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Using an Intervention Framework to Value Salient Ecosystem Services in a Stated Preference Experiment

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Abstract

To estimate the value of an improvement in the provision of an ecosystem service, analysts often use an intervention framework in a stated preference experiment. An intervention framework is defined by (i) an intervention, such as a publicly-funded program, and (ii) the intervention effect –the difference in the provision of the ecosystem service with and without the intervention. The contention of this paper is that if the purpose of an experiment is to estimate the value of the intervention *effect*, rather than the intervention itself, consideration needs to be given to the saliency of the service to the respondent population, because for salient services respondents often have prior beliefs about the intervention effect, and if these prior beliefs are different on average than implicitly assumed or explicitly presented in the choice experiment, the estimate of the value of the improvement will be biased. We emphasize that in some cases a structural model can be used to identify the value of the intervention effect, whereas for others, only the value of the intervention can be identified. We illustrate the issue using two case studies concerning ecosystem service provision on freshwater lakes, prevention of aquatic species invasions, and fish habitat enhancement.

Keywords: Stated preferences, contingent valuation, ecosystem services, invasive species, fish habitat

1. Introduction

Ecosystem services vary in their saliency to the people who benefit from them. Consider, for instance, biological diversity on the one hand, and a lake's fish population on the other. Biological diversity promotes the resiliency of natural ecosystems to external shocks in a manner that clearly benefits people (Tillman 1996; Worm et al. 2006), but this benefit is lost on most non-scientists. In contrast, a lake's fish population is a prominent and easily understood ecosystem service, where recreational anglers often have strong if not always correct beliefs about its current and future state. To estimate the value of an improvement in the provision of an ecosystem service, analysts often use an intervention framework in a stated preference experiment. An intervention framework is defined by (i) an intervention –usually a public program to improve the provision of the ecosystem service, such as a program to conserve open space, to protect an endangered species, etc.; and (ii) the intervention effect –the difference in the provision of the ecosystem service with and without the intervention. Intervention frameworks are often favored in stated preference experiments because they create a decision environment that is sensible, if not completely familiar, to the respondent. The contention of this paper is that if the purpose of an experiment is to estimate the value of the intervention *effect*, rather than the intervention itself, the analyst needs to give consideration to the saliency of the service to the respondent population, because for salient services respondents often have prior beliefs about the intervention effect, and if these prior beliefs are different on average than implicitly assumed or explicitly presented in the valuation exercise, the estimate of the value of the improvement will be biased.

Failure to properly identify a respondent's beliefs about the intervention effect implies that the analyst can only identify the average WTP for the intervention itself and *not* for the

differential provision of the ecosystem service embedded in the intervention effect. So, for instance, the analyst might ascertain the average WTP for a particular climate change mitigation *program* (the intervention), but without insight to the respondents' understanding of how climate will change in the absence of the program, the analyst is unable to make a claim about the value of the climate change mitigation attached to the program. In some circumstances this can be quite sufficient. For instance, in program benefit-cost analysis the analyst's objective is to determine how much a respondent is willing to pay for a program; the underlying intervention effect used by respondents to arrive at their valuations might be a matter of interest, but it's not critical to the objective. But often the analyst is interested in the intervention *effect* –the value of the differential provision of the ecosystem service: the expected loss from an aquatic species invasion, the value of a particular amount of biodiversity enhancement, the benefit of mitigating a particular aspect of climate change, and so forth. In these cases the intervention is primarily a vehicle to understand the value respondents place on ecosystem improvement, and so the analyst must accurately gauge the respondents' understanding of the improvement provided by the intervention. This paper develops this point and presents two case studies to demonstrate that as a practical matter it can be very difficult to identify the intervention effect, either because the ecosystem improvement in question is difficult to precisely define, or because respondents have beliefs about the baseline state of the ecosystem that are at odds with the researcher.

There are four basic reasons that identifying the intervention effect is important. First, it is useful for benefit transfer. For instance, an estimate of the average welfare cost of an aquatic species invasion at the lake level in Wisconsin is likely to be useful in evaluating the cost of invasions in similar lake districts from Maine to Minnesota. Second, it provides the basis for assessing convergent validity. Staying with our aquatic invasive species example, if both a

hedonic analysis and a contingent valuation analysis indicate similar welfare losses from an aquatic species invasion, managers and policymakers have greater confidence that these values accurately reflect the true cost of an invasion. Third, when combined with models describing ecosystem changes, intervention effects provide the opportunity for sound resource management and policy analysis. For example, a resource agency with a limited budget and tasked with controlling several different aquatic invasive species is likely faced with several management options that differentially prioritize the species. Having information about the value lake users place on controlling the different species is useful information in choosing among the options. Finally, there is value in basic scientific research to identify the benefits of improving and preserving ecosystem goods and services. For instance, a variety of studies in Maryland, Wisconsin, and Maine have examined the value of improving water quality (Leggett and Bockstael 2000; Poor et al. 2001; Moore et al. 2011). Such efforts contribute to a general broadening and deepening of understanding of the cost of letting aquatic ecosystems deteriorate.

In an intervention framework for ecosystem services that are not salient to survey respondents, researcher-provided statements about the degree of provision of the ecosystem service with and without the intervention (that is, statements asserting the intervention effect) are a reasonable way –often the only way –to establish the intervention effect for the experiment. For example, the famous Exxon Valdez valuation study (Carson et al. 2003) presented survey respondents with a program to prevent future oil spills. Respondents were told that scientists believe that another oil spill in Prince William Sound of Alaska "can be expected to occur" over the next ten years. Respondents also were told that with the oil spill prevention program in place it is "virtually certain there will be no large oil spill that will affect this area".[1] It is reasonable to

[1] The quotes are taken from the Valdez survey, which can be found at lead author Richard Carson's website: http://econ.ucsd.edu/~rcarson/AKsurvey.pdf.

believe that respondents do not have strong prior beliefs about the likelihood of an oil spill in the absence of the prevention program, and that they do not have strong prior beliefs about the likelihood of a spill after the prevention program is put in place, and so their expectations about future oil spills with and without the prevention program are based solely on what they're told in the survey instrument. The survey instrument, in other words, is the sole source of respondents' understanding of the intervention effect. Louriero and Loomis (2013) provide a more recent stated preference analysis of preventing oil spills in Europe that follows a similar pattern to the Valdez study of stating damages with and without a prevention program.

On the other hand, for the provision of salient ecosystem services the intervention effect presented in a survey instrument can be in contradiction, or at least not fully consistent, with a respondent's prior beliefs. For example, because climate change has become politicized, statements about the effect of mitigation measures might often contradict a respondent's prior beliefs. Lee and Cameron's (2008) contingent valuation study of U.S. citizens' willingness to pay (WTP) to mitigate climate change examined this issue. The authors observe, "popular support for climate change mitigation policy is noticeably greater when people perceive that climate change is likely to cause greater levels of harm" (p. 246). Cai et al. (2010), Carson et al. (2010) and Viscusi and Zeckhauser (2006) also find heterogeneous expectations of climate change damages.

