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Omitted Downstream Attributes and the Economic Benefits of Nutrient Reductions

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Abstract: Discrete choice experiments have been extensively used to value environmental quality; however, some important attributes may often be omitted due to design challenges. In the case of agricultural water pollution, omitting downstream water quality benefits could lead to biased or misinterpreted welfare estimates of local water quality attributes. Using a split-sample design and a statewide survey of Iowa residents, we provide the first systematic evaluation of the effects of omitting downstream water quality benefits, Gulf of Mexico hypoxic zone reduction in our case, on households' willingness-to-pay for water quality improvement. We find that omitting hypoxic zone reduction significantly reduces the total economic value of nutrient reduction programs but does not bias the marginal willingness-to-pay for local water quality attributes. We also find evidence showing that such omission, in line with the theoretical prediction, only changes the preferences of respondents who are aware of the downstream impacts of plans that led to local water quality improvement. In addition, our results show that providing information on the non-local water quality benefits of nutrient reduction increases support for water quality improvement plans among local residents who are not aware of the correlation between local and downstream water quality.

Keywords: Agricultural water pollution; Harmful algal blooms; Gulf of Mexico Hypoxia; Non-market valuation; Choice experiment

JEL Codes: Q53, Q51, Q15

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1. Introduction

One of the key advantages of discrete choice experiments, as compared to revealed preference methods such as hedonic pricing and recreation demand models, is their ability to experimentally design the attributes and associated levels so as to minimize the concern of omitted variable bias and multicollinearity (Freeman, Herriges, and Kling 2014; Holmes, Adamowicz, and Carlsson 2017; Phaneuf and Requate 2016). Still, researchers often have to exclude some relevant attributes from the choice profiles for the sake of cognitive burden to respondents (Hoyos 2010). When the attributes excluded from the choice design are perceived as correlated with those included, the estimates of the included attributes may still suffer from the infamous omitted variable bias.

This potential omitted variable issue is of particular relevance for studies quantifying the benefits of policies with transboundary impacts such as water quality improvement programs. Any reduction in local water pollution is likely to lead to improvement in downstream water quality as well. Most stated preference studies on the value of water quality, such as those reviewed in Johnston, Besedin, and Holland (2019), focus on changes in local attributes. This is in general a reasonable decision, as local water quality actions are likely to have a larger impact on local relative to downstream water quality, and all else equal residents are more likely to care more about local changes than more distant ones. However, if some respondents care about the downstream impacts of local water quality improvement programs, the omission of downstream water quality may not only underestimate the values of local programs but also lead to biased welfare estimates for changes in local water quality. This potential problem can be even more serious when researchers direct respondents to focus on the local water quality issues yet those issues are prevalent in a broader geographical region.[1] Although this problem is apparent, to our knowledge, no study explicitly examines the extent to which such omission affects the values of programs or the welfare estimates for included local attributes.[2]

Using a statewide survey of 853 residents in Iowa on their knowledge of and preferences for the Iowa Nutrient Reduction Strategy (INRS) with split-sample information experiments, the first contribution of our paper is exploring how omitting non-local water quality attributes would bias the marginal willingness-to-pay (WTP) for local water quality attributes. Specifically, we experimentally remove the downstream water quality attribute—changes in the size of hypoxic zone in the Gulf of Mexico—from the discrete choice experiment scenarios and test the effects on the welfare estimates for local attributes and total program benefits as measured by compensating variation (CV). We also explore if the information treatment effects are heterogenous across respondents with different perceptions of the correlation between local and downstream water quality. This exploration further contributes to the literature on distinguishing respondents' beliefs and knowledge

[1] Similiarly, stated preference studies on monetizing health benefits often describe the prevalence of the focused health issues across a broad geographic area but ask respondents to consider changes in a narrower region (Lindhjem et al. 2011).

[2] Bosworth, Cameron, and DeShazo (2009) study the omitted variable issue assuming no spatial spillover in the context of choosing health-improving environmental policies. They find that omitting the benefit of reducing morbidity and only including reduction in death led to upward biases in the values of reducing mortality *within a community*. Respondents can directly benefit from the reductions and consider the two benefits as substitutes. In our study, the omitted downstream benefit is likely a non-local, "non-use" value for most of the respondents where the perceived relationship between it and other local benefits may be murky or at least heterogenous across individuals. Therefore, the findings of Bosworth, Cameron, and DeShazo (2009) may not transfer to our case or others concerning non-local benefits. The interpretations of any resulting effects from the omission in our study could also differ from the substitution between attributes.

from preferences (e.g., Cameron, DeShazo, and Johnson 2011; Howard et al. 2020; Lusk, Schroeder, and Tonsor 2014).

On top of the primary methodological contributions, we provide one of the first empirical estimates for the economic benefits of nutrient reduction at the state level in the Mississippi/Atchafalaya River basin (MARB). Nutrient pollution from agricultural non-point source runoff is one of the most critical water resource issues in the United States today (Keiser, Kling, and Shapiro 2019). The Mississippi River/Gulf of Mexico Hypoxia Task Force has been established since 1997 to address hypoxia in the Gulf of Mexico and called upon the 12 states in the MARB to develop state-level nutrient reduction strategies. Implementing these efforts is costly—from 2009 to 2015, USDA's Natural Resources Conservation Service invested more than $6.7 billion in voluntary working lands conservation programs in the 12 MARB states (USEPA 2017).

Understanding the economic benefits stemming from reducing transboundary nutrient pollution is essential to justify these investments and to navigate the direction of conservation programs (Keiser et al. 2021). Van Houtven et al. (2014) and Nelson et al. (2015) respectively use contingent valuation to study the benefits of nutrient reduction from improving local water quality in eight southeastern states and the state of Utah. Zhang and Sohngen (2018) link the economic benefits of fewer harmful algal blooms (HABs) among recreational fishing with upstream nutrient reduction efforts in the Lake Erie basin. However, the economic benefits of reducing nutrient pollution in the MARB are thus far rarely studied.[3]

[3] Hoque and Kling (2016) use various methods, such as benefit transfer, in quantifying the economic benefits of conservation practices adopted as part of the INRS; however, their study is descriptive in nature.

Parthum and Ando (2020), to the best of our knowledge, is the only other study that focuses on the benefits of nutrient reduction in the MARB. They quantify the benefits of nutrient reductions in a HUC8 watershed in central Illinois. Their study is premised on that the local benefits are "overlooked" when quantifying the benefits of programs primarily concerned about water quality in the Gulf of Mexico. In their survey instrument, about half of the background information is on describing the hypoxic zone in the Gulf of Mexico and the link between local nutrient pollution and the hypoxic zone. They did not include any impacts on the hypoxic zone as an attribute in their choice experiment and instead, similar to what most existing studies did, asked the respondents to focus on the changes in the local watershed. Building on Parthum and Ando (2020), our study expands the understanding of not only the nexus between local and downstream water quality benefits but the benefits of nutrient reduction in the MARB.

