of the beaches on a specific lake (Fig. 3-1) to account for the similarities among them relative to beaches on other lakes.

In the repeated NL model, the probability of visiting beach j in nest k depends on three probabilities:

1) the probability of taking a trip in choice occasion t,

$$P_{nt}(trip) = \frac{\left(\sum_{k=1}^{K}\left(\sum_{j=1}^{J_k} e^{\frac{V_{nlmt}}{\lambda}}\right)^{\lambda/\sigma}\right)^{\sigma}}{e^{V_{nt,no\ trip}} + \left(\sum_{k=1}^{K}\left(\sum_{j=1}^{J_k} e^{\frac{V_{nlmt}}{\lambda}}\right)^{\lambda/\sigma}\right)^{\sigma}} \tag{3.4}$$

2) the probability of going to lake k,

$$P_{nt}(k|trip) = \frac{\left(\sum_{j=1}^{J_k} e^{\frac{V_{nlmt}}{\lambda}}\right)^{\lambda/\sigma}}{\sum_{k=1}^{K}\left(\sum_{j=1}^{J_k} e^{\frac{V_{nlmt}}{\lambda}}\right)^{\lambda/\sigma}} \tag{3.5}$$

and 3) the probability of going to beach j, conditional on taking a trip and going to lake k,

$$P_{nt}(j|k,trip) = \frac{e^{\frac{V_{njkt}}{\lambda}}}{\sum_{j=1}^{J_k} e^{\frac{V_{njkt}}{\lambda}}} \tag{3.6}$$

Multiplying these probabilities results in the unconditional probability of person n visiting beach j on lake k on day t,

$$P_{nt}(j,k) = P_{nt}(trip) * P_{nt}(k|trip) * P_{nt}(j|k,trip) \tag{3.7}$$

$$= \frac{e^{\frac{V_{nlmt}}{\lambda}} * \left(\sum_{j=1}^{J_k} e^{\frac{V_{njkt}}{\lambda}}\right)^{\frac{\lambda}{\sigma}-1} * \left(\sum_{k=1}^{K}\left(\sum_{j=1}^{J_k} e^{\frac{V_{nlmt}}{\lambda}}\right)^{\lambda/\sigma}\right)^{\sigma-1}}{e^{V_{nt,no\ trip}} + \left(\sum_{k=1}^{K}\left(\sum_{j=1}^{J_k} e^{\frac{V_{nlmt}}{\lambda}}\right)^{\lambda/\sigma}\right)^{\sigma}}$$

In this specification, λ is the lake level nesting parameter and σ is the trip level nesting parameter. λ measures the degree to which beaches are similar in a given nest and higher values of λ indicate that there is less correlation (more independence) among the alternatives in that nest. If $\lambda = 1$ the nested logit model converges with the conditional logit model. Likewise, σ measures the correlation in unobserved factors between the choice to take a beach trip and the choice not to take a beach trip.

3.4.2 Predicting trips

Using parameters estimated by Chen (2013), I can predict the number of trips taken to each beach site by residents of Ohio and parts of Michigan and Indiana. Since information about individual people or trips is unavailable, I construct my observations using the demographic characteristics of each census tract, weighted by population. I can then predict the total number of day trips to beach *j* on lake *k* for each representative person, n,[49]

$$\hat{Y}_n(j,k) = \sum_{t=1}^{T} \hat{P}_{nt}(j,k)$$
$$= \hat{P}_{n,june}(j,k) * 35 + \hat{P}_{n,july}(j,k) * 30 + \hat{P}_{n,aug}(j,k) * 31 + \hat{P}_{n,sept}(j,k) * 30 \quad (3.8)$$

[49] Predicted trips are calculated daily from May 27 - Sept. 30, 2010. Daily trips are aggregated by month because each month has a different average water temperature, which is a beach characteristic that influences utility and trips. Trips taken during the last five days in May are accounted for in June trips; therefore there are 35 choice occasions (potential beach days) in June, and 31, 31, and 30 in July, August, and September, respectively.

To calculate total trips to beach j on lake k, I multiply the trip estimates in Eq. (3.8) by the population for each census tract, n.

$$\widehat{Trips}(j,k) = \sum_{n=1}^{N} \hat{Y}_n(j,k) * population_n \tag{3.9}$$

I also predict how the number of trips to beach j on lake k will change if one or more beaches close because of an HAB.

$$\widehat{\Delta Y}_N(j,k) = \hat{Y}_N(j,k)\big|HAB\ scenario - \hat{Y}_N(j,k)\big|status\ quo \tag{3.10}$$

3.4.3 Estimating welfare losses with a function transfer

Through provision of utility, beaches provide value (welfare) to visitors and the level of value depends on the attributes of the beach and characteristics of the individual. If beach use is restricted because of an algal bloom or the quality of the beach is impaired, welfare is lost compared to the status quo conditions. Willingness to pay (WTP) measures the amount of money that makes someone indifferent between the status quo and the new scenario (Haab and McConnell 2002). In the case of HABs, WTP measures the amount of money that someone is willing to pay to avoid the negative impacts of algal blooms. In this study I estimate the value lost due to a beach closure. Average annual beach closures are presented in Appendix 3-A (Figure A3-A-1).

Welfare loss from the closure of one or more sites due to HABs is calculated using the estimated parameters from the nested logit model specified by Chen (2013). I compute the expected maximum utility that a person can attain in any given choice occasion, which is called their inclusive value (IV),

$$IV_{nt} = \ln\left(e^{V_{nt,notrip}} + \left(\sum_{m=1}^{K}\left(\sum_{l=1}^{J_m} e^{\frac{V_{nlmt}}{\lambda}}\right)^{\lambda/\sigma}\right)^{\sigma}\right) \tag{3.11}$$

Over the entire season, an individual's expected maximum utility is the sum of the IVs in each choice occasion, t,

$$IV_n = \sum_{t=1}^{T} IV_{nt} = IV_{n,june} * 35 + IV_{n,july} * 31 + IV_{n,aug} * 31 + IV_{n,sept} * 30 \tag{3.12}$$

Inclusive values are used to determine the WTP to avoid the negative HAB scenario. The expected maximum utility possible in the HAB scenario ($IV_n{}^1$) is subtracted from the expected maximum utility under the status quo ($IV_n{}^0$) and divided by the estimated parameter of travel cost $\hat{\beta}_{tc}$ multiplied by -1.

$$\Delta\widehat{W}_{FT,n} = \widehat{WTP}_{FT,n} = \frac{\left(IV_n{}^0 - IV_n{}^1\right)}{-\hat{\beta}_{tc}} \tag{3.13}$$

The total change in welfare from a HAB scenario ($\Delta\widehat{W}_{FT}$) is calculated by aggregating the WTP estimated by the function transfer ($\widehat{WTP}_{FT}$) for each person in the population. In Eq. (3.14), I multiply the WTP of a representative individual n by the population of the census tract represented by that individual. Then, total WTP is calculated by summing the WTP for each of the 4735 census tracts.

$$\Delta\widehat{W}_{FT} = \widehat{WTP}_{FT} = \sum_{n=1}^{4735} \frac{\left(IV_n{}^0 - IV_n{}^1\right)}{-\hat{\beta}_{tc}} * population_n \tag{3.14}$$

WTP per-trip-to-site is calculated by dividing total WTP calculated in Eq. (3.14) by the number of trips displaced (change in trips) from sites affected by a HAB calculated in Eq. (3.10),

$$\widehat{WTP}_{FT,S} = \frac{\widehat{WTP}_{FT}}{\Delta\widehat{Trips}_S} \tag{3.15}$$

S denotes the set of beaches closed because of the HAB. In the case of a beach closure, all trips to the affected beaches are lost, thus displaced trips equal all of the trips to those sites predicted under status quo conditions (Eq. (3.9)).

3.4.4 Estimating welfare losses with a value transfer

There are multiple approaches one can take to estimate aggregate welfare measures using value transfer, depending on the availability of data about displaced trips. If displaced trips are known from an external source, the analyst can multiply the WTP to avoid losing a trip by the number of displaced trips. In this study, information about displaced trips was unavailable; therefore, I predicted trips using a site choice model. Total WTP is calculated by multiplying the change in predicted trips (Eq. (3.10)) and the transferred per trip WTP value,

$$\Delta\widehat{W}_{VT} = \widehat{WTP}_{VT} = \widetilde{\mathrm{WTP}}\, per\ trip\ * \Delta\widehat{Trips}_S \tag{3.16}$$

where $\Delta\widehat{Trips}_S$ are the trips lost to sites S that were closed because of a HAB. $\widetilde{\mathrm{WTP}}$ is the per-trip willingness to pay estimated by an original study that is being transferred to the policy site.