The intervention framework is used often in stated preference surveys valuing ecosystem services, in particular interventions that involve the conservation of undeveloped land (Mogas et al. 2009; Boyle and Ozdemir 2009; Cunha-e-Sa et al. 2012; Schuefele and Bennett 2012), the conservation of specific species or groups of species (e.g. Czajkowski and Hanley 2009; Carlsson et al. 2010; Lew and Walmo 2011; Atkinson et al. 2012; Kragt and Bennett 2012),

outdoor recreation (Jeon and Herriges 2010; Hess and Beharry-Borg 2012), and water access (Brower et al. 2010; Akram and Olmstead 2010). Whether respondent expectations are relevant to the valuation of the intervention effect is a research judgment call. Consider recent studies that ask respondents about their WTP for programs that conserve land. It is reasonable to assume that residents of the UK do not have well-formed expectations over the intervention effect of programs to conserve land in Brazil (Atkinson et al. 2012). On the other hand, it is also reasonable to assume that respondents do have prior beliefs about the intervention effect –about the counterfactual if not the alternative condition imposed by the intervention –for local land conservation programs (e.g. Boyle and Ozdemir 2009; Mogas et al. 2009; Czaajkowski and Hanley 2009; Cunha-e-Sa et al. 2012; Schuefele and Bennett 2012).

Figure 1 draws on recent surveys to illustrate the heterogeneity of survey respondent beliefs about how they expect a local ecosystem service/good to change over the ensuing ten years in the absence of an intervention. The data are from surveys conducted by the authors between 2005 and 2011, and apply to lake users in northern Wisconsin. Clearly these lake users do not have uniform beliefs of baseline future ecosystem service provision on their lakes. For example, about 12% of recreational boaters think that an invasion of their favorite lake by the highly undesirable plant Eurasian Milfoil is imminent (Fig. 1.a), while 22% of lakeshore property owners think there is almost no chance that their lake will be invaded by the Milfoil (Fig. 1.b). About 60% of lakeshore property owners expect no future changes in their lake's fishing prospects while just under 30% are more pessimistic and expect a modest decrease (Fig. 1.c). Lakeshore property owners in particular are quite divided over the prospects for future neighboring development on their lakes (Fig. 1.d). If scope matters at all – and it should in a well-designed study – then respondents more pessimistic about future ecosystem service

provision will be willing to pay more for programs that conserve those services than respondents who are more optimistic. Thus, in addition to the usual explanation of heterogeneous preferences and income conditioning WTP estimates, heterogeneous expectations of baseline conditions will also systematically condition WTP. For example, results presented in section 3 of this paper show that the mean WTP for a 25% increase in a lake's fish population is $183 for respondents who expect a modest decrease in their lake's fish population and only $14 for respondents who expect no change. Further, in their responses in a choice experiment, respondents with heterogeneous expectations are likely to ignore or at best deviate from researcher-stated baseline conditions (as a good Bayesian would). We suspect that the problem of disentangling expectations and preferences in stated preference analyses is likely to be most acute for goods at the center of political debate (climate change mitigation, clean groundwater in areas of high concentration of natural gas and oil drilling), or local goods with high use value (lake fisheries, prevention of species invasions).

This paper expands on a recent paper by Provencher, Lewis, and Anderson (2012) – hereafter PLA – about identifying the value of a change in salient ecosystem services when the intervention effect is heterogeneous across respondents. PLA examined lakeshore property owners' WTP for a program to prevent invasion of their lake by an aquatic invasive species (Eurasian Water Milfoil, hereafter, milfoil). In the lake-rich region examined –the northern highlands lake district of Wisconsin –such invasions are highly salient threats to lakes, and so it is sensible to assume that lakeshore property owners have strong prior beliefs about the probability of an invasion in the absence of a prevention program. It follows that if two individuals are willing to pay the same amount for the prevention program, the individual who places a lower probability on an invasion over a specified time horizon expects a greater welfare

loss from an invasion. In the terminology we are using here, the prevention program is the intervention, and, assuming that respondents accept the assurance that the prevention program would keep the invasive species out of the lake, the intervention effect is the subjective probability that the lake will be invaded over the specified time horizon in the absence of the prevention program. The PLA study asked survey respondents about their subjective probabilities of an invasion over a 10-year period in the absence of a prevention program, and used these respondent probabilities and their responses to questions about their WTP for the prevention program in a structural econometric model to estimate the average expected loss from an invasion.

We present two case studies to examine the use of surveys to account for respondent heterogeneity over the effect of interventions in the provision of salient ecosystem services, emphasizing that the appropriate empirical approach greatly depends on the characterization of the intervention. As in the PLA study, both case studies apply to northern Wisconsin lakes. The first –again as in the PLA study—involves a program to prevent an aquatic species invasion. We construct a structural econometric model that accounts for heterogeneity across respondents in the subjective probability of an invasion under the counterfactual (no prevention program) to estimate the welfare loss from an invasion. What distinguishes this analysis from that in the PLA study is that, whereas the respondent sample in the PLA study is shoreline property owners, for whom the loss from an invasion is capitalized in the value of their shoreline property, in the analysis in this paper the respondent sample is composed of boaters–usually anglers—with the stated preference questions concerning their WTP to prevent an invasion on their *favorite lake*. Contrasting the econometric models for the two cases is instructive, and a comparison of the expected loss of an invasion for the two groups generates good insights about the distribution of

losses due to an aquatic species invasion. In particular, whereas PLA report that the average shoreline property owner is willing to pay $563 per year for a program to prevent a milfoil invasion, and would suffer an average loss of $2,106 per year from an invasion, we find that boaters are willing to pay $62 for a program to prevent a milfoil invasion on their favorite lake, and would lose an average of $98 per year from an invasion on their favorite lake. Our case study highlights the set of assumptions required for structural decomposition of WTP for the intervention and the welfare loss from an aquatic species invasion for recreational boaters on a lake. Of particular note, the analyst must assume a time-frame for the respondents' WTP, which includes a time-frame for their expectations of a Milfoil invasion. The time-frame was infinity for homeowners in the PLA study whose land capitalized losses from invasion, and the time-frame is assumed as the respondents' remaining lifetime in the structural model with non-landowning boaters.

In the case study above, the binary nature of the ecosystem change in question – presence/absence of milfoil –greatly simplifies the development of a structural model to disentangle preferences and expectations to identify the intervention effect. In many if not most applications, though, the analyst will encounter two substantial practical difficulties to identifying the intervention effect. The first is that the ecosystem service over which the intervention effect is defined may be difficult to quantify in a survey. This would apply, for instance, to improvements in climate (exactly what is meant by this?), or improvements in fishing quality (what is the appropriate metric for such an improvement?). Second, even if it is possible to quantify the underlying ecosystem good in a way that is clear and concise to the respondent, quantifying respondent expectations about the counterfactual state of the good is problematic when the counterfactual is a continuous *path*. Referring to our fishing quality

example, suppose the change in fishing quality is precisely defined as an immediate increase in the stock of fish species X. Identifying the intervention effect in this case requires information about the respondent's expectations for the future *path* of the fish stock.

These practical difficulties are manifest in our second case study, which applies to shoreline property owners and concerns a fish restoration program. To present the intervention in a generalizable way, respondents were told that it would increase fish populations "by twenty-five percent". Yet this is too vague to precisely quantify the intervention effect: What exactly is meant by a 25% increase in the fish population? What is the counterfactual to the restoration program envision by the respondent –will the population stay the same, increase anyway, or decline, and if so, by how much, and over what time frame? In this case, the best that can be achieved is a reduced form model in which survey questions aid the analyst in grouping respondents into subsets defined by their similarity in expressions of expected intervention effects. Consequently, whereas the value of the intervention can be estimated, the value of the intervention effect cannot, and the best the analyst can hope for is a degree of construct validity, in particular the finding that, all else equal, respondents who expect relatively low baseline conditions in the future are willing to pay more for the intervention.[2]

This reduced-form approach has been applied to stated preference analyses of climate change (e.g. Viscusi and Zeckhauser 2006; Lee and Cameron 2008; Cai et al. 2010) and endangered species conservation (e.g. Whitehead 1992). We show that separately estimating WTP functions for each group of respondents generates substantially different estimates than the parameterically restrictive case of including group-wise dummy variables in a single WTP function. Consistent with findings from climate change studies (Lee and Cameron 2008; Viscusi

[2] In practice, the ceteris paribus condition can be difficult to enforce. For instance, individuals who are willing to pay more for the intervention effect may be less pessimistic about the state of the world in the absence of intervention.

and Zeckhauser 2006), we find that respondents who expect no future change in their lakes' fish populations have a lower willingness-to-pay ($99 per year) than respondents who expect modest declines in their lakes' fish populations ($229 per year). We also find substantial differences when separately estimating willingness-to-pay functions across groups of respondent expectations compared to distinguishing groups in a single equation with group-wise dummy variables.