In our choice experiment, the four local water quality attributes are algal toxins and nitrate in drinking water sources, lake beach closures due to harmful algal blooms, and lake water clarity. Understanding these local benefits of nutrient reduction is crucial because many associated local policies, such as state-level cost-share conservation programs, could be important funding sources. The downstream water quality attribute, as described earlier, is the size of hypoxic zone in the Gulf of Mexico. This makes our study one of the first to simultaneously assess the benefits of improving local water quality and reducing the hypoxic zone in the Gulf of Mexico. These benefit estimates are also valuable for regional- or national-scale integrated assessment models (e.g., Corona et al. 2020; Lupi et al. 2020; Liu et al. 2020; Parthum and Ando 2020).

Leveraging our split-sample experiment, we further test the effect of providing information of downstream impacts on local citizens' preferences for water quality improvement programs before presenting the choice experiment scenarios. Therefore, this article also contributes to the literature on information provision in stated preference studies (e.g., Bateman and Mawby 2004; Needham et al. 2018; Tienhaara et al. 2022).[4] Specifically, in one version of the survey, we provide information on the hypoxia issue in the Gulf of Mexico and ask for respondents' perceptions and attitudes toward the downstream water quality issue. We compare the results with those from another version of the survey without information on the hypoxic zone and the associated attitudinal questions. Similar to our exploration of heterogeneity in the effects of omitting non-local water quality attributes, we investigate if information heterogeneously affects respondents with different levels of awareness of the downstream hypoxic zone.

Our results show that omission of the downstream water quality attribute leads to an underestimate of the total welfare of water quality improvement programs. We find that Iowa households, on average, are willing to pay $19.1/month for a benchmark nutrient program that could result in 25% less nitrate in source water, 50% less algal toxin detected in source water and HAB-related beach closure, 10% increase in lake water clarity, and 10% smaller hypoxic zone in the Gulf of Mexico. This welfare estimate significantly drops to $17.7/month when not including the reduction in the size of the hypoxic zone as an attribute in the choice experiment, and further declines to $12.8/month when omitting the information and

[4] A large strand of literature begins with the premise that information is exogenous and uses split-sample information treatment to test the effects of information on welfare estimates in stated preference experiments (e.g., Czajkowski, Hanley, and LaRiviere 2016, Davis and Metcalf 2016, Needham et al. 2018). Our exploration synthesizes both the effects of attribute omission and information provision and therefore adds to the literature on the concern of endogeneity between knowledge, information, and the profile design.

attitudinal questions on the hypoxia issue as well as the downstream hypoxia attribute.

We find that omitting the downstream water quality attribute does not significantly bias the marginal WTP for local water quality benefits. In contrary to our hypothesis that omitting downstream attributes would lead to biased coefficients for the local attributes, this finding suggests that on average respondents do not consider any potential changes in other attributes not included in the scenarios. In addition, providing downstream information makes respondents less likely to choose the status quo alternative and therefore increases welfare estimates, measured by CVs, for implementing nutrient reduction scenarios that can improve water quality from the current status. Lastly, consistent with our theoretical predictions, we find suggestive evidence showing that the omission of the downstream attribute may bias the status quo effect (i.e., change the tendency to support alternative scenarios with water quality improvements) for those who are more aware of the downstream impacts of local programs or think the local and downstream water quality improvements are positively correlated.

Our findings have two important policy implications. If the goal of the study is to quantify the total benefit of the program, including more comprehensive descriptions of the benefits and a more complete set of attributes is of first order consideration. Omitting downstream or non-local benefit attributes or the associated descriptions could lead to an underestimation of the total economic benefits of nutrient reduction programs, which could lead to a downward bias in the estimated benefit-cost ratio for the proposed policy. On the other hand, if the goal is to measure the benefits of each individual aspect of the program such as algae-related beach closure in local lakes, the omission of some variables is less of a concern. Our results therefore support the “exogeneity” property held by choice experiments in the context of agricultural water conservation.

In the next section, we provide background information about the nutrient reduction programs with a focus on the INRS. Section 3 illustrates a simple theoretical framework of the omitted attribute issue. Sections 4 and 5 describe the study design, survey implementation, and the empirical framework. In section 6, we present the main results of the effects of omitting downstream attribute and information as well as the heterogeneous treatment effects by respondents' familiarity with downstream water quality issues. Section 7 concludes and discusses implications for future research.

2. Hypoxic Zone in the Gulf of Mexico and the INRS

The term "hypoxia" simply means a deficiency of oxygen and is operationally defined by convention as water with less than 2 mg/L of oxygen (Bianchi et al. 2010). Hypoxic zones in both coastal oceans and freshwater systems have occurred naturally in areas that have the requisite combination of weather patterns, ocean geography, currents, and nutrients; however, their magnitude and extent around the world have increased dramatically over the past 50 years as a result of human activities (Diaz and Rosenberg 2008, Rabotyagov et al. 2014, Breitburg et al. 2018). In the Gulf of Mexico, the seasonal hypoxic or "dead" zone occurs every year in the summer off the coasts of Louisiana and Texas. Hypoxia can cause fish to leave the area and can cause stress or death to fish and bottom dwelling organisms that cannot move out of the hypoxic zone. Despite years of nutrient reduction efforts, the long-term average size of the hypoxic zone in the northern Gulf of Mexico is around 5,000 square miles every summer, which is substantially larger than the 2035 target of 1,900 square miles set by the Mississippi River/Gulf of Mexico Hypoxia Task Force.[5] Hypoxia is believed to be caused primarily by excess nutrients, which promote algal and attendant zooplankton growth, delivered from the MARB, with agricultural nitrogen and phosphorus loadings as the primary source. The associated organic matter sinks to the bottom where it decomposes, consuming available oxygen. Stratification of fresh and saline waters prevents oxygen replenishment by mixing of oxygen-rich surface water with oxygen-depleted bottom water (Rabotyagov et al. 2014).

Massive federal and state funding has been devoted to incentivize farmers' voluntary adoption of key conservation practices designed to combat the runoff problems that pose significant risk to Iowa's and the nation's streams and rivers. At the national level, spending on federally funded conservation programs is projected to be over $6 billion annually during the five-year life of the 2018 Farm Bill. The two largest federal conservation programs, the Conservation Stewardship Program and the Environmental Quality Incentives Program, had $2.2 and $1.8 billion in total obligations in 2020, respectively. Both programs provide financial and technical assistance to farmers adopting conservation practices on working lands that can reduce nutrient loadings.

At the state level, the first bill signed by Iowa Governor Kim Reynolds in 2018 allocates $156 million over 12 years to encourage the adoption of conservation practices such as cover crops, bioreactors, and saturated buffers. With the aim of improving water quality, and as part of the 12 Hypoxia Task Force states, Iowa developed the INRS in 2014, which set a goal of reducing annual agricultural non-point-source generated nitrogen and phosphorus load

[5] The average size of hypoxic zone was 5,408 square miles between 2016 and 2020 (NOAA 2020).

by 41% and phosphorus load by 45% in Iowa's waterways. The strategy describes several land use changes that could achieve those reductions, such as widespread adoption of conservation practices in farming, land retirement, and wetland restoration (INRC 2020).

Reduction in both nitrogen and phosphorus runoff, primarily from agricultural sources, is necessary because although nitrogen is the limiting nutrient for marine waterbodies like the Gulf of Mexico, phosphorus matters more for freshwater lakes and streams in Iowa. In 2022, there are still over 700 Iowa waterbodies designated as Impaired Waters by U.S. EPA, which represents 56% of all Iowa rivers and streams and 67% of Iowa lakes and reservoirs (Iowa DNR 2022a). This is problematic because Iowa lakes not only provide valuable recreational opportunities with Iowans spending over one billion dollars in recreational activities in their 2019 lake trips (Wan et al. 2022), but many lakes also serve as an important source of drinking water for Iowa communities (IEC 2022; Iowa DNR 2022b).