This approach accounts for the popularity of the beach in terms of visits, but does not account for any differences in the number or quality of choice alternatives. In this transfer, the number of choice alternatives in the same nest is quite different between the original study and the policy site. Chen considers two SE Michigan beaches in the Lake Erie nest, but in this study there are two Michigan beaches plus 65 Ohio beaches that are substitutes in the choice set. Without accounting for these alternatives, the estimate reported by Chen may overestimate the welfare loss incurred from the closure of a typical Lake Erie beach because in my policy setting there are more alternatives to choose from within the same nest, thus avoiding choosing more costly out of nest alternatives.

Without trip data, the analyst could use aggregate welfare measures generated in the original study that estimates seasonal values of individual beaches. In the context of the current study, this would mean using the aggregate seasonal welfare losses estimated in Chen (2013). This approach accounts neither for the frequency of visits to the transfer site nor the availability of substitute sites. Another approach involves predicting displaced trips using a participation model, as I do in this study.

3.5 Data

3.5.1 Travel cost

Both benefit transfer methods employed in this study use results from Chen (2013) to estimate welfare loss from hypothetical beach closures in Lake Erie. The benefit function transfer uses parameters estimated using a nested logit model. In this model, the deterministic portion of utility depends on the price of the trip (travel cost) and beach characteristics that are indicative of quality Eq. (3.17). Parameters (βs) are presented in Table 3-1.

$$\begin{aligned} V_{njkt} &= \beta_p * price + \beta_q * beach\ quality_{jkt} \\ &= \beta_{tc} * travel\ cost_{njk} + \beta_l * \log\left(beach\ length_{jk}\right) + \beta_t * temperature_{jkt} \\ &\quad + \beta_{cd} * closure\ days\ of\ 2010_{jk} + \beta_r * regional\ dummies_{jk} \end{aligned} \tag{3.17}$$

HABs will likely result in beach closures in Lake Erie's western and central basins, which include beaches in southeast Michigan and northern Ohio. However, beach choices are not limited to Lake Erie beaches. Sites in the choice set include other Michigan and Ohio beaches within 250 miles of representative individuals[50] because the probability of people making single

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[50] The residence for each representative individual is modeled as the center of the census tract that they represent.

day trips to beaches further than 250 miles is low (Parsons and Hauber 1998).[51] The universal choice set of beaches includes 357 Michigan beaches located in the Lower Peninsula along Lakes Michigan, Huron, and St. Clair and 67 beaches along Lake Erie. All beaches are public access sites. The average census tract has 162 site alternatives in their choice set.

Table 3-1. Estimated parameters from the repeated nested logit model, Chen (2013)

Levels of Nested Logit Model	Variables	Estimates	t Statistics
Beach Level	Travel Cost	-0.026***	-82.61
	Log (Length)	0.075***	22.47
	Temperature	0.033***	27.94
	Closure Days of 2010	-0.011***	-22.42
	LP Northeast	-0.031	-0.53
	LP Mid-East	-0.733***	-12.01
	LP Southeast	-0.786***	-12.67
	LP Northwest	0.745***	12.64
	LP Mid-West	0.684***	11.31
	LP Southwest	0.339***	5.60
Lake Level	Nesting Parameter	0.383***	68.87
Trip/No Trip Level	Nesting Parameter	0.536***	53.20
No Trip	Male	-0.124***	-8.04
	Age	0.003***	4.43
	White	-0.056**	-2.32
	Education Years	-0.105***	-33.40
	Full-Time Employed	0.038**	2.08
	Retired	0.187*	6.43
	Children under 17	0.067***	3.84
	Constant	7.558***	62.89

Note: *10% significance level; **5% significance level; *** 1% significance level

[51] Chen (2013) found that only 1% of people taking day trips visited a beach located more than 250 miles away. Murray et al., (1999) reported that visitors traveled, on average, 53.5 miles for a single day trip to a Lake Erie beach.

To maintain consistency, travel cost is computed the same as Chen (2013).

$$\begin{aligned} Travel\ cost &= monetary\ cost + time\ cost \\ &= round\ trip\ travel\ distance * \$0.2422\ per\ mile \\ &\quad + round\ trip\ travel\ time * \left(\frac{annual\ income}{2{,}000}\right) * \left(\frac{1}{3}\right) \end{aligned} \tag{3.18}$$

Travel cost per mile includes the operating costs (gas, maintenance, and tires) plus depreciation as reported by the American Automobile Association (AAA, 2011). It is important to note that Chen's calculation of driving costs is more conservative than other studies, as she computes marginal travel costs instead of average travel costs.[52] Assumptions regarding travel cost computations are important to consider when comparing values generated by different travel cost studies as they can significantly affect total welfare estimates. This cost is calculated for average sedans, as well as, SUV and minivans. Chen computed a weighted average for Michigan vehicles by type, based on the Insurance Institute of Michigan's estimates of registered vehicles in the state from a 2007 Insurance Institute of Michigan report. In this essay, I assume that the distributions of car types in Michigan, Ohio, and Indiana are similar, thus allowing me to use the same travel cost estimate. To maintain consistency with the estimated parameters, I use the same 127 choice occasions as the original study – days between May 27, 2011 (Memorial Day weekend) and September 30, 2011.

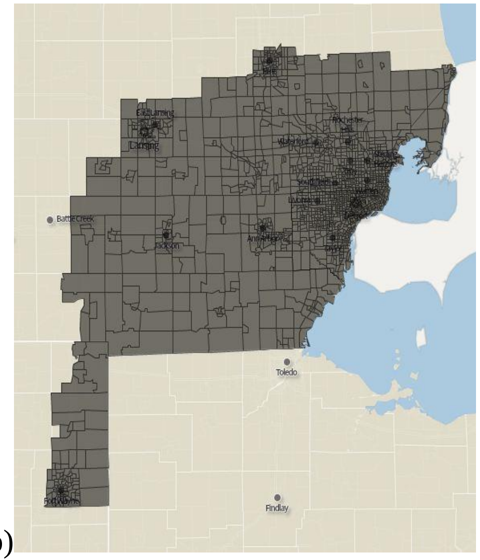
[52] Chen omits the cost of insurance since this is a sunk cost that does not increase because of additional miles driven to a beach. Additionally, Chen computes the marginal depreciation rate by determining how much total depreciation costs increase when yearly miles driven increases from 10,000 to 15,000 and then dividing the change in depreciation by 5,000 miles. Using average depreciation costs would increase driving cost by nearly 20 cents per mile.

3.5.2 Demographic data

As shown in Figure 3-2, study area includes 2,936 census tracts in Ohio, 1,702 census tracts in Michigan that are east of I-69, and 102 census tracts in Indiana that are east of I-69 and north of Fort Wayne. The population represented by these census tracts is most likely to visit Lake Erie beaches for a day trip. Demographic attributes of a census tract are used to construct each observation, which is weighted by the population of that census tract to represent all residents in that area. Demographic data were collected from the 2012 American Community Survey (ACS) 5-year Estimates (U.S. Census Bureau 2014).

Table 3-2 summarizes the demographic characteristics of the population. Distances and travel times were computed using PC*Miler and represent the miles and hours traveled between the center of each census tract and the 424 beaches included in the universal choice set (depicted in Figure 3-2(c)).