In the next section we present the first case study –the prevention of milfoil on the respondent's favorite lake. The structural model developed for the analysis is similar to that used in PLA for lakeshore property owners, but whereas PLA assumed that respondents understood that the effects of invasions would be capitalized in property values, and therefore took the "long view" on the value of the prevention program, in the model developed here we assume that, all else equal, younger respondents are willing to pay more for a prevention program than older respondents, because they expect to use the lake for more years. Section III presents the second case study concerning the willingness of shoreline property owners to pay for an increase in fish populations. We conclude the paper in Section IV with summary remarks.

2. Binary change in an ecosystem service – Aquatic invasive species prevention

2.1 Model setup

In this section we focus on developing a simple model of willingness-to-pay for a program to prevent a binary negative shock to an ecosystem service. We focus on a recreational boater's willingness-to-pay for a program to prevent an aquatic species invasion on their favorite lake – the application in this section. Let $L(\boldsymbol{z})$ denote the annual loss from an invasion, where $\boldsymbol{z}$ denotes a vector of variables affecting boater utility, and let P denote the probability of an invasion during the year. The WTP to assure no invasion in the initial year (year 0) is the

expected loss from an invasion during year 0, $P{\cdot}L(\boldsymbol{z})$. Conditional on no invasion in year 0, the willingness to pay to ensure no invasion in year 1 is equal to this same value discounted. The probability of no invasion in year 0 is 1-P, so the unconditional WTP to ensure no invasion in year 1 is $\frac{1-P}{1+r}P \cdot L$. By extension, the annual WTP to ensure no invasion is:

$$WTP(z,r) = P \cdot L + \frac{1-P}{1+r}P \cdot L + \left(\frac{1-P}{1+r}\right)^2 P \cdot L + \cdots = P \cdot L(z) \cdot \sum_{t=0}^{T} \left(\frac{1-P}{1+r}\right)^t \quad (1)$$

In PLA, an infinite horizon is used for (1) since the survey respondents were shoreline landowners and the invasive species is capitalized into their land values. Given the lack of such capitalization with a population of recreational boaters, assuming an infinite horizon is not justified. We therefore specify T as the respondent's expected remaining life span, and examine the sensitivity of results to different assumptions about T. The expression in (1) can be simplified as the infinite horizon WTP minus the infinite horizon WTP discounted at year $T+1$:

$$WTP(z,r) = P \cdot L(z) \cdot \sum_{t=0}^{\infty} \left(\frac{1-P}{1+r}\right)^t - \frac{P \cdot L(z)}{(1+r)^{T+1}} \cdot \sum_{t=0}^{\infty} \left(\frac{1-P}{1+r}\right)^t$$

$$= P \cdot L(z) \cdot \left(\frac{1+r}{r+P}\right) - \frac{P{\cdot}L(z)}{(1+r)^{T+1}} \cdot \left(\frac{1+r}{r+P}\right) = \left(\frac{P{\cdot}L(z)}{r+P}\right)\left[\frac{(1+r)^{T+1}-1}{(1+r)^T}\right] \quad (2)$$

The empirical challenge is separately identifying $L(\boldsymbol{z})$ and P. The nonlinearity of WTP provides a means for this, but relying on the structural specification for identification is not ideal. The approach taken instead is the one taken in PLA: query respondents as to their subjective probabilities P, in which case P is data rather than a parameter requiring estimation.

Each respondent j is presented with a referendum on a prevention program that includes a per-trip fee for the prevention program. Presumably respondents respond by comparing the annual cost to them implied by the referendum, c_j, to their annual WTP to ensure no invasion. Rather than presenting respondents with a simple yes/no question, we allow respondent uncertainty about how they would vote on the referendum if it were actually to be held. We

prompt respondents to pick a probability on a line from 0 to 1 and derive a log likelihood function of the respondents' probability of voting for the referendum. Formally, respondent j's expression of uncertainty with regard to the referendum vote is introduced by specifying their willingness to pay for the prevention program, WTP_j^{PP}, as a random variable:

$$WTP_j^{PP} = WTP_j - \varepsilon_j = \left(\frac{P_j \cdot L(z_j)}{r+P_j}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right] - \varepsilon_j \ . \tag{3}$$

The probability of voting "yes" on the referendum is then,

$$\pi_j = \Pr(WTP_j^{PP} > c_j) = Pr\left(\left(\frac{P_j \cdot L(z_j)}{r+P_j}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right] - c_j > \varepsilon_j\right). \tag{4}$$

Assuming that ε_j is logistically distributed with scale parameter σ, we have,

$$\pi_j = \frac{exp\left(\left(\frac{P_j \cdot L(z_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right] - \frac{c_j}{\sigma}\right)}{1+\exp\left(\left(\frac{P_j \cdot L(z_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right] - \frac{c_j}{\sigma}\right)} \tag{5}$$

Different respondents who face the same annual payment c and possess the same characteristics z may still arrive at different values of π_j due to unobserved differences among them. We account for this by expanding $L(z_j)$ to the following linear form:

$$L(z_j) = \beta z_j + v_j \tag{6}$$

Where v_j is an individual-specific random constant known by the respondent but not the researcher. Substituting (6) into (5) gives:

$$\pi_j = \frac{exp\left(\left(\frac{P_j \cdot (\beta z_j + v_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right] - \frac{c_j}{\sigma}\right)}{1+\exp\left(\left(\frac{P_j \cdot (\beta z_j + v_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T+1}-1}{(1+r)^{T}}\right] - \frac{c_j}{\sigma}\right)}. \tag{7}$$

From the perspective of the analyst, v_j is a random variable, and since respondents choose the probability value π_j by picking a point along a line, in the case where v_j is distributed

logistically with scale parameter φ, this probability can be explicitly defined by appealing to the logistic probability density function. After algebraic manipulation (see appendix), the probability that the respondent selects probability Pr_j is:

$$\Pr_j = \frac{\exp\left[\frac{\sigma\left(r+P_j\right)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\left[\ln\left(\frac{\pi_j}{1-\pi_j}\right)+\frac{c_j}{\sigma}\right]+P_j\cdot\left(\beta z_j\right)}{\varphi}\right]}{\varphi\left[1+\exp\left[\frac{\sigma\left(r+P_j\right)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\left[\ln\left(\frac{\pi_j}{1-\pi_j}\right)+\frac{c_j}{\sigma}\right]+P_j\cdot\left(\beta z_j\right)}{\varphi}\right]\right]^2} \tag{8}$$

The sample likelihood function is the product of the probabilities in (8). The set of parameters is $\{\sigma, \beta, \varphi, r\}$. As reported, the set is $\{\sigma/\varphi, \beta/\varphi, 1/\varphi, r\}$.