Programs that improve the quality of water in Iowa benefit not only Iowans but citizens of downstream states. Estimates show that Iowa accounts for 15%–20% of nutrients that contribute to the hypoxic zone in the Gulf of Mexico, which can lead to algal blooms and fish kills (Hoque and Kling 2016). Surprisingly, there are few available studies on the value that downstream residents place on the likely improvement in water quality in the MARB and the Gulf of Mexico should Iowa and other Corn Belt states adopt practices to reduce the level of nutrients in the water leaving those states. There are two categories of water quality related benefits: (a) benefits from water quality improvements in downstream states that occur because Iowa has improved the quality of water flowing out of the state; and, (b) the benefits that accrue to anyone who values reductions in the hypoxic zone in the Gulf of Mexico. Our study therefore contributes to the literature by quantifying these thus far overlooked benefits.

3. Omitted Variables and Omitted Benefits: An Illustration

To illustrate the potential problems resulting from omitting changes in downstream water quality in the choice scenarios, we start with a canonical random utility model (RUM) where the indirect utility of individual i choosing a certain nutrient reduction management plan j is a function of the assumed changes in water quality and an error term:

$$U_{ij} = \boldsymbol{x_{ij}^L}\boldsymbol{\beta_i^L} + \beta_i^D x_{ij}^D + \beta_i^{SQ} SQ_{ij} + e_{ij} \tag{1}$$

where $\boldsymbol{x_{ij}^L}$ is a vector of changes in local water quality attributes from the associated nutrient reduction plan j; x_{ij}^D denotes the change in downstream water quality; $SQ_{ij} = 1$ if plan j is the current situation, 0 otherwise; and e_{ij} is a random error term.

As noted earlier, many existing non-market valuation studies with choice experiments omit critical downstream water quality attributes. When x_{ij}^D is not included in the choice scenarios, we can write the indirect utility function as:

$$U_{ij} = \boldsymbol{x_{ij}^L}\boldsymbol{\beta_i^L} + z_{ij}^D + \beta_i^{SQ} SQ_{ij} + e_{ij} \tag{2}$$

where z_{ij}^D is the value stemming from the perceived improvement in downstream water quality for individual i, which we assume, without loss of generality, to be a linear function of the local water quality improvement in scenario j. That is, $z_{ij}^D = \boldsymbol{f}(\boldsymbol{x_{ij}^L}, SQ_{ij}) = \boldsymbol{x_{ij}^L}\boldsymbol{\alpha_i^L} + \gamma_i^{SQ} SQ_{ij}$, where $\boldsymbol{\alpha_i^L}$ captures the downstream benefits determined by the changes in $\boldsymbol{x_{ij}^L}$. Because in theory $\boldsymbol{f}(\boldsymbol{x_{ij}^L}, SQ_{ij} = 0) \geq \boldsymbol{f}(\boldsymbol{x_{ij}^L}, SQ_{ij} = 1)$, $-\gamma_i^{SQ}$ captures the downstream benefits from solely knowing that a nutrient reduction plan is implemented. Equation (2) can be rewritten as:

$$U_{ij} = \boldsymbol{x}_{ij}^{L}\widetilde{\boldsymbol{\beta}_i^{L}} + \widetilde{\beta_i^{SQ}} SQ_{ij} + e_{ij} \tag{3}$$

where $\widetilde{\boldsymbol{\beta}_i^{L}} = \boldsymbol{\beta}_i^{L} + \boldsymbol{\alpha}_i^{L}$ and $\widetilde{\beta_i^{SQ}} = \beta_i^{SQ} + \gamma_i^{SQ}$. By estimating a model omitting x_{ij}^{D}, one would obtain the potentially biased coefficients of local water quality, $\widetilde{\boldsymbol{\beta}_i^{L}}$, and status quo effect, $\widetilde{\beta_i^{SQ}}$. Therefore, whether and how the estimates of the true $\boldsymbol{\beta}_i^{L}$ and β_i^{SQ} are biased hinges on the omitted values captured by $\boldsymbol{\alpha}_i^{L}$ or γ_i^{SQ}.

When x_{ij}^{D} is not accounted for in the model, it is not immediately clear the degree to which $\boldsymbol{\beta}_i^{L}$ would be biased. The first extreme case is when, given $\boldsymbol{x}_{ij}^{L}$, a respondent has a clear perception of the (positive) correlation between $\boldsymbol{x}_{ij}^{L}$ and x_{ij}^{D} and could determine the exact changes in x_{ij}^{D} based on the perceived correlation with $\boldsymbol{x}_{ij}^{L}$.[6] That is, an individual can determine their z_{ij}^{D} solely based on $\boldsymbol{x}_{ij}^{L}$ and does not rely on SQ_{ij}, which would result in $\widetilde{\boldsymbol{\beta}_i^{L}}$ being an upward biased estimator for $\boldsymbol{\beta}_i^{L}$; however, $\widetilde{\beta_i^{SQ}}$ is still an unbiased estimator for β_i^{SQ}. The opposite extreme case is when, given $\boldsymbol{x}_{ij}^{L}$, a respondent simply believes that downstream water quality would improve but has no idea about the exact level of change (i.e., the *perceived* correlation between $\boldsymbol{x}_{ij}^{L}$ and x_{ij}^{D} is zero). In this case, $\gamma_i^{SQ}(\leq 0)$ would capture all the values stemming from the fact that respondents prefer the water quality improvement plan over the current status although they do not know the exact potential changes in downstream water quality. Therefore, $\widetilde{\beta_i^{SQ}}$ would be a downward biased estimator for β_i^{SQ},

[6] Note that we focus on the perceived correlation instead of the actual correlation between local and downstream water quality, $\mathrm{cor}\left(\boldsymbol{x}_{ij}^{L}, x_{ij}^{D}\right)$, as documented in scientific literature (for a review, see Rabotyagov et al. 2010), because we are interested in how the perceived change in downstream water quality would affect the values that respondents place on local changes.

while $\widetilde{\boldsymbol{\beta}_i^L}$ is an unbiased estimator for $\boldsymbol{\beta}_i^L$.

Empirically, both cases are possible. Some respondents, when assessing the scenarios with changes in local attributes, do not or are unable to evaluate the potential changes in downstream water quality. For these respondents, excluding the downstream attributes would be less likely to affect the estimates of local water quality attributes. On the other hand, if respondents have strong beliefs or sufficient knowledge on the correlations between local and downstream water quality, they are more likely to choose the scenarios with greater improvement in local water quality because of the implied downstream water quality benefits.