(b)



(c)

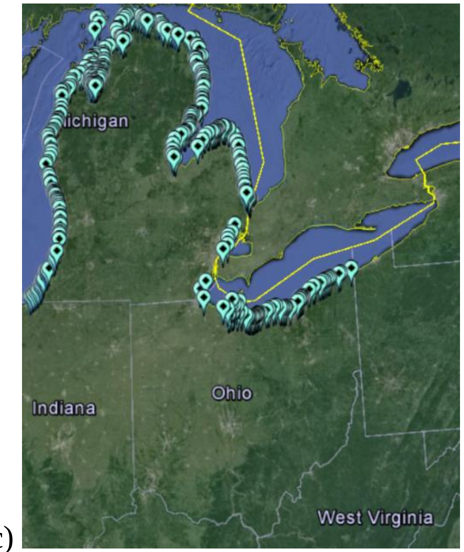


Figure 3-2. (a) Origin zones for the selected study area; (b) Census tracts in Michigan and Indiana; (c) Great Lakes beaches in the universal choice set

Table 3-2. Comparison of demographic characteristics in Chen (2013) and the 2008-2012 5-year estimates used in the benefit transfers

	Chen (2013)	Current Benefit Transfer Study			
	Michigan	Ohio	Michigan	Indiana	Combined
Total population (18 years and older)	7,561,510	8,811,640	7,561,510	4,883,604	21,256,754
Sample used in study	2,537 survey respondents	2936 census tracts	1702 census tracts	102 census tracts	4740 census tracts
People represented by census tracts	n/a	8,803,060	4,475,838	284,035	13,562,933
Demographic Characteristics of Sample (18 years and older)					
Age (Mean)	44.4	47.6	47.0	46.2	47.4
Income (Mean, $1000)	81,900	64,575	68,933	57,434	65,863
Education Years (Mean)	14.8	13.5	13.8	13.3	13.6
Male (%)	47.8	48.0	47.8	48.3	48.0
White (%)	90.9	85.4	75.6	85.1	82.2
Employed Full-Time (%)	52.2	57.9	52.7	58.9	56.2
Retired (%) [proxy is % over 65]	19.2	18.6	17.2	17.1	18.1
Children under 17 (%)	35.0	31.3	32.5	32.8	31.7

Source: U.S. Census Bureau, American Community Survey (ACS) 2008-2012 5-year estimates (www.factfinder.com)

3.5.3 Beach data

Figure 3-2(c) presents the location of all beaches and Figure 3-3 shows the beaches along Lake Erie.

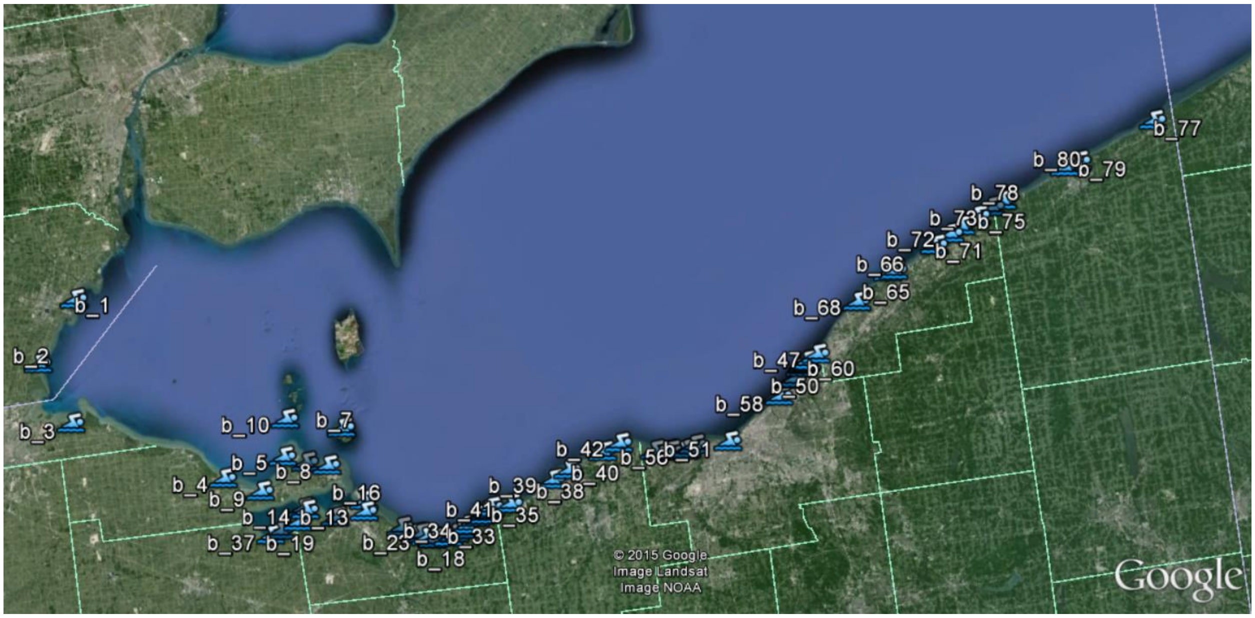


Figure 3-3. Location of Lake Erie beaches in Michigan and Ohio

Data about beach characteristics are obtained from a variety of publicly available sources as described in Table 3-3. Information about presence of algal biomass would benefit this study because I could then estimate welfare losses from marginal changes in water quality due to HABs. Unfortunately, I cannot make the connection between degrees of presence of algal bloom biomass and beach visitation, but welfare loss can be estimated when beaches are closed completely. Future studies could add value to this research area by estimating marginal welfare loss from varying levels of algal biomass at beaches. This is discussed further in Section 3.7.

Table 3-3. Sources of beach data

Beach Attributes	Description	Source(s)
Length	Length of beach in miles	Ohio Department of Health (ODH), 2014 Michigan Department of Environmental Quality (MDEQ), 2014 Google Earth, 2014
Temperature	Average monthly temperature of surface water at points closest to each beach	NOAA, 2012 and 2014
Closure days	Number of days that beach specific advisories were issued in 2010[53]	OH Department of Health, 2014 MI Dept. of Environmental Quality, 2014
Regional dummies	Six binary variables that indicated the region in which the beach was located: Northwest, Midwest, Southwest, Northeast, Mideast, Southeast. Beaches in Ohio were assigned the Southeast region.	Chen, 2013

3.6 Results

Willingness to pay (WTP) to avoid beach closures is estimated for 33 beaches in the western basin[54] and 34 additional beaches in the central basin. The WTP can be viewed as the welfare loss incurred when beaches close due to HABs. Summary characteristics of the 67 beaches are presented in Appendix 3-A (Table A3-A-1) and the beach data are available upon request. The location of each beach is shown in Figure 3-3.

[53] Although beach advisories are issued, visitors can make up their own mind about beach use.
[54] Harmful algal blooms in Lake Erie are larger and more intense in the western basin of the lake, thus beaches located in this region are more likely to close due to HABs compared to the central and eastern basin sites.

3.6.1 Predicting displaced trips

Single day trips are predicted for residents within 250 miles of each beach, which includes residents in Ohio as well as parts of Michigan and Indiana.[55] First, I use Eq. (3.7) to predict the probability of taking a trip to beach j on lake k in the absence of beach closures. By aggregating over choice occasions for the full population using Eq. (3.9), I predict the number of single-day trips taken to each beach during the summer season. Predicted trips for each of the 67 beaches are presented in Appendix 3-B (Table A3-B-1).[56]

Since records about beach trips are largely unavailable for the sites in this study, it is difficult to evaluate the accuracy of the trip predictions generated by the transfer model. Visitor records, if they are available, do not typically differentiate between beach use and general site use, which may include hiking and other recreation. To evaluate trip predictions, I compare them to previously reported trip estimates for beaches at Maumee Bay State Park and Headlands State Park. Maumee Bay is located 15 miles east of Toledo and would be a prime candidate for beach closure in the event of a HAB. Under normal (no HAB) conditions, I predict that people will take 269,352 day trips to the beach at Maumee Bay State Park. Sohngen et al. (1999) reported that there were approximately 238,000 beach users during summer months in 1998. As a rough

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[55] Sohngen and coauthors (1999) reported that 92% of single day trips at Maumee Bay State Park Beach were made by Ohio residents and 8% from Michigan residents. At Headlands State Park Beach, Ohio residents made 100% of the single day trips.