2.2 Background and data

Eurasian watermilfoil (*Myriophyllum spicatum*) is an invasive aquatic plant that has become a major nuisance in the lake country of the northern U.S. and Canada. It is spread by boaters who inadvertently transport fragments of the plant that have become attached to their boats, anchors and trailers (Johnson, Ricciardi & Carlton, 2001). While the impact of milfoil varies considerably from lake to lake (Madsen, 1998; Smith & Barko, 1990), it has been associated with rapid growth leading to dense mats of floating vegetation that have been blamed for ‘‘clogging’’ infected lakes, interfering with a lake’s ecology (Boylen et al. 1999; Madsen et al. 1991), and interfering with recreation activities (Eiswerth et al. 2005). Milfoil first invaded southern Wisconsin waters in the 1960s and spread to northern Wisconsin in the early 1990s. Empirical estimates of the welfare loss from milfoil invasions have been conducted on shoreline property owners with hedonic (Horsch and Lewis 2009) and contingent valuation analysis (Provencher et al. 2012), and range from capitalized present values of approximately $23,000 to $32,000.

The sample used for estimation was taken from participants of a trip diary program conducted during the 2011 and 2012 boating season in northern Wisconsin. Participants were recruited at public landings of 136 lakes in Vilas and Oneida Counties between Memorial Day weekend and Labor Day, as a part of a larger survey focusing on invasive species. The sampled lakes were chosen to represent variation in size, popularity, distances from population centers, and presence of invasive milfoil. Sampling was evenly divided between weekdays and weekends, and lakes were visited at different times of day throughout the study period to ensure all types of boating activities were likely to be encountered. All boating parties encountered at the boat landing were approached and the adult owner of the boat was invited to participate in the study. At the end of each boating season, a 14-page follow-up survey containing the contingent valuation question was mailed to respondents. The survey protocol followed the tailored design method (Dillman, 2007) and participants received a payment of $25 on completion. Regular contact was maintained throughout the diary period, and five separate contacts (an announcement postcard, survey packet, reminder postcard, replacement survey packet, and a final postcard) were made regarding the follow-up survey. In all 3,004 participants were recruited into the broader study with 1,969 completions. After accounting for 39 undeliverable surveys, the response rate was 66%. Completion of the CV question was conditioned on respondents believing that their favorite lake was currently not invaded by milfoil, a conditioning that excluded 1,081 respondents from the final estimation dataset. A further 128 respondents were excluded because they owned property on the lake.[3] After filtering the remaining sample for item non-response on all required elements for our analysis, 767 respondents were retained for estimation.

[3] Property owners were excluded because for them the payment scenario may not be incentive compatible; because many if not most have private ramps onto their lake, they would not face the launch fee used in the scenario.

2.2.1 Annual probability of invasion

To estimate P_j, respondents were asked for their best guess of the likelihood that their favorite lake would become invaded in the next five years:

> Based on the information just provided and your previous understanding of Eurasian water milfoil (EWM) invasions, what would be your best guess of the percent chance that your favorite lake *(from question 10)* will become infested with EWM within the next five (5) years?
> *(Mark your answer by placing an X on the scale below at the appropriate spot)*
>
> 0% 10 20 30 40 50 60 70 80 90 100

A follow-up question asked of respondents about their best guess of the percent chance that their favorite lake will become infested with EWM within the next *ten* years. The theoretical model in equation (2) depicts respondents with a constant annual probability of invasion. These five- and ten-year probabilities were then annualized as follows:

$$P_{jt} = 1 - (1 - p_{jt})^{\frac{1}{t-1}} \tag{9}$$

where p_{jt} is respondent j's stated probability over horizon t, in this case either t=5 or t=10. With probability responses over both a five- and ten-year horizon, we examined whether the two horizons generated significantly different annual probabilities of invasion. First, a linear spline was estimated that implicitly assumes respondents have a constant P over the first five years, and a different constant P from years five to ten:

$$P_{j10} = 1 - \frac{p_{j10} - p_{j5}}{1 - P_{j5}} \tag{10}$$

Second, we simply averaged P_{j5} and P_{j10}, $P_j = (P_{j5} + P_{j10})/2$. A simple linear regression of the spline probability on the average probability revealed that the two approaches were mostly the same, with an R^2 of approximately 0.96. We therefore use the simple average of P_{j5} and P_{j10} for all remaining calculations of the annual probability of a milfoil invasion for each respondent j.

Finally, 77 respondents predicted $P_{j5} \geq P_{j10}$; these were dropped from analyses, leaving a final sample size of 690 respondents for welfare analysis.[4]

2.2.2 Valuation question

The scenario presented to respondents describes a referendum for an invasive species prevention and early detection program that would make it "highly unlikely" that milfoil becomes a problem on their favorite lake, with boaters paying a per-trip fee for the program. Conventional stated preference protocols were followed. Respondents were told the number of regional lakes currently infested with milfoil, the regional rate of spread of the species, and the consequences of an invasion. We consulted with local lake managers and ecologists to construct a realistic program consisting of i) paid staff to monitor the lake and boats at the launch for milfoil, ii) construction of boat washing stations at the launch, and iii) boater education. A short "cheap talk" script precedes the description of the referendum scenario and implores respondents to "think about the following referendum scenario as if you are really going to vote on it." Consistent with the theoretical model developed in *2.1*, respondents report the *probability* that they would vote yes:

> What is the percent chance that you would vote "Yes" on the referendum to fund the program to prevent milfoil on your favorite lake, if the cost to you added $___ per trip that you visit the lake?
>
> *(Mark your answer by placing an X on the scale below at the appropriate spot)*
>
> 0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

The referendum presents the program cost in terms of a cost per trip, but the model used to estimate the WTP function builds off PLA's model and casts the program cost in annual terms. Figure 2 presents the simple conceptual approach to converting the change in trip cost associated

[4] Respondents had a mean age of 52 years (s.d. = 6.3 years) and were overwhelmingly male (82%) with median levels of education and household income at an associate degree and earning $65,000 to $80,000 per year. Most respondents were either employed full time (68%) or retired (25%).

with the prevention program to an annual cost. The figure depicts annual demand for trips to the lake in question. The respondent is confronted with a referendum in which the trip cost rises from TC1 to TC2. The total number of trips taken each year falls from A to B. The annual cost is the difference TC2-TC1 multiplied by the number of trips taken at the higher trip cost (B), *plus* the consumer surplus lost due to fewer trips taken to the lake because of the higher cost (surplus triangle eab in Figure 2). This annual cost is area abcd. In the survey we asked respondents how many trips they took to the lake in the boating season just ended, and how many fewer trips they would take to the lake at the higher trip cost. This allowed us to calculate the surplus triangle eab in Figure 2. Of course, the demand for trips is not necessarily linear, but the average reported change in annual trips due to the referendum is small—1.19 trips (s.e.=0.45), and so we consider the approximation of surplus described above to provide a reasonable estimate of the true surplus.

An important specification question is the relevant time horizon T_j to assume for the responses to the referendum. If respondents were shoreline property owners similar to the sample used in PLA, then an infinite horizon is appropriate since Milfoil is capitalized into land values (Horsch and Lewis 2009). However, our sample only includes boaters who do not own property on their favorite lake, and so the appropriate time horizon is not so obvious. We attempted to estimate T as a parameter –the average time horizon –but the highly non-linear structure of the model did not allow convergence. Therefore, we use data on survey respondents' ages to set T for respondent j to be T_j=max(80-age$_j$, 5). This approach presumes that respondents' time horizon is their expected remaining life span, where the age of 80 is a middle ground between the World Bank's estimated 2013 lifespan for Canadians (81 years) and

Americans (79 years). Respondents over age 75 are assumed to use a five-year time horizon. We conducted sensitivity analyses with regard to these assumptions, as discussed below.