As a result, we have the first testable hypothesis:

$$\begin{aligned} H_o&: \widetilde{\boldsymbol{\beta}_i^L} = \boldsymbol{\beta}_i^L \\ H_1&: \widetilde{\boldsymbol{\beta}_i^L} \neq \boldsymbol{\beta}_i^L \end{aligned} \tag{H1}$$

where rejecting the hypothesis indicates that the marginal benefits of local water quality improvements are biased when downstream water quality attributes are omitted. Another hypothesis is:

$$\begin{aligned} H_o&: \widetilde{\beta_i^{SQ}} = \beta_i^{SQ} \\ H_1&: \widetilde{\beta_i^{SQ}} \neq \beta_i^{SQ} \end{aligned} \tag{H2}$$

where rejecting the hypothesis suggests that, when omitting the downstream attribute, the CVs for moving away from the current status are biased regardless of whether the marginal utilities of local benefits are biased or not.

We argue that the extent to which the $\widetilde{\boldsymbol{\beta}_i^L}$ and $\widetilde{\beta_i^{SQ}}$ are biased is an empirical question. The context of the choice, the knowledge level of respondents, and the design of the experiment can all influence how the downstream water quality benefits are captured by $\boldsymbol{\alpha_i^L}$ and γ_i^{SQ}. For instance, it is common to see a choice experiment with verbiage such as: "*please consider the following options that only differ in the attributes described …*" In this case, we might expect respondents would be more likely to follow a "what you see is all there is" heuristic and only focus on the attributes included (Enke 2020; Kahneman 2011). Therefore, we further hypothesize that the effects of omitting downstream information are heterogenous across respondents with different levels of knowledge and awareness of downstream water quality issues. As noted earlier, for respondents with perfect knowledge and the ability to determine the exact changes in x_{ij}^D based on $\boldsymbol{x_{ij}^L}$, hypothesis one will be rejected so $\widetilde{\boldsymbol{\beta_i^L}} \neq \boldsymbol{\beta_i^L}$ but $\widetilde{\beta_i^{SQ}} = \beta_i^{SQ}$. For those "semi-informed" respondents who do not know the exact change in x_{ij}^D based on $\boldsymbol{x_{ij}^L}$ but expect that downstream water quality would be improved, we expect that hypothesis two will be rejected so $\widetilde{\beta_i^{SQ}} \neq \beta_i^{SQ}$ but $\widetilde{\boldsymbol{\beta_i^L}} = \boldsymbol{\beta_i^L}$. Lastly, for those who are not at all aware of downstream water quality issues, in theory both hypotheses will be rejected.

4. Study Design, Implementation, and Data

To separately test the effects of omitting downstream water quality attributes and the associated information entirely, we developed three versions of a survey (a control and two treatments). In the control (hereafter the baseline version), the survey begins with questions soliciting respondents' perceptions of and attitudes toward water quality and nutrient pollution issues within the state of Iowa, followed by a choice experiment on preferences for programs with potential improvement only in local water quality attributes. No information or question regarding the hypoxia issue is provided prior to the choice experiment.

The first treatment (hereafter the downstream information version) adds additional information and questions on the hypoxic zone in the Gulf of Mexico and its association with local water quality prior to the choice experiment. This mimics many existing DCE designs where some attributes were highly relevant and thus mentioned in the survey but omitted in the choice experiment due to design or space constraints. The effects of downstream water quality information on the WTPs for local benefits can be isolated through contrasting the marginal utility estimates and the status quo effect based on the samples of the baseline and downstream information version. The key question to answer is whether this information provision would significantly change marginal WTPs of the local water quality attributes and/or the total economic benefits of the program.

The second treatment (hereafter the full version) further adds the change in the Gulf of Mexico hypoxic zone size as an attribute in the profile of the choice scenario. By comparing the results of the downstream information and full versions, we are able to evaluate the impacts of omitting downstream water quality attributes on the total value of local nutrient reduction efforts and if such omission would bias welfare estimates for local water quality attributes. This treatment therefore challenges a canonical assumption that respondents would make their choices based only on the exogenously varying attributes provided in the choice scenarios.

In each of the three versions, we asked respondents to answer four two-alternative choice questions. Each choice question consists of an "action" alternative with improvements in water quality and increase in monthly water bill as well as a status quo alternative with no change from current water quality conditions. Figure 1 is an example choice scenario in the full version, with both the hypoxia zone information and attribute included.[7]

We included four local water quality attributes in the choice experiments of all three versions—number of days algal toxins are detected in source water (toxin), nitrate concentration in source water (nitrate), average number of days of beach closures due to algal blooms (closure), average water clarity in Iowa's lakes (clarity). The full version further includes the average size of hypoxic zone in the Gulf of Mexico (hypoxia) as a downstream water quality attribute. The current conditions and the levels of proposed changes of the water quality attributes are summarized in table 1.[8] The payment vehicle is designed as a monthly surcharge to the household water bill.

To create the choice experiment design, we first ruled out likely implausible scenarios such as those with no change in local water quality attributes but reduction in the size of hypoxic zone and generated the design based on maximizing the efficiency of a multinomial

[7] We introduce the hypoxia issue with the following statement: "(S)ome water in Iowa flows to the Mississippi River and eventually to the Gulf of Mexico. As a result, nutrients in Iowa's waterways can affect water downstream. One issue caused by excessive nutrients is a hypoxic zone, sometimes referred to as a dead zone, an area of water with low levels of oxygen. Hypoxic zones have endangered marine life in the Gulf of Mexico and other places around the world." The statement is followed by questions regarding respondents' familiarity of the issue and perceived correlation between local and downstream water quality. See question 20 to 23 of the complete survey instrument of the full version in Appendix C.

[8] We base the current conditions of toxin, nitrate, and closure presented in the choice questions on the information summarized in Tang et al. (2018). We based the current condition of hypoxia on the size of hypoxic zone in the northern Gulf of Mexico in summer 2019 (USEPA 2019). The levels of changes in toxin, nitrate, and closure are simple projections based on the goal of 45% reduction of both nitrogen and phosphorus. The change in clarity is based on a model characterizing the relationships between nitrogen, phosphorus, and Secchi depth in Iowa. The change in hypoxia is based on the estimate that Iowa contributes 15%–20% of the nutrients that lead to the hypoxic zone. The levels are deemed reasonable by limnologists and participants in the cognitive interviews during the survey development. Also, we use percentage changes instead of absolute changes based on feedback from the cognitive interview.

logit model with repeated choices in NGENE 1.2.1. We extracted the priors from a pretest conducted in June 2019 based on an experiment design using the same algorithm but with zero priors. We have 40 choice scenarios blocked into 10 blocks with the D-error of the design being 1.6390. Note that, although the changes of the five water quality attributes are likely correlated, they can still change independently because of many reasons. For example, excessive phosphorus is the main driver of algal blooms in fresh water lakes, but hypoxic zones in marine water is mainly driven by nitrogen. A program focusing only on reducing phosphorus could mitigate algal blooms in local lakes but could have little impact on the hypoxia in the Gulf of Mexico. Moreover, a phosphorus reduction program can spatially target watersheds and lakes with beaches yet not serving as drinking water sources. Most importantly, we do not find evidence suggesting that citizens believe that the water quality attributes are highly correlated nor do they find any of the scenarios in our choice experiment implausible in the cognitive interviews.[9] Therefore, we do not explicitly design the choice profiles to incorporate the complex and uncertain correlations between the water quality attributes. Indeed, as we discussed at the very beginning of the paper, a key feature of choice experiments is to keep the necessary independence between the attributes for identifying the parameters of interest.