[56] In their 2010 annual report, the Ohio Department of Natural Resources (ODNR) estimates the number of visitor occasions at East Harbor State Park, Headlands State Park, and Geneva State Park as 1.56 million, 4.37 million, and 730,000, respectively (Ohio Department of Natural Resources, 2010). Averaging across all park sites, 9.5% of visits are beach occasions, but this estimate does not account for the fact that some parks do not have beaches while others are popular beach destinations. Furthermore, there is no differentiation between single day trips and multiple day trips to particular site. Applying this assumption to the reported site visits, beach trips are estimated to be approximately 148,000, 415,150, and 69,000, respectively. It is unclear that this estimate accurately reflects beach trips because of the assumptions used in the estimation, but it provides a general ballpark prediction. Using the transfer model in this study, I predict single day trips to the same beaches as 129,482, 190,090, and 69,076, respectively.

approximation, Weicksel and Lupi (2013) estimated 178,500 day trips to the Maumee Bay State Park beach by consulting with park employees and reviewing annual reports. Predicted trips estimated by the model transferred in this study deviate from the previously reported estimates by 13% and 51%, respectively. Sohngen and coauthors (1999) also report trips at Headlands beach. They estimated 224,000 trips during the summer of 1998, whereas I estimate 190,090 trips (15% fewer trips).

3.6.2 Benefits transfer – individual beach closures

Welfare values are calculated using two benefit transfer methods – value transfer and function transfer. Individual closures of the 67 beaches are simulated and the seasonal inclusive value (IV) from Eq. (3.12) is used to calculate how much people are willing to pay to avoid the loss of each site. Eq. (3.14) is used to estimate the WTP to avoid the loss of a trip to each site. Two metrics are reported, 1) the WTP to avoid the loss of a trip to each site and 2) aggregate welfare losses associated with a season-long closure. Welfare losses from closures at selected beaches are presented in Table 3-4 and results for the full choice set of beaches are presented in Appendix 3-B (Table A3-B-2).

Table 3-4. Welfare losses for selected **individual** beach closure scenarios

Beach Closed	State	Basin Region	Per-trip-to-site loss (2015$[a])			Aggregate Seasonal Loss (2015$[a], millions)		
			Value transfer	Function transfer	% deviation	Value transfer	Function transfer	% deviation
Sterling State Park	MI	Western	18.08	17.77	-1.7	12.32	12.11	-1.7
Luna Pier City Beach	MI	Western	18.08	16.44	-9.1	5.93	5.39	-9.1
Maumee Bay State Park	OH	Western	18.08	16.39	-9.3	4.87	4.42	-9.3
East Harbor State Park	OH	Western	18.08	15.90	-12.1	2.34	2.06	-12.1
Headlands State Park	OH	Central	18.08	16.05	-11.2	3.44	3.05	-11.2
Geneva State Park	OH	Central	18.08	15.95	-11.8	1.25	1.10	-11.8
Lakeshore Park	OH	Central	18.08	15.87	-12.2	0.50	0.44	-12.2
Average Western Basin	--	Western	18.08	15.92	-12.0	2.21	1.99	-10.1
Average Central Basin	--	Central	18.08	15.91	-12.0	2.20	1.94	-11.9
Average Lake Erie	--	--	18.08	15.91	-12.0	2.21	1.96	-11.0

[a] $1.05 (Y2015) = $1(Y2011) * 236/225 (Price Index 2015 / Price Index 2011), Bureau of Labor Statistics (2015)

I compare the WTP generated by the function transfer to the value for Lake Erie reported by Chen (2013, Table 15) -- i.e., $18.08 to reflect 2015 dollars[57] using the Consumer Price Index-U (Bureau of Labor Statistics, 2015). Using the function transfer, I find that beachgoers would be willing to pay $15.91, on average, to avoid the loss of a beach trip. Depending on the beach site, WTP calculated by a function transfer is 2% to 12% lower than the WTP reported by Chen (2013), but overall the estimates are similar (see Figure 3-4).

Previously estimated values for Maumee Bay State Park Beach and Headlands State Park Beach were, respectively, $25.60 and $15.50 per single day trip (Sohngen et al., 1999). Adjusted for inflation, these values are $37.07 and $22.44, in 2015 dollars[58] (Bureau of Labor Statistics, 2015). Using a benefit function transfer, I estimate per trip values at these two beaches as $16.39 and $16.05, respectively. These estimates are somewhat lower, likely due in part to differences in the assumptions for travel costs. Following Chen (2013), the per-mile travel cost used in this study accounts for marginal vehicle depreciation, which is lower than average vehicle depreciation that is frequently considered in travel cost calculations in other studies.

The value transfer estimates seasonal welfare losses from beach closures by using Chen's (2013) participation model to predict visits to each of the 67 beaches and then multiplying the predicted displaced trips and the WTP per trip estimated by Chen. Welfare losses from season-long closures average $1.96 million per site using the function transfer and $2.2 million per site using the value transfer with displaced trips predicted by the model.

[57] $1.05 (Y2015) = $1(Y2011) * 236/225 (Price Index 2015 / Price Index 2011).
[58] $1.45 (Y2015) = $1(Y1998) * 236/163 (Price Index 2015 / Price Index 1998).

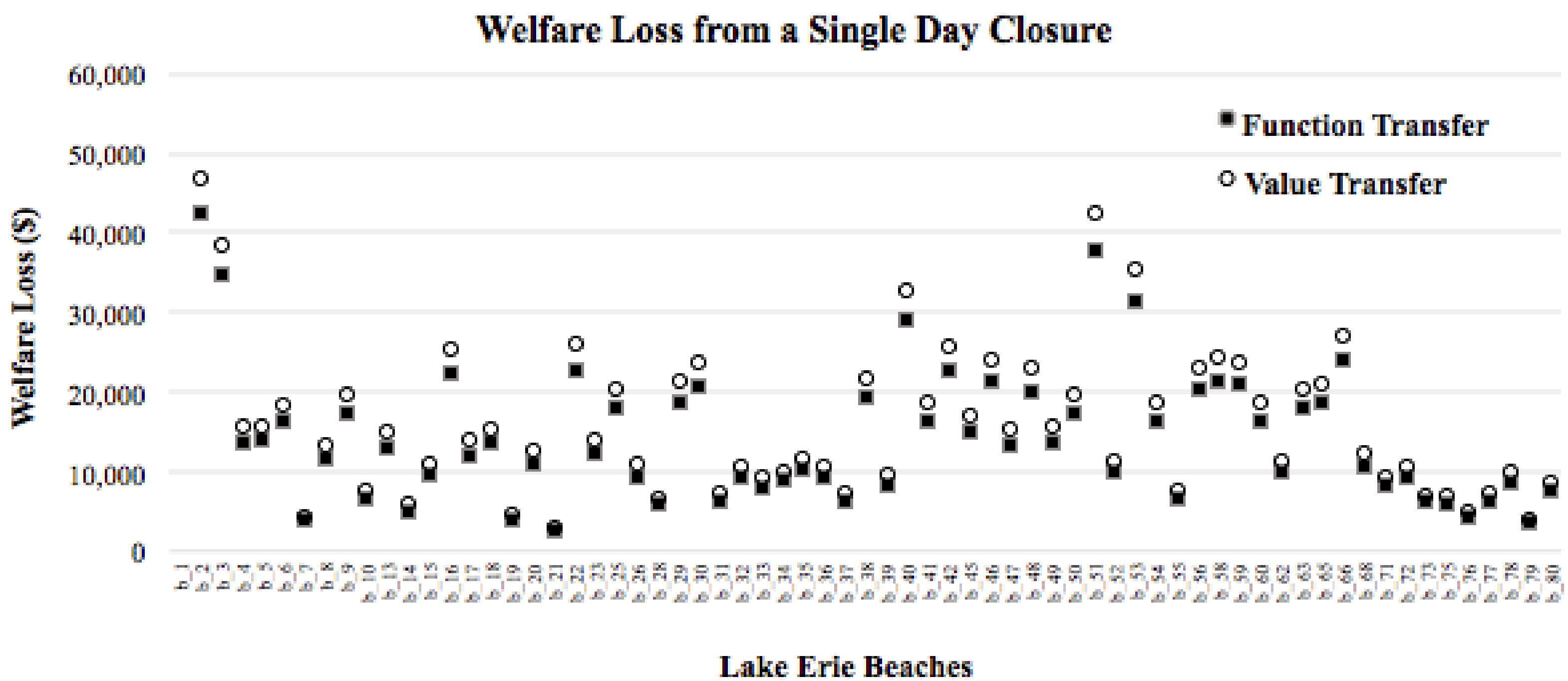

Figure 3-4. Comparing estimated welfare loss computed by a function transfer and a value transfer for single-day closures for individual beaches

Compared to the value transfer estimates, welfare losses from the function transfer are, on average, 11% lower for each trip and the deviations are fairly constant across sites. When evaluating welfare loss from closures at individual sites it is not clear how much is gained by using the more complicated benefit function transfer.