2.3 Results

Maximum likelihood estimation was used to estimate all parameters in (8) with original code in Matlab. Estimated parameters are presented in Table 1. Estimated parameters include two scale parameters, a constant, and a discount rate. The discount rate is the only intuitive parameter estimate in table 1, and results imply that respondents discount the future at a reasonable 9%. Our focus in this study is on disentangling expectations and preferences, rather than on the covariates that condition the estimated loss from a Milfoil invasion, and so the only parameter of the loss function is the constant term $\hat{\beta}$.[5]

Welfare estimates are reported in Table 2, and major findings include the following. First, respondents' average WTP for the prevention program is $62, but the estimated annual loss from a Milfoil invasion is $98, as calculated at the sample average annual invasion probability (P=0.154) and remaining life (T=28.1). The 95% confidence intervals of these two values do not cross, providing strong evidence that willingness-to-pay estimates for programs can be far lower than loss estimates when respondents do not expect an imminent binary shock to a salient ecosystem service. Second, results from sensitivity analyses are quite robust to the researcher's assumption regarding respondents' time horizon, as welfare estimates generally fall (increase) by small amounts when the assumed time horizon increases (decreases). Finally, in Figure 3 we use the results to plot the estimated nonlinear functional relationship between WTP for the Milfoil prevention program (WTP^{PP}) and the annual probability of a Milfoil invasion, showing that as

[5] Estimation generates $\hat{\beta}/\hat{\varphi}$. The estimated loss is calculated by dividing through by $1/\hat{\varphi}$.

the probability of a milfoil invasion increases the WTP for the prevention program converges on the loss from an invasion.

The sample used for estimation is conditioned on survey respondents believing that their favorite boating lake is not currently invaded with Milfoil – indeed, one cannot ask a survey respondent about a prevention program if they believe their lake is invaded with Milfoil. However, at the time of our survey, 39% of our survey respondents' favorite lakes actually do have Milfoil according to the Wisconsin DNR. We re-estimated the loss from a Milfoil invasion with a sample that excludes respondents who are wrong about their lake being Milfoil free, and find the estimated loss to be $94, well within the 95% confidence interval of the $98 estimate reported in Table 2. The fact that including survey respondents who are wrong about their favorite lake's Milfoil status has no effect on welfare estimates is not surprising since we expect many boaters' survey answers are in response to the well-documented fear of what Milfoil can do to their lake, even if the effects are not currently noticeable. For example, despite being barely noticeable for its first 60 years of existence, the Chesapeake Bay experienced a well-documented and often cited doubling of area affected by Milfoil between 1960 and 1961 (Orth and Moore 1984).

3. Continuous change in an ecosystem service –Improving a fishery

Valuing continuous changes in a salient ecosystem service presents challenges beyond those found in valuing binary changes. As developed in section 2, binary changes present a simple case that can be exploited in a tractable structural model because the intervention effect is well defined, with commonly understood outcomes (e.g. invasion vs. no invasion), and subjective expectations that are relatively easily elicited and represented over the two possible outcomes. Continuous changes present researchers with the challenge of communicating the

continuum. This challenge is not only about the "continuousness" of the ecosystem service per se, but also pertains to the lack of a common well-understood and well-accepted metric in which to describe the continuum. How does one communicate, for instance, a change in a lake fishery? A fishery is a multi-dimensional attribute –a set of species, for instance, with age classes within each species –and the typical respondent surely would not be able to quantify in cardinal terms expected changes of even one of these attributes. The most the analyst can expect from the respondent is an ordinal quantification of the changes in the states of attributes along a Likert scale or similar scale, or more realistically, an ordinal quantification of the change in a broad-based index of the state of fishery –an ordinal change, in other words, of the "overall" state of the fishery.[6]

Such an approach is used, for example, in Lee and Cameron's (2008) climate change CV study. The study inquired about respondents' ordinal expectations of broadly-defined future damages in the absence of intervention over eight separate measures: agriculture/water, ecosystems, human health, oceans/weather, equity/fairness, domestic cost shares, and international cost shares. Respondents were asked to select their expectations for each of the 8 measures via a Likert scale from "extremely harmed" to "extremely improved". Similarly, in an analysis of willingness to pay to protect the endangered loggerhead sea turtle, Whitehead (1992) inquired as to respondents' expectations that the species would go extinct via a Likert scale from "definitely will become extinct" to "definitely will not become extinct".

Unlike the invasive species case we analyzed above, where expected changes were quantified and modeled within standard frameworks of economic theory and probability theory, in this situation it is not possible to develop a fully structural choice model because the expected

[6] Alternatively, researchers could present survey respondents with a multi-metric index representing biotic integrity of a water body (Johnston et al. 2011).

future state of the ecosystem attribute is not expressed precisely, and so it is not possible to disentangle the WTP for an intervention program and the welfare loss associated with a change in the ecosystem attribute in question. Yet it often remains a matter of policy interest whether individuals who expect a decline in the state of the ecosystem attribute are willing to pay more to see an improvement than those who do not. In their WTP function, Lee and Cameron included dummy variables based on the aforementioned Likert scales, finding that these variables do indeed impact WTP in the expected way.[7] Other authors represented expectations similarly (e.g. Whitehead 1992; Viscusi and Zeckhauser 2006; Cai et al. 2010). An alternative, less parametric approach is to estimate different WTP functions for groups of individuals with different ordinal expressions of the future state of the attribute.

In this section we empirically evaluate an improvement in a fishery. The intervention is a fish restoration program in the same study area –northern Wisconsin—as the invasive species study presented in section 2. Whereas that study involved recreational boaters, this study involves shoreline property owners who responded to a 2008 survey that presented a program to fund aquatic habitat restoration to increase the fish population on the respondent's lake. Recreational fishing is one of the primary activities that attract people to purchase shoreline property in this region, and lakeshore residents are typically well-versed in their lake's fishery.

3.1. Data

Data for the analysis is from a 2008 web and mail survey of a sample of lakeshore property owners in Vilas County, Wisconsin. The sample was drawn from shoreline property owners identified from local tax rolls. The sampling of properties was not random, but instead favored properties on smaller lakes to assure adequate representation of such lakes, though we

[7] Lee and Cameron grouped expected future damages from climate change into categories "substantially harmed", "moderately harmed", "moderately improved", and "substantially improved", with "no change" as the omitted category.

found no statistical effect of lake size on WTP. Overall, 2,955 households were contacted in the 2008 survey, with 1565 (53%) providing usable responses. Of those responding to the survey, 983 were asked to answer the questions about fish restoration[8].

The choice scenario was framed as a lake-wide referendum for a restoration program that would increase the fish population in the respondent's lake by 25%. The scenario design followed conventional protocols for contingent valuation. Respondents were told that the restoration program would not change the mix of fish species on their lake (bass, muskellunge, walleye, etc.), and that the program would increase fish populations through habitat restoration by other property owners on their lake, and not through stocking.[9] Respondents were told that habitat restoration activities would include placing downed logs and planting native vegetation in the lake shallows, and adding spawning gravel. Importantly, respondents were told that such a program would involve habitat restoration by several property owners on their lake, but not by them. These property owners would agree to develop and maintain fish habitat along their shoreline with the support and expertise of state conservation organizations. We consulted with a variety of biologists in construct a realistic restoration scenario and included a short "cheap talk" script. Respondents were given an annual cost of the fish restoration program and asked to pick from categories that reflect the probability they would vote for the referendum (i.e. 0-10%, 10-20%, etc.). This question was repeated in a follow-up contingent valuation question with a different annual cost.[10] At all bid levels respondents frequently chose a probability category other than 0-10% or 90-100%, indicating substantial respondent uncertainty.