The survey was implemented in August 2019 following a three-stage contact approach with both mail and internet response options (Dillman, Smyth, and Christian 2014). The initial invitation was sent to 2,800 Iowa households. A total of 853 surveys with usable

[9] During the survey design stage, four cognitive interviews of a total of 15 randomly selected Iowans were done to gain understanding of how potential respondents would interpret survey questions and if all information and questions can be universally understood by respondents.

responses were received during the data collection period (a 30.5% response rate). Table 2 shows the summary statistics of key socio-demographics and water quality perceptions of respondents by survey version answered. Overall, the average age of our respondents is 59 years old, 43% are female, 78% have some college education or above, 57% are employed full- or part-time, and 56% visited at least one lake in Iowa in 2018. The average Likert scores of the three questions regarding respondents' perceptions and awareness of water quality in the state of Iowa are not significantly different across the three treatments.[10] The statistics show that the sample is well balanced and the randomization is successful. More descriptive information about the survey respondents' views about water quality, conservation practices, and the INRS can be found in Shr and Zhang (2021).

To explore if the impacts of the treatments are heterogeneous among respondents who see the association between local and downstream water quality differently, the survey included questions about respondents' subjective assessment on such associations after the choice experiment questions. Specifically, the following question is included after the choice experiment: "If the nitrate levels in Iowa's water were reduced, what do you think would happen to the hypoxic zone in the Gulf of Mexico?" As we present later, we find the treatment effects are heterogenous across respondents with different perceptions of the local and downstream water quality correlation.

To mitigate potential biases in the marginal utility estimates led by hypothetical choices, we include a cheap talk script immediately before the choice question set to ask the

[10] The three questions are: (*a*) "Overall, how would you rate the water quality in Iowa's lakes?" (*b*) "How familiar are you with water quality issues in Iowa's lakes?" and, (*c*) "How aware are you of algal blooms in Iowa's lakes?"

respondents to make decisions as though faced with an actual fee increase in their water bill (Cummings and Taylor 1999; Penn and Hu 2019). In addition, to make the choice experiment incentive compatible, the script also states that "[Y]our answer will be used by researchers and policymakers to design the most appropriate water quality management to suit the needs of Iowans," to increase the consequentiality (Carson, Groves, and List 2014; Vossler and Watson 2013). A similar description is also included in the consent form explaining "[T]he results of this research study will be made available to Iowa policymakers and the general public to help in future decision-making regarding water quality and safety for Iowans." Indeed, only 2.2% of the respondents answered "definitely not" to our policy consequentiality question: "[D]o you think the information gathered in this survey will affect decisions about water quality management and policies in Iowa?" Therefore, our results are not likely to suffer from the hypothetical biases led by the answers from respondents who perceive the survey as inconsequential (Herriges et al. 2010).[11]

5. Econometric Model

Following the modern discrete choice experiment method (Holmes, Adamowicz, and Carlsson 2017), the utility derived from alternative j in choice scenario s for individual i is a function of the attributes (x_{js}) included in choice scenarios and an unobserved component (e_{ijs}). That is, we can write the utility function as:

$$U_{ijs} = \boldsymbol{x}_{js}\boldsymbol{\beta}_i + e_{ijs} \tag{4}$$

[11] Still, we conduct robustness checks by excluding those respondents who consider the survey was inconsequential.

where $\boldsymbol{x}_{js}$ is a vector of the attributes, which normally include a cost (price) attribute of alternative j in scenario s; $\boldsymbol{\beta}_i$ is a vector of individual-specific marginal utilities of the corresponding attributes; and, the error term e_{ijs} captures the factors that affect the utility but are unobservable to the researcher. With e_{ijs} following IID Type-I extreme value distributions, the probability of choosing j among all J alternatives in a scenario can be written as the conventional logit formula. We assume $\boldsymbol{\beta}_i$ is single-modal continuously distributed and model the choice probability using random parameter logit (also often called mixed logit) models (Revelt and Train 1998).

To examine the impacts of downstream water quality information on the preference parameters, we use the data from the baseline and downstream information versions and estimate the following model:

$$U_{ijsv} = \sum_{v} \begin{pmatrix} \beta_{iv}^{tox} toxin_{jsv} + \beta_{iv}^{nit} nitrate_{jsv} + \\ \beta_{iv}^{cls} closure_{jsv} + \beta_{iv}^{clr} clarity_{jsv} + \beta_{iv}^{SQ} SQ_{jsv} \end{pmatrix} + \beta_i^{cost} Cost_{jsv} + e_{ijsv} \tag{5}$$

where subscript $v = \{v_{baseline}, v_{downstream}\}$ indicates the survey version. Equation (5) allows us to explicitly model the information effects by the heterogeneous marginal utilities of local water quality attributes and the status quo effect between the two versions. We use likelihood ratio tests between the unrestricted and restricted (with $\beta_{iv_{baseline}}^{\cdot} = \beta_{iv_{downstream}}^{\cdot}$) models to test if the information significantly affects the marginal utilities of local water quality attributes and the status quo effect.

Similarly, the potential omitted downstream water quality benefits and/or omitted variable biases in local water quality benefit estimates can be investigated by running the following:

$$U_{ijsv} = \sum_{v} \begin{pmatrix} \beta_{iv}^{tox} toxin_{jsv} + \beta_{iv}^{nit} nitrate_{jsv} + \\ \beta_{iv}^{cls} closure_{jsv} + \beta_{iv}^{clr} clarity_{jsv} + \beta_{iv}^{SQ} SQ_{jsv} \end{pmatrix} + \beta_{i}^{hyp} hypoxia_{jsv} + \beta_{i}^{cost} Cost_{jsv} + e_{ijsv} \quad (6)$$

where subscript $v = \{v_{downstream}, v_{full}\}$, and $hypoxia_{jsv} = 0$ if $v = \{v_{downstream}\}$. A positively significant $\beta_i^{hypoxia}$ therefore indicates significant omitted downstream benefits. We can use likelihood ratio tests between the unrestricted and restricted (with $\beta^{\cdot}_{iv_{downstream}} = \beta^{\cdot}_{iv_{full}}$) models to test if the marginal utilities of local water quality attributes are biased because of the omission of downstream water quality attributes in the choice alternatives.

Intuitively, reducing toxin, nitrate, closure, and hypoxia are amenities to everyone, thus we assume that the associated marginal utilities follow zero-bounded triangular distribution. The marginal utility of increasing clarity, however, is assumed to be normally distributed to allow the possibility that some respondents may prefer murkier water. For example, some anglers might not necessarily prefer clearer water because some game fishes, such as walleye, have higher catch rates in murkier water (Zhang and Sohngen 2018). Thus, while some respondents may tend to stay with the current status, others might prefer a plan with changes. Therefore, the status quo effect is assumed to be normally distributed. Lastly, to ensure the cost parameter has the theoretically correct sign, we use zero-bounded triangular distribution to model its distribution. All estimations are perform using `mlogit` (version 1.1-1) in `R` (Croissant 2020). We estimate the models with 2,000 Halton draws and panel techniques to accommodate repeated choices.