3.6.3 Benefits transfer – regional beach closures

In the previous section welfare losses were estimated for individual beach closures and I analyzed the deviation between estimates using two transfer methods. However, in the event of a HAB, it is likely that an entire group of beaches would close due to the presence of microcystin. Group closures, or what I will call regional closures, have different welfare impacts because as more beaches close beachgoers have fewer choice alternatives to which they can substitute their trips. As the number of alternatives declines, fewer total trips are taken because individuals opt for not taking a trip thus trips are permanently lost instead of being displaced. Group closures are simulated and I compare how welfare estimates differ between value and function transfers.

We consider four scenarios, 1) two Michigan beaches close, 2) six Western Lake Erie beaches close, 3) all 33 WLEB beaches close, and 4) all 67 MI and OH Lake Erie beaches close. Welfare estimates from the value and function transfer are presented in Table 3-5. Compared to deviations observed in the individual beach closure estimates, I find that regional closures result in very different estimates of welfare loss. Furthermore, although the value transfer predicted larger welfare losses for individual closures, this method predicts significantly lower welfare losses for the regional closures. Deviations between welfare estimates increase exponentially as more beaches close. Welfare losses from the function transfer are up to 106% larger than the estimates calculated with the value transfer.

Table 3-5. Welfare losses for selected **regional** beach closure scenarios

Beaches Closed	Per-trip-to-site loss (2015$[a])				Aggregate Loss Per Day (2015$[a] thousand)			
	Value transfer	Function transfer	95% CI[b]	% deviation	Value transfer	Function transfer	95% CI[b]	% deviation
2 Michigan Beaches	18.08	19.01	[13.98; 23.13]	5.1	143.69	151.09	[111.09; 183.85]	5.1
6 Western Basin beaches	18.08	20.12	[18.88; 21.64]	11.3	233.45	259.78	[192.05; 324.50]	11.3
33 Western Basin beaches	18.08	23.46	[21.78; 25.50]	29.7	573.73	744.32	[547.40; 1011.38]	29.7
67 Lake Erie Beaches	18.08	37.21	[33.61; 42.73]	105.8	1163.60	2,394.38	[1808.46; 3109.35]	105.8

[a] $1.05 (Y2015) = $1(Y2011) * 236/225 (Price Index 2015 / Price Index 2011), Bureau of Labor Statistics (2015)

[b] A 95% confidence interval is constructed for the function transfer value using 120 sets of beta coefficients estimated by bootstrapping the model in the original study.

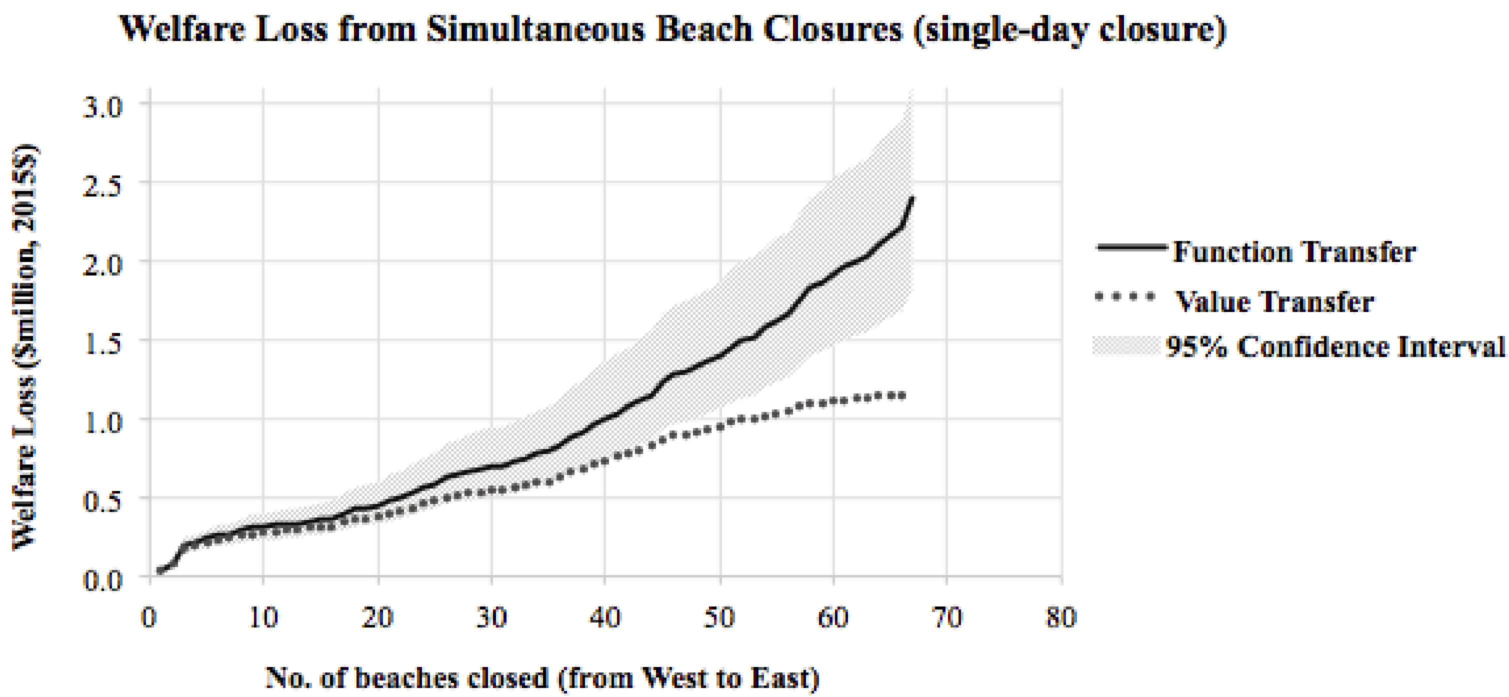

Figure 3-5. Comparing estimated welfare loss computed by a function transfer and a value transfer for single day closures to groups of beaches in Lake Erie

A 95% confidence interval is constructed for the function transfer value using 120 sets of beta coefficients estimated by bootstrapping the model in the original study.

To further examine scenario four, consider a case in which a HAB originates at the western most point of Lake Erie and spreads eastward causing sequential beach closures from west to east. Figure 3-5 shows how estimates of daily welfare losses differ between the two transfer methods. As more beaches close the deviation between the welfare estimates increases exponentially.

3.7 Discussion and conclusions

Benefit transfers are often viewed as a simpler alternative to an original valuation study, but transfers are not easy to conduct and require considerable care and careful analysis to obtain reliable value estimates. Previous research has shown that transfer error can be reduced by using behavioral information about trip demand (Parsons and Kealy 1994; Zandersen et al. 2007; Deacon and Kolstad 2000). But behavioral information is not often readily available and it may be expensive or time-consuming to acquire.

In this essay, value transfer and function transfer were used to estimate welfare loss from hypothetical beach closures resulting from persistent HABs in Lake Erie. A benefit function transfer was essential to estimate trip demand (number of trips) and demand elasticity (change in trips). Trip demand data were unavailable for 63 of the 67 sites included in this study and no current data was available regarding trip substitution between sites or demand elasticity. Transferring Chen’s (2013) model allowed me to estimate how many trips Ohio, Michigan, and Indiana residents would take to Lake Erie beaches and which sites they would visit under normal (no HAB) conditions. Then, I simulated beach closures that would result from HABs and evaluated how trip demand would change and how much value would be lost.

If trip data had been available, these results suggest that a value transfer would have yielded nearly the same welfare estimates as the function transfer when considering the closure of a single beach. However, the deviation between these estimates increases exponentially as more beaches are closed. In the case of regional closures, welfare estimates from the value transfer are substantially lower than the estimates generated by the function transfer. Without data to estimate the "true" value of beach access, it is difficult to determine which model performs "best" but economic intuition points to two main benefits of the function transfer when estimating welfare loss from regional closures. First, by reflecting trip elasticity, the function transfer accounts for trips that are completely lost rather than ones that are displaced. Second, estimating trip substitution better reflects the choice set in the policy setting, which can be substantially different than the choice set in the original study. Estimates are better if the scale of beach closures is similar between the policy site and the original study site.