[8] Each survey respondent received two of three possible CV questions on fish restoration, green frog conservation, and invasive species prevention/control.
[9] We distinguished habitat restoration from stocking because many anglers strongly prefer wild fish to stocked fish.
[10] On the mail version of the survey the amount of the annual cost on the follow-up was randomly assigned, whereas the web version lowered the annual cost if the respondent initially stated that the probability of a "yes" vote was less than 50%, and raising it if the probability was greater than 50%. On the Internet survey respondents who indicated on both contingent valuation questions that their probability of a "yes" vote was 0-10%, or who indicated on both

Several questions preceding the CV question concerned how the respondents would characterize their "interest in fishing" and "the fishing quality on your lake". In addition, we probed respondents about their baseline expectations for their lake's fish population in the absence of the intervention. Respondents were asked, "How would you expect the quality of fishing on your lake to change over the next 10 years?" The five alternative responses and the number of respondents choosing each alternative are presented in Figure 1.c. The vast majority of respondents chose "No change" (571 responses) or "Modest decline" (280 responses).[11] For sample size considerations we restricted the analyses to these two groups of respondents, referring to them below as the "No Change" (NC) expectation group and the "Modest Decline" (MD) expectation group.

3.2 Results

We estimated separate models for the NC and MD expectation groups. Separate estimation across expectation groups imposes fewer assumptions since parameters are allowed to differ across groups. The econometric model used in estimation is complicated by the fact that, rather than answering a Yes/No referendum question, respondents chose probability intervals concerning whether they would say "Yes" to a referendum for the habitat restoration. The econometric model is structurally identical to that used in PLA's analysis of willingness to pay for a program to *control* invasive Milfoil populations on lakes where the invasive species is already present, and we refer readers to that paper for the technical development.

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questions that their probability of a "yes" vote was 90-100%, were also asked to state the amount that would leave their probability of voting "yes" at "about 50%".

[11] The other categories "severe decline", "modest increase", and "substantial increase" included sample sizes of 42, 84, and 6 respectively.

The vector of independent variables is kept simple because our focus is on identifying the average household WTP for the fish restoration program rather than the covariates that condition this WTP. We condition WTP on the respondents' interest in fishing (1: low, 6: high) and the respondents' perception of the quality of fishing on their lake (1: very poor, 5: excellent).[12] The estimated model parameters include a scaled constant β_0 / φ, the bid coefficient $1/\varphi$, the scale ratio σ / φ, the vector of coefficients on independent variables scaled by φ, and a random effects standard error ϑ representing the standard deviation of a respondent-specific unobservable that is constant across CV questions.

The estimation results in Table 3 support several conclusions. First, respondents with greater interest in fishing are willing to pay more for the fish habitat restoration program. Second, the estimated mean welfare gain from the fish population increase is considerably lower for the NC expectation group than for the MD expectation group. The confidence intervals for the welfare gains – calculated with the Krinsky-Robb approach – do not overlap across the two groups. These general conclusions hold whether we include household income in the estimation sample or not, though in Table 3 we present the model without income.

In Table 4 we evaluate whether the WTP divergence across the two expectation groups is due to respondent characteristics, rather than the different baseline expectations. The primary result is that there appears to be no large differences in characteristics that would likely be correlated with fishing preferences across the two groups; it appears that the

[12] We also checked a specification that augmented the right-hand side variables to include the household's annual income, though this cuts the sample size from 571 to 489 (no increase sample) and from 280 to 223 (modest decline sample). WTP results are marginally – though not statistically – higher when income is included. Results are available from the authors upon request.

most likely explanation for the divergence in the WTP estimates across the two groups is the difference in their stated expectations.

Lastly, we evaluate the standard practice of estimating the WTP function by combining expectation groups in a pooled regression with dummy variables to distinguish the effect of expectations (Whitehead 1992; Viscusi and Zeckhauser 2006; Lee and Cameron 2008; Cai et al. 2010), as opposed to separately estimating WTP for the NC and MD groups. Separate estimation is equivalent to estimating a pooled regression with an interaction between expectation dummies and all other covariates. Results are presented in the last column of table 3 and differ substantially from separately estimating WTP across the two groups. Separate (joint) estimation generates average WTP estimates of $99 ($14) for the NC group, and $229 ($183) for the MD group. In addition, a likelihood ratio test strongly rejects the null hypothesis that the two groups can be estimated together (1% level). Our conclusion is that when facing the prospect of estimating WTP for continuous changes in a salient ecosystem service without a WTP function that allows for structural decomposition of expectations and preferences, researchers should at minimum examine whether a less parametric approach of separately estimating WTP across groups of respondent expectations is preferred statistically and/or generates meaningfully different results.

4. Conclusion

With the understanding that a realistic decision scenario is more likely to elicit true preferences, stated preference surveys often present the change in an ecosystem good in terms of an intervention framework in which a public agency develops a program/strategy for increasing the provision of the good. The effect of the intervention is either stated or is

implicit in the elucidation of the program/strategy. Past literature on information effects have shown how survey information about the intervention effect can alter respondents' willingness to pay (e.g. Ajzen et al. 1996; Hoehn and Randall 2002; Cameron 2005; Lew et al. 2010). Our study takes a different tack, and inquires about respondents' subjective beliefs regarding the baseline conditions of the resource without the intervention. This approach allows us to value the change in the underlying good, rather than simply the value of the program/strategy. For an example from this study, a respondent's willingness-to-pay for a labor intensive program to monitor and prevent invasive milfoil propagules from entry into a lake is not the same thing as the welfare losses that would accrue to a respondent from an invasion (the good). In many cases the valuation of interest is the program/strategy itself: Are people willing to pay for the program/strategy? In some other cases the valuation of interest is the change of the good, and respondents have little prior knowledge about the current state of the good and how it is expected to change over time. In both of these cases, there is no issue of the respondent's prior expectations about the current and future state of the good confounding the analysis.

For cases where the analyst wants to know the value of a change in the provision of the good, and the good is salient, as is often the case with goods at the center of political debate, or with local goods with high use value, respondent expectations confound the measurement of the value of the change in the good. We submit that in such cases where both the good and changes in the good are easy to define, it is possible for the analyst to disentangle the respondent's preferences and expectations using structural modeling with subjective expectations elicited in the survey instrument. Otherwise, as we show in the case of fish habitat improvement, the best the analyst can do is value the program/strategy, and

demonstrate that measures correlated with respondent subjective expectations affect the valuation of the program/strategy, a form of construct validity. Deriving the value of the change in the good itself is beyond the available tools, and is likely to remain so.