6. Empirical Results

6.1 Main Results

Table 3 presents the estimation results of the model pooling the baseline and downstream information versions, i.e., equation (5).[12] Model 1 is the unrestricted model that allows heterogeneity for the marginal utilities of water quality attributes between the two versions. All the estimates have the expected signs—respondents prefer reduction in algal toxin, nitrate, and beach closure. We also find that our respondents on average prefer clearer lakes. A noticeable difference between the two versions is the coefficients of status quo—when the downstream impact information was not provided, respondents tend to stay with the current status. However, the significantly negative coefficient of status quo under the downstream information version shows that respondents, on average, prefer alternatives with improvement in water quality. Model 2 imposes the equality restriction on the status quo effect across the two versions. The likelihood ratio test against model 1 strongly rejects the null hypothesis that the two status quo coefficients are equal (p-value = 0.006). The increased Akaike information criterion (AIC) in model 2 also indicates that the model fit deteriorates from model 1.

Model 3 imposes the equality restrictions on the four local water quality attribute parameters across the two versions. The likelihood ratio test of model 3 against model 1 fails to reject the hypothesis that the four sets of local water quality parameters are jointly significantly different (p-value = 0.2690). Consistently, the AIC indicates that model 3 is the

[12] The spread coefficient of zero-bound triangular distribution equals to its mean coefficient, so we do not report the spread coefficients of the toxin, nitrate, closure, and cost parameters for the sake of brevity.

preferred specification (note that the marginal utility coefficients of all four local water quality attributes are significant at the 5% level).[13] Model 4 assumes that the information treatment had no effect on preferences by imposing the equality restrictions on all parameters across the two versions. However, the likelihood ratio test against model 3 rejects the hypothesis that the status quo effects are the same (p-value = 0.005). Furthermore, the AIC of model 4 increases from that of model 3 suggesting an inferior model fit.[14]

We therefore conclude that providing information regarding the downstream impacts of nutrient reduction programs does not significantly change the marginal utilities of the local water quality attributes. However, the downstream information induces respondents to more likely choose the action alternatives over the current status. As we discuss in more detail later, these results suggest that, without the disclosure of the downstream impacts, respondents are less likely to choose the plans with water quality improvement. This will result in lower total program benefits measured by CVs. Still, the large and significant standard deviation parameters of the status quo effect show that there is considerable heterogeneity among the decisions between action and no action.

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[13] The status quo by construction captures the unobserved effects. Comparing the results of model 1 and 3 therefore shows that the unobserved effects can be well modeled by simply allowing for the heterogeneity in the status quo parameter.

[14] Figure B1 in Appendix B presents the kernel density plots of the individual WTPs using the conditional-on-individual-taste approach (Train 2009) of each attribute based on model 3 in table 3. Given that the standard deviations of clarity are insignificant regardless of the specifications, we estimate the models with clarity being non-random, and the results are virtually identical. In addition, we estimate models that replace all zero-bounded triangular distributions with log-normal distributions, but the models fail to converge. To test if the results are sensitive to answers from respondents who consider the survey to be inconsequential, we run the models by excluding those responses and present the results in Table A1 in Appendix A. The results are robust to the sample exclusion.

Table 4 reports the estimation results of the model pooling the downstream information and full version (with size of hypoxic zone included in the attribute set), i.e., equation (6). Model 1, again, is the unrestricted model that allows heterogeneity in all parameters, other than the cost parameters, across the two versions. The coefficient of hypoxia is positive and significant, indicating the respondents indeed consider reducing hypoxia a key benefit of in-state nutrient reduction plans. Models 2, 3, and 4 are specifications parallel to those in table 3. Model 4, however, is the preferred specification based on AIC, and the likelihood ratio tests of model 4 against models 2 and 3 do not reject the hypothesis that the parameters are different across the two versions.[15] Although we cannot reject the null hypothesis that the status quo effects are the same across the two versions, we note that the status quo coefficient of the information version being smaller than that of the full version is consistent with the theoretical prediction in equation (3) where $\widetilde{\beta_i^{SQ}} = \beta_i^{SQ} + \gamma_i^{SQ}$ and $\gamma_i^{SQ} < 0$.

We find the inclusion of the downstream water quality attribute does not significantly change citizens' preferences for local water quality attributes nor the likelihood of moving away from the current status (the p-value of the likelihood ratio test between models 3 and 4 is 0.1687, the smallest among all). That is, we do not find evidence to reject the two hypotheses stated in section 3—that the omission of the downstream water quality attribute would bias the welfare estimates of included local water quality attributes and status quo effect. This finding demonstrates that our choice experiment is immune to omitted variable

[15] Figure B2 in Appendix B presents the kernel density plots of the WTPs of each attribute based on model 4 in table 4. We run the models by excluding those answers from respondents who consider the survey to be inconsequential and present the results in Table A2 in Appendix A. The results are again insensitive to the exclusion.

biases and holds the "exogeneity" property.[16]

Based on the estimation results above showing only the status quo effect is affected by the provision of downstream information, we pool the data from all three versions and run the following model, to calculate the CVs for hypothetical water improvement plans based on the three versions of the survey:

$$U_{ijsv} = \boldsymbol{X}_{jsv}\boldsymbol{\beta}_i + \beta^{SQ}_{iv_{basline}} SQ_{jsv_{baseline}} + \beta^{SQ}_{iv_{treatment}} SQ_{js\dot{v}} + e_{ijs} \tag{7}$$

where $\boldsymbol{X}_{jsv} = \{toxin_{jsv}, nitrate_{jsv}, closure_{jsv}, clarity_{jsv}, hypoxia_{jsv}, Cost_{jsv}\}$ and $\dot{v} = \{v_{downstream}, v_{full}\}$.[17] We use the same assumed distributions of parameters and number of Halton draws as those used in models in Table 3 and 4. Table 5 reports the WTPs for each of the water quality attributes using the Delta method (Greene 2018).

In summary, on average, respondents are willing to pay \$4.7/month to reduce the number of days that algal toxin are detected in the source of their drinking water by 50%, \$2.8/month to reduce nitrate concentration in source water by 25%, \$3.1/month to cut the number of days that lake beaches are closed due to algal blooms in half, \$1.9/month for increasing lake water clarity by 10%, and \$1.4/month to reduce the size of the hypoxic zone in the Gulf of Mexico by 10%. In a follow-up question asking for the least important attribute, regardless of the inclusion of hypoxia, more than half of the respondents said that reduction in beach closure is the least important attribute to them, while both drinking water related attributes

[16] To test if our results are sensitive to the assumption of homogenous cost parameter across all three versions. We also estimate models with samples of each version and present the results in Table A3 in Appendix A. With the cost parameters being similar across all three models, the results overall resemble those in model 1 of Table 3 and 4.

[17] Table A4 in Appendix A presents the full estimation results.

are least likely to be chosen as least important.

For illustration purposes, we calculate the CVs, as measured by monthly water bill, based on a plan promising a 50% reduction in toxin, 25% reduction in nitrate, 50% reduction in closure, 10% increase in clarity, and 10% reduction hypoxia. The CV for such a plan under the baseline version is $12.8/month, and adding downstream information prior to the choice experiment increases the CV by 38% to $17.7/month. Therefore, informing respondents about the downstream benefits of nutrient reduction plans does greatly increase the total welfare estimate of the plan, which is predominately driven by the tendency to vote for plans with improvement in water quality. The impact of the inclusion of downstream water quality attributes in the choice experiment is, by design, the WTP for reducing the size of the hypoxic zone by 10% ($1.4/month).[18] These results highlight the advantage of stated choice experiments at allaying the concerns of endogeneity. Still, the omission of key downstream impacts may result in underestimation of the total program benefits.