A limitation of this study is that I was only able to estimate welfare loss of beach closures due to HABs, but HABs create recreational welfare loss even when beaches remain open because water quality is severely degraded. Environmental disasters can degrade beach recreation experiences absent a closure. Additionally, if a closure occurs, welfare losses can exist well after the beach reopens due to degraded beach conditions (Deacon and Kolstad 2000). Furthermore, the stigma of poor beach quality can remain long after the environmental disaster is over. Deacon and Kolstad (2000) refer to this as the "perceptually degraded period."

Finally, I emphasize the value of considering applications for future benefit transfer when designing original valuation studies to make them more amenable to transfers. There are at least two actions that researchers can take in this regard. First, researchers can report useful value metrics that can be easily transferred to policy sites. For example, Parsons et al. (2009)

calculated a metric (loss-to-trips ratio) that could be easily transferred to other policy sites. Additionally, it is essential to report information about the choice sets so that characteristics of site alternatives can be compared between the study site and policy site. The size of the choice set and the attributes of site alternatives have a significant impact on welfare values, especially when evaluating regional resource changes. Second, because information about displaced trips is often not available or outdated, researchers can estimate models that can be used in the future to generate trip demand at policy sites. In the context of travel cost studies, this means determining the proportion of the population that uses the recreational amenity. The study by Chen (2013) used a population wide survey to identify beach users. This research design allowed beach values to be scaled up to the entire Michigan population. In addition to reducing the risk of selection bias, which is a concern for beach intercept surveys, the study is also a prime candidate for future benefit transfer because the model can be updated and transferred using population demographics and beach characteristics of a policy site.

APPENDICES

APPENDIX 3-A BEACH CHARACTERISTICS

Table A3-A-1. Characteristics of Lake Erie beaches

ID	Beach Name	Beach Length (mi.)	Mean Water Temperature				Closure Days (2010)
			June	July	Aug.	Sept.	
1	Sterling State Park	0.30	72.87	81.20	78.91	70.01	2
2	Luna Pier City Beach	0.42	73.16	81.20	78.87	70.06	25
3	Maumee Bay State Park	1.48	72.96	81.01	78.43	69.84	15
4	Camp Perry	0.43	72.82	81.05	78.37	69.75	15
5	Catawba Island State Park	0.66	73.08	80.82	78.35	70.00	0
6	East Harbor State Park	0.92	72.21	80.60	78.70	70.43	0
7	Kelleys Island State Park	0.07	70.54	79.29	79.10	71.26	0
8	Lakeside Beach	0.33	71.81	80.11	78.82	70.61	2
9	Port Clinton (Deep\Lakeview)	0.62	73.16	80.95	78.28	69.83	7
10	South Bass Island State Park	0.07	71.06	79.64	78.81	70.77	0
13	Battery Park	0.10	71.39	80.01	78.72	70.46	2
14	Bay View East	0.16	70.99	79.55	78.84	70.68	40
15	Bay View West	0.10	70.99	79.55	78.84	70.68	15
16	Cedar Point Chausee	6.90	70.99	79.55	78.84	70.68	10
17	Chappel Creek	0.33	72.18	80.12	80.37	71.62	21
18	Cranberry Creek	0.16	72.89	81.24	80.50	71.98	14
19	Crystal Rock	0.04	70.99	79.55	78.84	70.68	40
20	Darby Creek	0.33	72.13	79.94	80.19	71.47	25
21	Edson Creek	0.16	72.86	80.62	80.14	71.53	73
22	Fichtel Creek	0.66	72.18	80.12	80.37	71.62	4
23	Hoffman Ditch	0.16	71.13	79.37	78.78	70.64	14
25	Huron River East	0.98	71.13	79.37	78.78	70.64	12
26	Huron River West	0.66	70.79	79.01	79.04	70.58	31
28	Lion's Park	0.07	70.99	79.55	78.84	70.68	28
29	Old Woman's Creek East	0.33	72.89	81.24	80.50	71.98	9
30	Old Woman's Creek West	0.16	72.89	81.24	80.50	71.98	1
31	Pickerel Creek	0.16	70.99	79.55	78.84	70.68	32
32	Sawmill Creek	0.66	70.79	79.01	79.04	70.58	30
33	Sherod Creek	0.66	72.13	79.94	80.19	71.47	41
34	Sugar Creek	0.16	72.18	80.12	80.37	71.62	28
35	Vermilion River East	0.66	71.69	79.62	80.13	71.50	32
36	Vermilion River West	0.33	72.86	80.62	80.14	71.53	34
37	Whites Landing	0.04	70.99	79.55	78.84	70.68	22
38	Century Beach	3.28	70.94	78.58	79.48	71.24	27

Table A3-A-1. (cont'd)

39	Lakeview Beach	1.11	70.68	78.29	79.70	71.42	47
40	Miller Beach	0.29	70.10	77.78	79.47	71.42	0
41	Showse Park	0.33	71.53	79.41	80.09	71.55	14
42	Veterans' Beach	0.07	69.95	77.84	79.19	71.21	0
45	Arcadia Beach	0.48	67.35	75.39	78.58	71.71	29
46	Bay Park Beach	0.24	69.16	77.22	79.00	71.34	20
47	Clarkwood Beach	0.21	66.70	75.33	78.61	71.74	29
48	Clifton Beach	0.72	68.88	77.24	78.87	71.46	29
49	Columbia Park Beach	0.56	69.16	77.22	79.00	71.34	40
50	Edgecliff Beach	0.26	66.70	75.33	78.61	71.74	20
51	Edgewater State Park	0.56	68.41	76.93	78.69	71.67	12
52	Euclid State Park	0.66	67.91	75.64	78.67	71.83	47
53	Huntington Beach	1.64	69.22	77.44	79.01	71.29	16
54	Moss Point Beach	0.28	66.70	75.33	78.61	71.74	22
55	Noble Beach	0.06	66.70	75.33	78.61	71.74	42
56	Parklawn Beach	0.08	69.01	77.13	78.94	71.44	13
58	Shoreby Club Beach	0.03	68.19	75.80	78.88	72.15	7
59	Shorehaven Beach	0.28	66.70	75.33	78.61	71.74	14
60	Sims Beach	0.59	66.70	75.33	78.61	71.74	28
62	Villa Angela State Park	0.30	67.91	75.64	78.67	71.83	41
63	Wagar Beach	0.34	69.01	77.13	78.94	71.44	27
65	Fairport Harbor	0.82	64.55	75.74	78.08	71.18	11
66	Headlands State Park	4.50	64.74	75.65	78.23	71.38	14
68	Overlook Beach Park	0.07	65.73	75.63	78.14	71.38	20
71	Perry Township Park	0.17	65.09	76.17	78.11	70.89	20
72	Lakeshore Reservation	0.52	65.52	76.21	77.93	70.85	20
73	Bill Stanton Community Park	0.09	65.52	76.21	77.93	70.85	20
75	Madison Township Park	0.12	65.52	76.21	77.93	70.85	20
76	Arcola Creek Park	0.10	64.51	76.27	77.74	70.83	20
77	Conneaut Township Park	0.82	65.48	76.05	77.13	70.12	9
78	Geneva State Park	0.20	64.51	76.27	77.74	70.83	5
79	Lakeshore Park	0.33	63.86	76.14	77.23	70.58	37
80	Walnut Beach	0.36	63.81	75.82	77.40	70.91	10