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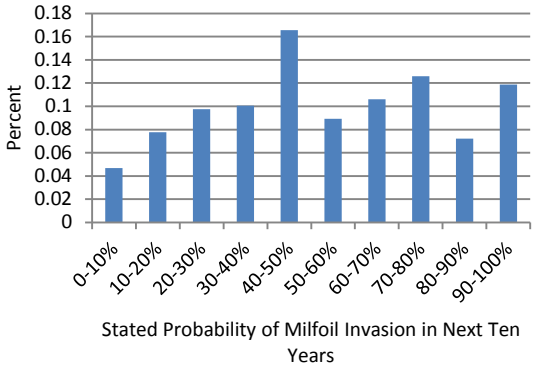
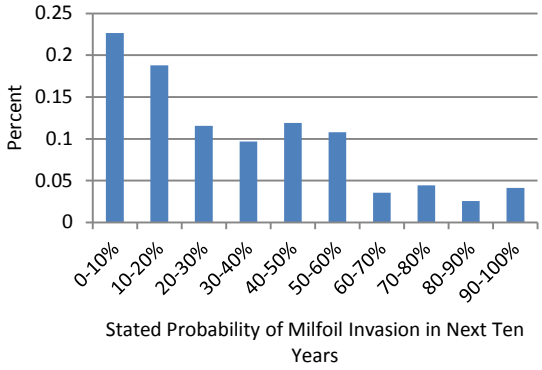
Figure 1. Survey respondent expectations of baseline environmental changes that affect the provision of salient ecosystem services on freshwater lakes

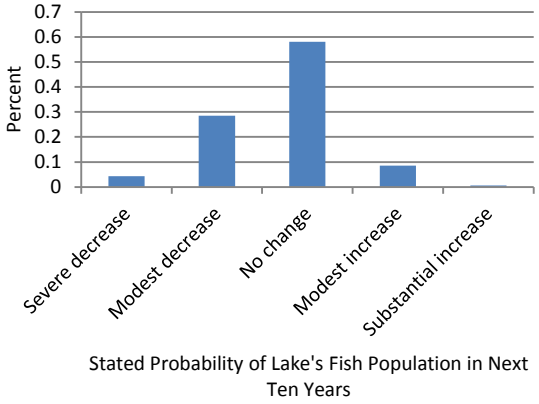
1.a Boater's expectations of a Milfoil invasion within the next ten years (n=707)



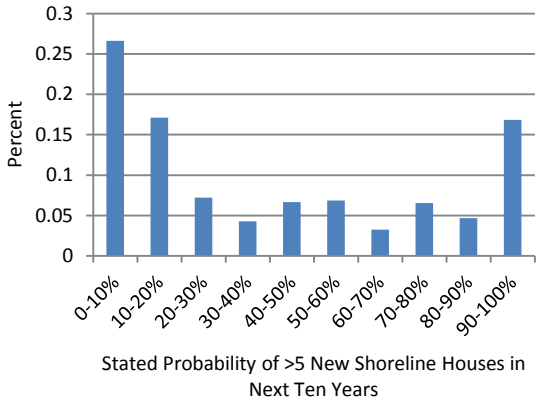
1.b Shoreline owner's expectations of Milfoil invasion within the next ten years (n=900)



1.c Shoreline owner's expectations of changes in fish populations over next ten years (n=983)



1.d Shoreline owner's expectations of shoreline development (5 new houses) over next ten years (n=1,473)



Notes: All figures are from stated preference survey respondents associated with freshwater lakes in the lakes of Vilas and Oneida counties in northern Wisconsin, USA. 1.a is from 2010-2011 surveys of boaters, 1.b and 1.c are from a 2008 survey of shoreline property owners; 1.d is from a 2005 survey of shoreline property owners.

Figure 2. A boater's annual cost of the prevention program is approximated as area abcd (see text).

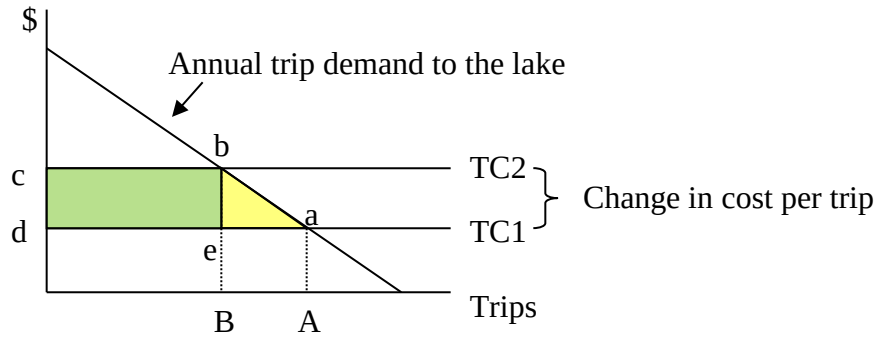
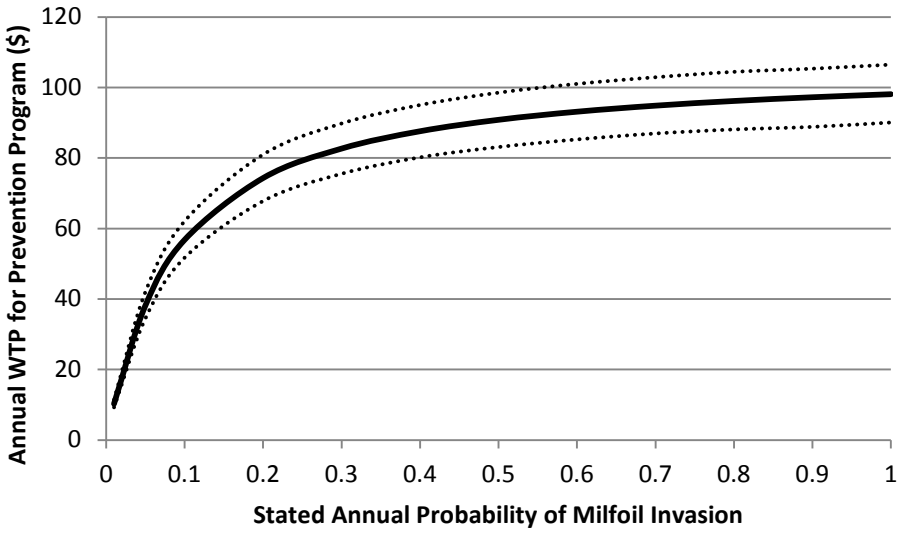


Figure 3. Relationship between willingness-to-pay for Milfoil prevention program and stated probability of a Milfoil invasion (sample average probability = 0.154)



Note: dashed lines represent 95% confidence intervals calculated with Krinsky-Robb method.

Table 1. Estimation results for Milfoil prevention by recreational boaters

Parameter	Estimate	Standard Error	t-Statistic
Constant (β/φ)	7.09	0.42	16.71
Discount rate (r)	0.09	0.005	19.21
Scale parameter ($1/\varphi$)	0.072	0.002	29.39
Scale ratio (σ/φ)	0.63	0.12	5.36

N=690, LL=-3253.76

Table 2. Sensitivity of WTP ($) estimates to assumed respondent time horizon, where T=max(80-age, 5)

	Mean Loss ($) from Milfoil Invasion		Mean WTP ($) for Milfoil Prevention Program	
	Estimate	**95% Confidence**	**Estimate**	**95% Confidence**
T	98.09	{89.20, 105.68}	62.12	{56.46, 67.00}
T+5%	96.29	{88.29, 104.47}	61.13	{55.86, 66.44}
T-5%	98.41	{89.91, 106.76}	62.32	{57.04, 67.78}
T+10%	95.34	{87.22, 103.49}	60.56	{55.49, 65.64}
T-10%	99.61	{91.07, 108.00}	62.94	{57.39, 68.35}
T+20%	93.64	{85.87, 101.52}	59.44	{54.43, 64.40}
T-20%	102.34	{93.51, 111.28}	64.22	{58.48, 69.80}
T+50%	89.66	{82.48, 97.07}	56.38	{51.75, 60.98}
T-50%	115.16	{104.91, 125.69}	68.45	{61.85, 75.05}

*Note: all confidence intervals calculated with the Krinsky-Robb method.