To calculate the total benefit across all households in Iowa, we derive the individual WTPs of each household using the specification in equation (7) and reweight the observations to match the household income distribution of Iowa based on the 2019 ACS 1-year estimates. With no downstream information provided and only local water quality benefits included, the state-wide annual total benefit from the benchmark plan in the previous paragraph is about $213 million. The total benefit increases to $297 million with the provision of downstream information and $319 million by further including the benefit from reducing

[18] We note that, contrasting the differences between the results of the baseline and full versions resembles a scope test (Bishop and Boyle 2017). Our goal is exactly to disentangle the effects of added/omitted information and attributes from the total effect focused in a conventional scope test.

hypoxic zone in the Gulf of Mexico.[19] In terms of the total annual costs for all nutrient reduction efforts in Iowa, the total funding from the Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP) between 2018 and 2020 is $146 million (Du et al. 2022), and a 12-year state-level water quality bill of $156 million was signed to further assist the cost-share programs for infrastructure on agricultural land in 2018. These result in an annual payment of $62 million for working farmland and edge-of-field conservation practices. Although we refrain ourselves from providing an exact benefit-cost ratio with precise cost estimates, our results suggest that the nutrient reduction efforts are likely to pass the benefit-cost test.

6.2 The Heterogeneous Effect of Information Provision and Intended Omission

We find that our respondents are less likely to choose the current status when the downstream impact information is provided. Here we further explore if such effect is heterogenous between respondents with different levels of knowledge of the hypoxia issue. Before the choice experiment, the survey asked: “How familiar are you with the hypoxic zone issue in the Gulf of Mexico?” to which nearly 40% of respondents answered “not at all familiar.” Therefore, we estimate the hypoxia and status quo parameters of those who are “not at all familiar” or at least “somewhat familiar” with the hypoxic zone in the Gulf of Mexico separately.

[19] Assuming only those 66% respondents who answered “probably will” or “definitely will” to our payment consequentiality question (in contrast to those who answered definitely not, probably not, or not sure) would pay the costs, the annual total benefits are $141 million, $196 million, and $210 million with different assumptions of information provision and the inclusion of downstream water quality benefit.

Model 1 of table 6 presents the estimation results of the model paralleled to model 3 in table 3 with the separate status quo parameters for respondents who are unfamiliar or familiar with the hypoxia issue. The downstream information significantly decreases the utilities of choosing status quo for both types of respondents (0.3868 vs. -0.8051 and -1.1212 vs. -2.0791), and such effect is stronger among respondents who are more familiar with the hypoxia issue. This finding supports our hypothesis and again highlights the role of education and information to affect citizens' valuations for environmental programs (Barkmann et al. 2008; Hoyos 2010; MacMillan, Hanley, and Lienhoop 2006). In addition, similar to other survey studies, on average, our respondents are likely to be more aware and knowledgeable about water quality issues in general and hypoxia in particular, than all Iowans. Therefore, the effect of information may be even more pronounced in terms of mitigating the undervaluation of nutrient reduction programs when the potential participation bias is corrected. Another caveat is that, although the choice scenarios did not include changes in the size of the hypoxic zone as one of the attributes, respondents who are at least slightly familiar with the hypoxia issue still appear to take most of the downstream effects into consideration, and thus are more likely to move away from status quos.

Although we do not find a significant effect of omitting downstream attributes for all respondents, such effect, as noted in our theoretical illustration, can be different across respondents with different knowledge or awareness of downstream water quality issues. We therefore explore such heterogeneity in model 2 of table 6 and uncover an effect of omitting the downstream attribute among respondents who are more aware of downstream water quality issues.

The results show that the marginal utility for reducing hypoxic zone is only significant among respondents who are at least familiar with the hypoxia issues (i.e., 0.5717 with the standard error being 0.2606). By comparing the coefficients of status quo effects across two versions by whether a respondent is at least slightly familiar with the hypoxia issue (-0.9584 vs. -0.7957 and -2.6218 and -1.5182), the inclusion of the hypoxia attribute more strongly affects the preferences for those who are more informed about the hypoxia. The result suggests that, when downstream impacts are not included in the attributes, the status quo effect would capture some of the benefits of perceived downstream water quality improvement (i.e., γ_i^{SQ} in equation (3)), for people who are aware of the downstream impacts.[20] Moreover,

We also solicit respondents' perceived correlation between the nutrient levels in Iowa and hypoxia in the Gulf of Mexico. Response options include the hypoxic zone would be much smaller, slightly smaller, the same, slightly larger, much larger, and "I don't know." We classify respondents who answered much smaller or slightly smaller to this question as those who consider downstream water quality is "correlated" with nutrient pollution in Iowa. Respondents who answered otherwise are classified as those who consider downstream water quality and nutrient pollution in Iowa is "uncorrelated." We then estimate the hypoxia and status quo parameters for these two types of respondents separately.

Table 7 presents the estimation results, which largely show the same implications as those from the heterogeneity between respondents who are familiar with the hypoxia issue and those who are not in Table 6. In model 1, we find the downstream information decreases

[20] This can also be observed by directly comparing the status quo effects between those who are unfamiliar and familiar under the downstream information version (-0.9584 vs. -2.6218) in model 2.

the marginal utility of choosing the status quo. However, the effect is only significant for those who do not believe the local and downstream water quality positively correlate.[21] This finding suggests that the information has stronger effects on the preferences of respondents who are not at all familiar with the issue of the hypoxic zone in the Gulf of Mexico than on those who are at least somewhat familiar with the issue.

In model 2, the inclusion of the hypoxia attribute has a stronger effect on the preferences of those who are better informed. The marginal utility of status quo for those who are at least somewhat familiar with the hypoxia issue increases from -2.3656 to -1.3553. This is again consistent with our theoretical predictions and what we find from model 2 in Table 6. Overall, the estimates support that the heterogeneity presented here highlights the role of education and provides suggestive evidence for the theoretical prediction that the omitted downstream benefits may be captured by the status quo effect among respondents who are aware of those benefits, which was masked by the average effect among all respondents.

7. Conclusion

Using a split sample design and a discrete choice experiment survey of 853 Iowa households, we provide one of the first estimates for the state-wide economic benefits of nutrient reduction programs in the MARB, and find that respondents are willing to pay for

[21] With these results, we acknowledge that we cannot completely rule out the demand effect—information in surveys can affect respondents' beliefs about "appropriate" responses (Carlsson, Kataria, and Lampi 2018)—on making respondents more likely to choose the policy options. However, the downstream information having little effect on the preferences of those who are aware of the positive correlation between upstream and downstream water quality indicates that the demand effect does not play a significant role in our case.

improving both local and downstream water quality when we provide adequate information.

We also show that omitting downstream water quality attributes does not significantly change the marginal WTPs for local water quality attributes; however, it could lead to a noticeable underestimate of the total benefits of nutrient reduction programs. Our results suggest that such omission is more likely to change the probability of choosing the status quo rather than directly impacting the marginal utilities of local water quality attributes. This could be due to cognitive constraints of residents to fully comprehend the complex natural processes governing the dynamics of local and downstream water quality. We find that for residents who are more knowledgeable about the positive correlation between local and downstream water quality improvements, the omission of downstream attributes may bias the status quo effect (the value of moving away from the current status). That is, those respondents will place the values for improving downstream water quality into plans with actions. Overall, our findings suggest that respondents do use both the available information provided in the survey and their possessed knowledge when making choices.