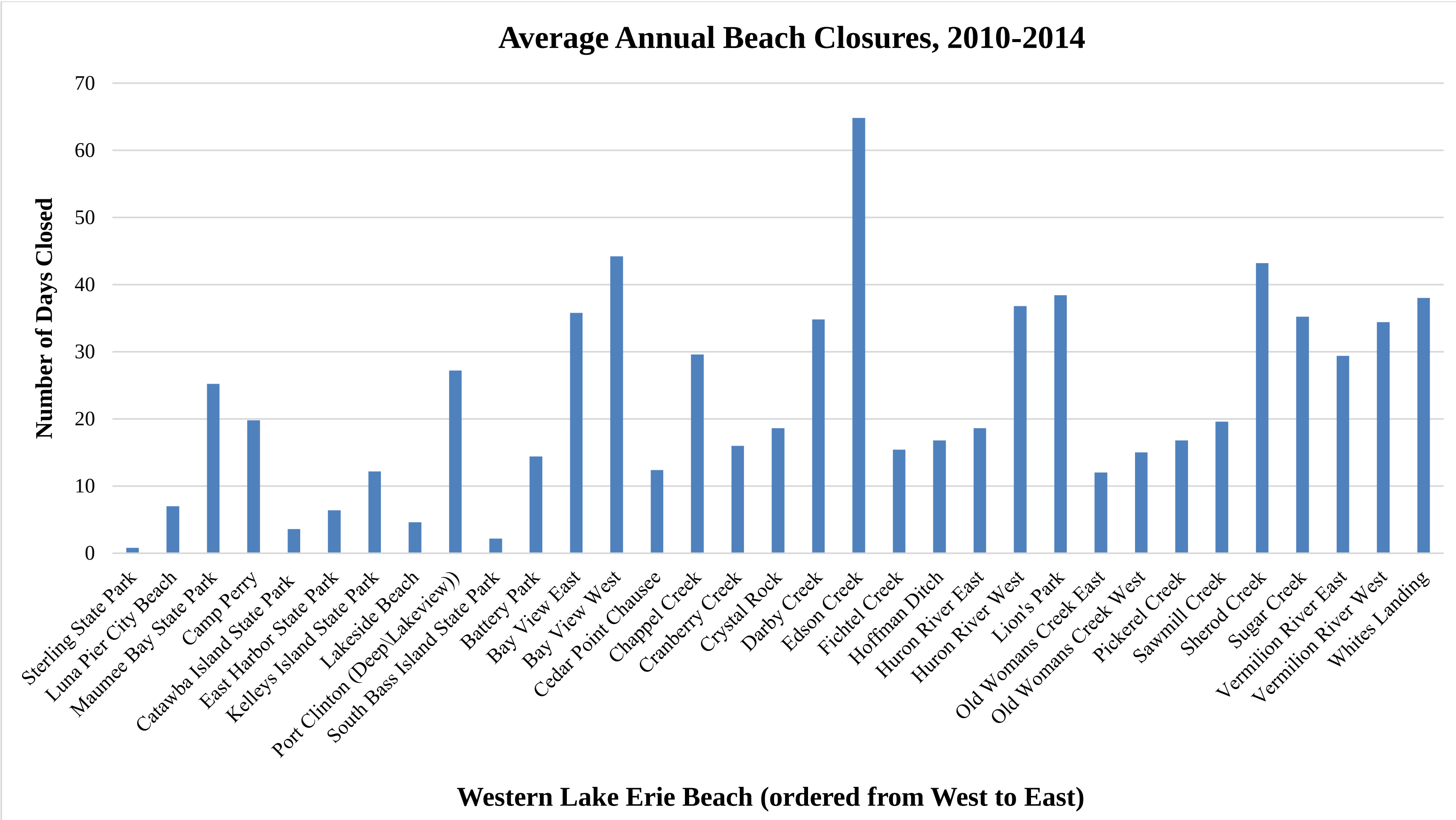

Figure A3-A-1 Average Annual Beach Closures of 33 Western Lake Erie Beaches, 2010-2014

APPENDIX 3-B PREDICTED TRIPS AND WELFARE ESTIMATES

Table A3-B-1. Predicted single day trips to Lake Erie beaches

ID	Beach Name	Predicted Trips May[a] 27 - Sept. 30
1	Sterling State Park	681,286
2	Luna Pier City Beach	327,996
3	Maumee Bay State Park	269,352
4	Camp Perry	110,371
5	Catawba Island State Park	111,166
6	East Harbor State Park	129,482
7	Kelley's Island State Park	30,912
8	Lakeside Beach	92,543
9	Port Clinton (Deep\Lakeview))	139,531
10	South Bass Island State Park	54,683
13	Battery Park	104,950
14	Bay View East	41,023
15	Bay View West	76,537
16	Cedar Point Chausee	177,780
17	Chappel Creek	97,708
18	Cranberry Creek	108,595
19	Crystal Rock	31,454
20	Darby Creek	89,432
21	Edson Creek	20,725
22	Fichtel Creek	182,112
23	Hoffman Ditch	97,794
25	Huron River East	143,222
26	Huron River West	76,070
28	Lion's Park	47,108
29	Old Woman’s Creek East	150,533
30	Old Woman’s Creek West	166,492
31	Pickerel Creek	50,528
32	Sawmill Creek	74,939
33	Sherod Creek	64,519
34	Sugar Creek	70,962
35	Vermilion River East	82,724
36	Vermilion River West	74,997
37	Whites Landing	51,876
38	Century Beach	153,665

Table A3-B-1. (cont'd)

39	Lakeview Beach	67,634
40	Miller Beach	230,015
41	Showse Park	130,346
42	Veterans' Beach	181,730
45	Arcadia Beach	120,658
46	Bay Park Beach	169,352
47	Clarkwood Beach	106,927
48	Clifton Beach	161,357
49	Columbia Park Beach	109,971
50	Edgecliff Beach	137,833
51	Edgewater State Park	297,964
52	Euclid State Park	80,028
53	Huntington Beach	249,735
54	Moss Point Beach	131,873
55	Noble Beach	54,621
56	Parklawn Beach	162,307
58	Shoreby Club Beach	171,750
59	Shorehaven Beach	167,507
60	Sims Beach	130,457
62	Villa Angela State Park	79,196
63	Wagar Beach	143,578
65	Fairport Harbor	148,236
66	Headlands State Park	190,090
68	Overlook Beach Park	86,464
71	Perry Township Park	66,010
72	Lakeshore Reservation	73,875
73	Bill Stanton Community Park	49,431
75	Madison Township Park	47,827
76	Arcola Creek Park	34,146
77	Conneaut Township Park	50,135
78	Geneva State Park	69,076
79	Lakeshore Park	27,691
80	Walnut Beach	61,141

[a] The five days in May are included in the June count, therefore June has 35 choice occasions

Table A3-B-2. Change in trips and welfare estimates for closing a beach, measurements in single day trips and 2015 dollars

ID	Site of Beach Closure	Predicted change in trips to site (single day trips)	Change in seasonal welfare ($), function transfer	Welfare/change in trips to site ($), function transfer
1	Sterling State Park	-681,286	-11,530,760	16.93
2	Luna Pier City Beach	-327,996	-5,135,156	15.66
3	Maumee Bay State Park	-269,352	-4,204,814	15.61
4	Camp Perry	-110,371	-1,671,798	15.15
5	Catawba Island State Park	-111,166	-1,680,970	15.12
6	East Harbor State Park	-129,482	-1,960,548	15.14
7	Kelleys Island State Park	-30,912	-464,142	15.02
8	Lakeside Beach	-92,543	-1,396,443	15.09
9	Port Clinton (Deep\Lakeview)	-139,531	-2,114,913	15.16
10	South Bass Island State Park	-54,683	-822,427	15.04
13	Battery Park	-104,950	-1,584,118	15.09
14	Bay View East	-41,023	-616,243	15.02
15	Bay View West	-76,537	-1,153,099	15.07
16	Cedar Point Chausee	-177,780	-2,699,994	15.19
17	Chappel Creek	-97,708	-1,471,405	15.06
18	Cranberry Creek	-108,595	-1,637,374	15.08
19	Crystal Rock	-31,454	-472,163	15.01
20	Darby Creek	-89,432	-1,346,723	15.06
21	Edson Creek	-20,725	-310,221	14.97
22	Fichtel Creek	-182,112	-2,757,515	15.14
23	Hoffman Ditch	-97,794	-1,474,170	15.07
25	Huron River East	-143,222	-2,165,814	15.12
26	Huron River West	-76,070	-1,145,561	15.06
28	Lion's Park	-47,108	-708,383	15.04
29	Old Woman’s Creek East	-150,533	-2,276,187	15.12
30	Old Woman’s Creek West	-166,492	-2,520,547	15.14
31	Pickerel Creek	-50,528	-760,309	15.05
32	Sawmill Creek	-74,939	-1,127,596	15.05
33	Sherod Creek	-64,519	-969,864	15.03
34	Sugar Creek	-70,962	-1,066,734	15.03
35	Vermilion River East	-82,724	-1,244,878	15.05
36	Vermilion River West	-74,997	-1,128,402	15.05
37	Whites Landing	-51,876	-780,665	15.05
38	Century Beach	-153,665	-2,324,679	15.13
39	Lakeview Beach	-67,634	-1,017,637	15.05
40	Miller Beach	-230,015	-3,500,394	15.22
41	Showse Park	-130,346	-1,967,906	15.10