Table 3. Estimation Results for Fish Restoration program

	Expectation of Future Fish Populations		
Parameter	No Change (NC)	Modest Decline (MD)	Both together
Constant (β_0/φ)	2.10** (0.41)	3.52** (0.66)	1.09** (0.16)
Bid coefficient ($1/\varphi$)	4.79** (0.45)	6.67** (0.77)	1.25** (0.16)
Scale ratio (σ/φ)	0.94 (0.04)**	1.12** (0.07)	0.59** (0.02)
Fishing interest (1: low; 5: high)	0.46** (0.10)	0.52** (0.14)	0.25** (0.04)
Fishing quality (1: poor; 5: excellent)	0.12 (0.11)	0.21 (0.17)	0.05 (0.04)
Random effects standard deviation (ϑ)	2.40** (0.18)	2.39** (0.27)	0.03 (0.21)
Expect no change (1:yes, 0:no)			-0.21** (0.09)
Log-Likelihood	-2456.6	-1276.09	-3871.25
N	571	280	851
Estimated annual WTP for the restoration program ($) – Respondents who expect "no change" (NC group)	$99	-	$14
95% Confidence Interval	{54, 139}		{-78, 88}
Estimated annual WTP for the restoration program ($) – Respondents who expect "modest decline" (MD group)	-	$229	$183
95% Confidence Interval		{187, 270}	{87, 275}

Notes: Confidence intervals calculated with the Krinsky-Robb method.

Table 4. Average Characteristics of samples that expected a "modest decline" versus "no change" in future fishing quality on their lake

	Expect a modest decline in future fishing quality (MD group)	Expect no change in future fishing quality (NC group)
Fishing interest (1: low, 5: high)	3.31	3.14
Fishing quality (1: poor, 5: excellent)	3.25	3.43
Volunteer activities (1=yes, 0=no)	0.38	0.35
Lake Association member (1=yes, 0=no)	0.58	0.58
Income (1,000s $)	135	154
Lake Size (Acres)	98	104

Appendix 1. Derivation of Eq. (8)

We start with equation (7) in the text, and name it (A1) here:

$$\pi_j = \frac{exp\left(\left(\frac{P_j\cdot(\beta z_j+v_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]-\frac{c_j}{\sigma}\right)}{1+\exp\left(\left(\frac{P_j\cdot(\beta z_j+v_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T+1}-1}{(1+r)^{T}}\right]-\frac{c_j}{\sigma}\right)} \quad \text{(A1)}$$

In the survey, the respondent chooses the probability value π_j by picking a point along a linear line. Multiplying both sides of (A1) by $1+\exp\left(\left(\frac{P_j\cdot(\beta z_j+v_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]-\frac{c_j}{\sigma}\right)$ gives,

$$\pi_j\left(1+\exp\left(\left(\frac{P_j\cdot(\beta z_j+v_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]-\frac{c_j}{\sigma}\right)\right) = exp\left(\left(\frac{P_j\cdot(\beta z_j+v_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]-\frac{c_j}{\sigma}\right) \quad \text{(A2)}$$

Now, multiply (A2) through by $exp\left(\frac{c_j}{\sigma}-\left(\frac{P_j\cdot(\beta z_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right)$ to give,

$$\pi_j\left(exp\left(\frac{c_j}{\sigma}-\left(\frac{P_j\cdot(\beta z_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right)+\exp\left(\frac{v_j}{\sigma(r+P_j)}\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right)\right) =$$

$$\exp\left(\frac{v_j}{\sigma(r+P_j)}\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right) \quad \text{(A3)}$$

Therefore,

$$exp\left(\frac{c_j}{\sigma}-\left(\frac{P_j\cdot(\beta z_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right) = \exp\left(\frac{v_j}{\sigma(r+P_j)}\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right)\frac{(1-\pi_j)}{\pi_j} \quad \text{(A4)}$$

Therefore, after taking logs of both sides and isolating v_j,

$$v_j = \sigma(r+P_j)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right] ln\left\{\frac{\pi_j}{1-\pi_j}exp\left(\frac{c_j}{\sigma}-\left(\frac{P_j\cdot(\beta z_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right)\right\} \quad \text{(A5)}$$

Therefore,

$$v_j = \sigma(r+P_j)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\left\{\ln\left(\frac{\pi_j}{1-\pi_j}\right)+\frac{c_j}{\sigma}-\left(\frac{P_j\cdot(\beta z_j)}{\sigma(r+P_j)}\right)\left[\frac{(1+r)^{T_j+1}-1}{(1+r)^{T_j}}\right]\right\} \quad \text{(A6)}$$

Therefore,

$$v_j = \sigma(r + P_j)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\left[\ln\left(\frac{\pi_j}{1-\pi_j}\right) + \frac{c_j}{\sigma}\right] - P_j \cdot (\beta z_j) \tag{A7}$$

From the perspective of the analyst, v_j is a random variable, and so the probability that respondent j chooses probability π_j in the referendum question is implicitly defined by the equality in (A7). In the case where v_j is distributed logistically with scale parameter φ, this probability can be explicitly defined by appealing to the logistic pdf (not cdf as usual):

$$\Pr(v_j = \sigma(r + P_j)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\left[\ln\left(\frac{\pi_j}{1-\pi_j}\right) + \frac{c_j}{\sigma}\right] - P_j \cdot (\beta z_j)) = \frac{\exp\left[\frac{\mu - v_j}{\varphi}\right]}{\varphi\left[1+\exp\left[\frac{\mu - v_j}{\varphi}\right]\right]^2} \tag{A8}$$

Therefore, assuming μ=0, the probability of the observed response is,

$$\Pr(v_j = \sigma(r + P_j)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\left[\ln\left(\frac{\pi_j}{1-\pi_j}\right) + \frac{c_j}{\sigma}\right] + P_j \cdot (\beta z_j)) = \frac{\exp\left[\frac{v_j}{\varphi}\right]}{\varphi\left[1+\exp\left[\frac{v_j}{\varphi}\right]\right]^2} \tag{A9}$$

The sample likelihood function is the product of these probabilities. Estimated parameters include the set $\{\sigma, \beta, \varphi, r\}$. An algebraic expansion of the expression for v_j generates:

$$\frac{v_j}{\varphi} = \frac{1}{\varphi}\left\{\sigma(r + P_j)\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\left[\ln\left(\frac{\pi_j}{1-\pi_j}\right) + \frac{c_j}{\sigma}\right] - P_j \cdot (\beta z_j)\right\} \tag{A10}$$

$$=> \frac{v_j}{\varphi} = \frac{\sigma}{\varphi} r\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\ln\left(\frac{\pi_j}{1-\pi_j}\right) + \frac{\sigma}{\varphi}\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]P_j \cdot \ln\left(\frac{\pi_j}{1-\pi_j}\right) + \frac{1}{\varphi} r\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]c_j +$$

$$\frac{1}{\varphi}\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]P_j \cdot c_j - \frac{\beta}{\varphi} P_j \cdot z_j \tag{A11}$$

$$=> \frac{v_j}{\varphi} = \gamma_3 r\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]\ln\left(\frac{\pi_j}{1-\pi_j}\right) + \gamma_3\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]P_j \cdot \ln\left(\frac{\pi_j}{1-\pi_j}\right) + \gamma_2 r\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]c_j +$$

$$\gamma_2\left[\frac{(1+r)^{T_j}}{(1+r)^{T_j+1}-1}\right]P_j \cdot t_j - \gamma_1 P_j \cdot z_j \tag{A12}$$

Where, $\gamma_1 = \frac{\beta}{\varphi}$; $\gamma_2 = \frac{1}{\varphi}$; $\gamma_3 = \frac{\sigma}{\varphi}$. We report estimates of the parameters $\left\{\frac{\beta}{\varphi}, \frac{1}{\varphi}, \frac{\sigma}{\varphi}, r\right\}$ in Table 1.