Table A3-B-2. (cont'd)

42	Veterans' Beach	-181,730	-2,757,080	15.17
45	Arcadia Beach	-120,658	-1,823,803	15.12
46	Bay Park Beach	-169,352	-2,566,657	15.16
47	Clarkwood Beach	-106,927	-1,616,145	15.11
48	Clifton Beach	-161,357	-2,444,182	15.15
49	Columbia Park Beach	-109,971	-1,659,698	15.09
50	Edgecliff Beach	-137,833	-2,086,899	15.14
51	Edgewater State Park	-297,964	-4,555,715	15.29
52	Euclid State Park	-80,028	-1,205,543	15.06
53	Huntington Beach	-249,735	-3,807,352	15.25
54	Moss Point Beach	-131,873	-1,995,665	15.13
55	Noble Beach	-54,621	-821,696	15.04
56	Parklawn Beach	-162,307	-2,458,499	15.15
58	Shoreby Club Beach	-171,750	-2,605,149	15.17
59	Shorehaven Beach	-167,507	-2,542,156	15.18
60	Sims Beach	-130,457	-1,974,472	15.14
62	Villa Angela State Park	-79,196	-1,193,066	15.06
63	Wagar Beach	-143,578	-2,172,252	15.13
65	Fairport Harbor	-148,236	-2,255,998	15.22
66	Headlands State Park	-190,090	-2,906,145	15.29
68	Overlook Beach Park	-86,464	-1,305,788	15.10
71	Perry Township Park	-66,010	-996,099	15.09
72	Lakeshore Reservation	-73,875	-1,117,106	15.12
73	Bill Stanton Community Park	-49,431	-745,427	15.08
75	Madison Township Park	-47,827	-721,654	15.09
76	Arcola Creek Park	-34,146	-514,831	15.08
77	Conneaut Township Park	-50,135	-773,620	15.43
78	Geneva State Park	-69,076	-1,049,227	15.19
79	Lakeshore Park	-27,691	-418,530	15.11
80	Walnut Beach	-61,141	-935,935	15.31

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CONCLUSION

Innovative agri-environmental programs have the potential to enhance the provision of ecosystem services (ES) using limited conservation funds, but to be cost-effective, these programs must be attractive to farmers and landowners. Additionally, previous research has emphasized the importance of targeting high priority land, which implies the need to accurately predict environmental outcomes from beneficial management practices (BMPs) on specific fields. Furthermore, more research is needed to understand how accurate information about environmental benefits influences the decisions of land managers. Field experiments and randomized control trials can be used to analyze how information and different conservation program designs affect farmers' decisions and program outcomes. It is also important to understand how society values the benefits generated by improved management of agricultural landscapes because communities are affected by production externalities.

In this dissertation, I analyzed how conservation programs can be designed to abate phosphorus runoff more cost-effectively, and I estimated the impact of agricultural phosphorus runoff on the value of recreational amenities. In the first two essays, I evaluated farmer preferences for different types of conservation incentives and I analyzed how transaction costs affect participation in agri-environmental programs and the cost-effectiveness of different programs. In the third essay, I estimated welfare loss from beaches closures due to harmful algal blooms (HABs), which are spurred by excess agricultural phosphorus runoff. Results of this research were discussed in previous sections, but here I briefly review the main conclusions and discuss lessons learned.

As presented in Essay 1, pilot auction experiments were used to test farmer preferences for alternative incentives for BMP adoption, including direct payments, green BMP insurance, tax credits, and price premiums tied to stewardship certification. Direct payments and tax credits were found to be the most cost-effective incentives for two reasons. First, unlike the certification program, they were capable of targeting funds to high priority lands. Second, farmers were willing to participate in these two programs for lower payments than the program offering BMP insurance, which was viewed to have high transaction costs.

In Essay 2, two conservation auctions were conducted in NW Ohio in which farmers were invited to submit bids for the lowest payment that they would require to adopt a BMP. Only 1% of the 1,085 invited landowners submitted a bid. A follow-up questionnaire revealed that almost one-third of respondents did not know about the auction and a quarter of respondents indicated that they were ineligible for the program. Of the 195 respondents who were knowledgeable and eligible, primary participation deterrents included confusion about the bidding process, not wanting to adopt an eligible BMP, land rental agreements that made participation difficult, and a belief that their bid was unlikely to be accepted.

Reflecting upon experiences conducting the experimental and real auctions, it is important to acknowledge how participation is influenced by the environment in which individuals make decisions. Despite farmers' overall willingness to engage in the experimental pilot auctions, participation in the real auctions was low due to the transaction costs involved with learning about the auction program and formulating a bid. Farmer reluctance to submit a bid highlighted an important tradeoff that they consider in decision-making – the tradeoff between the time required to learn about a new program with uncertain benefits and the opportunity to fund new practices.

Although economic experiments conducted in a lab are useful to understand human behavior, this research highlights the importance of engaging farmers in field experiments and randomized control trials in which the decisions that they make have greater consequence in their daily lives. For example, although existing land rental agreements did not affect farmers' willingness to bid in the pilot auctions, rental agreements deterred participation in the real conservation auctions because coordinating with a landowner or renter increased the time and effort required to submit a bid. There also seemed to be confusion about how rental agreements influenced program eligibility. In addition to motivating the importance of using field experiments to understand farmer behavior, the example of land rental is noteworthy because farmland rental is increasingly prevalent, especially in the Midwest where more than half of cropland is rented (NASS 2014). Therefore, it is critical to design policies to engage both landowners and renters in order to target the most vulnerable areas of a watershed.

One of the challenges encountered in the Tiffin BMP Auction Program was how to accurately predicted phosphorus runoff because researchers and practitioners are uncertain about the movement of soluble reactive phosphorus (SRP) in subsurface drainage systems, which are widespread in Midwestern cropland. Not only does this challenge limit certainty about which practices to fund, it also limits the ability to develop accurate modeling tools to use with farmers for management planning. Improving our ability to model or measure environmental benefits could improve agri-environmental policy design in two ways. First, if we can predict where certain BMPs will have the greatest impact, we can better target funding to high priority fields. Second, information generated by these models can inform farmers about how their conservation effort can make the most impact. This knowledge may encourage them to engage further in conservation programs, particularly programs like conservation auctions that pay for high-impact projects.

Currently, research on farmers' behavioral responses to environmental information is scarce. There is a growing literature on how behavioral "nudges" can be used to increase participation in environmental programs and promote adoption of conservation practices (Sheeder and Lynne 2011, Thaler and Sunstein 2008). Examples of nudges that could increase participation in agri-environmental programs include providing landowners information about potential environmental benefits from BMPs on their land. Another nudge strategy is to offer social comparisons, comparing actions and environmental impacts of one farm to those of neighboring farms. In the context of reverse auctions, information to signal the probability of bid acceptance could nudge some farmers to submit a bid by reducing the uncertainty of bid acceptance.

In the final essay of this dissertation, I used two benefit transfer approaches to estimate welfare loss from beach closures due to harmful algal blooms in Lake Erie. Compared to a simple value transfer, a function transfer yielded similar welfare losses when a single beach closed because of a HAB. However, HABs typically affect large areas of the lake, resulting in closures of clusters of adjacent beaches. Estimated welfare losses from regional closures differed between the two transfer approaches because the value transfer was not able to capture the full welfare loss when the choice set is restricted and substitute sites are not available.

Finally, it is important to recognize that both the consequences and the causes of agricultural phosphorus loss have multiple facets that extend beyond those discussed here. Recreational losses are one of many negative impacts from HABs, and HABs are only one of many consequences of agricultural nutrient loss. Furthermore, depending on which BMP is implemented, improved management can mitigate multiple environmental externalities, including water quality degradation, greenhouse gas emissions, and biodiversity loss. Developing ways to measure and value aggregate benefits of BMPs is challenging, but these methods are necessary to support the design of agri-environmental programs that enhance suites of ES that people value.

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