Our results have important policy implications—the welfare estimates of water quality improvement programs can be underestimated when the programs do come with downstream water quality benefits that are neither fully disclosed nor included as attributes in the scenarios. Our findings highlight that, without cognitively overloading respondents, stated preference surveys should include as many key benefits of a program as possible to fully account for its total value (Hoyos 2010), especially when policymakers are trying to win public support for such programs. Omitting important downstream water quality benefits, such as hypoxic zone effects, or by extension other co-benefits to nutrient reduction, such as pollinator habitat protection, could lead to an underestimate of the benefit-cost ratio.

Furthermore, our findings highlight the importance of presenting the information on the downstream or non-local environmental benefits, even when the choice experiments cannot incorporate them as an attribute.

Our results also indicate that, when status quo effects are accounted for, the values of local water quality attributes are robust to the omissions of both downstream water quality information and associated attributes. These results demonstrate the experimental nature of choice experiments, which prevents the values of the included attributes from omitted variable biases. We acknowledge that such a finding might not be universal, especially when respondents are very familiar with the goods or services being valued and are able to assess the correlations between the omitted and included attributes. We argue that is, fortunately, less likely in the field of environmental valuation. More future research is needed to further test the external validity of our results.

How much researchers can learn about people's preferences using discrete choice experiments is inherently bounded by respondent's mental constraint (Hess, Stathopoulos, and Daly 2012; Swait and Adamowicz 2001). Although there is no clear guideline on how many attributes can be included in the choice or how complex a choice experiment can be, researchers nearly always need to reasonably limit the dimension of their choice experiment design (Caussade et al. 2005; Hensher 2006; Johnston et al. 2017). On the one hand, our results provide some assurance for practitioners by showing that the marginal utility estimates of the included attributes are not prone to omitted variable biases; however, on the other hand, they highlight that welfare estimates should be used with caution, especially when the estimates are used to quantify/predict the total benefits of any future programs. In light of these caveats, although many studies have investigate the issue of attribute non-attendance, when respondents ignore one or more of the attributes in the choice experiment, which can bias the welfare estimates (e.g., Sandorf, Campbell, and Hanely 2017, Scarpa et al. 2013), the effects from "uninvited" attributes may be another area for further investigation.

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Tables

Table 1. Attributes and Levels in Choice Experiment

Attribute	Levels of change	Current condition described
Toxin: number of days algal toxins are detected in source water	Reduce by 50%	68% of Iowa public water treatment plants using surface water detected toxins in their source water. The actual number of days toxins are detected per year can vary across the state.
Nitrate: nitrate concentrations in source water	Reduce by 25% Reduce by 50%	The average nitrate concentration in Iowa waterways was about 6.8 mg/liter. The actual concentration can vary across the state.
Closure: average number of days of beach closures due to algal blooms	Reduce by 50%	The average Iowa lake beach is closed for six days a year because of algal blooms.
Clarity: average water clarity in Iowa's lakes	Increase by 10% Increase by 20%	The current average water clarity in Iowa's lakes is about five feet.
Hypoxia: average size of hypoxic zone in the Gulf of Mexico	Reduce by 10% Reduce by 20%	The current size of hypoxic zone in the Gulf of Mexico is about 7,000 square miles.
Cost: monthly surcharge on water bill	\$5 \$10 \$20	There is no additional surcharge on monthly water bill.

Table 2. Summary Statistics of Key Socio-demographic Variables by Survey Version

Variables	Baseline (N = 285)	Downstream Information (N = 278)	Full (N = 290)	P-value*	Total
Age (Years)	60.35	58.27	57.72	0.1211	58.78
Female (%)	41.91%	42.53%	43.46%	0.9333	42.65%
Some College and above (%)	77.94%	79.01%	77.03%	0.8572	77.97%
Employed (%)	54.58%	57.95%	59.36%	0.5063	57.32%
Visited lakes in 2018 (%)	55.36%	57.91%	53.66%	0.5932	55.62%
Water quality rating[a]	3.17	3.07	3.09	0.3152	3.11
Water quality issue familiarity[b]	2.48	2.54	2.48	0.6846	2.50
Awareness of algal blooms[c]	2.60	2.71	2.67	0.5031	2.66

[a] "Overall, how would you rate the water quality in Iowa's lakes?" (Likert scale from 1 to 5).

[b] "How familiar are you with water quality issues in Iowa's lakes?" (Likert scale from 1 to 5).

[c] "How aware are you of algal blooms in Iowa's lakes?" (Likert scale from 1 to 5).

*: p-value of F-test for between group variations.

Table 3. Baseline and Downstream Information Model Versions

	Model 1		Model 2		Model 3		Model 4
	Baseline	Downstream Information	Baseline	Downstream Information	Baseline	Downstream Information	Baseline + Downstream Information
Means	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)
Toxin (-50%)	1.4437***	0.9511***	1.1884***	1.2531***	1.1839***		1.1903***
	(0.3001)	(0.2816)	(0.2781)	(0.2881)	(0.2117)		(0.2110)
Nitrate (-25%)	0.7153***	0.4580***	0.5791***	0.6349***	0.5976***		0.5999***
	(0.1806)	(0.1661)	(0.1582)	(0.1593)	(0.1260)		(0.1255)
Closure (-50%)	0.8690***	0.5041*	0.7589***	0.7514***	0.6924***		0.6973***
	(0.2783)	(0.2718)	(0.2572)	(0.2608)	(0.1969)		(0.1969)
Clarity (+10%)	0.2808*	0.2831*	0.1092	0.5344***	0.2845**		0.2830***
	(0.1620)	(0.1623)	(0.1480)	(0.1595)	(0.1143)		(0.1152)
Status Quo	0.2200	-1.7618***	-0.7482***		-0.1488	-1.4088***	-0.7631***
	(0.3710)	(0.4061)	(0.2834)		(0.2904)	(0.3124)	(0.2800)
Cost	-0.2222***		-0.2261***		-0.2212***		-0.2213***
	(0.0228)		(0.0235)		(0.0225)		(0.0226)
Standard Deviations (for normally distributed random parameters)							
Clarity	0.0713	0.0772	0.0826	0.5317	0.0741		0.0584
	(1.5843)	(1.4739)	(1.4814)	(0.3712)	(1.3366)		(1.6524)
Status Quo	4.1827***	3.3608***	3.8296***		4.0829***	3.4111***	3.8162***
	(0.4434)	(0.3597)	(0.3306)		(0.4258)	(0.3598)	(0.3170)
AIC	1873.27		1879.63		1865.75		1872.36
Log Likelihood	-921.64		-926.82		-922.88		-928.18
K	15		13		10		8
Observations	1868		1868		1868		1868

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Toxin, nitrate, closure, hypoxia, and cost are assumed to be zero-bounded triangular distributed, and their spread coefficients equal to the mean coefficients. Standard errors are robust and clustered at the respondent level.

Table 4. Downstream Information and Full Version Models

	Model 1		Model 2		Model 3		Model 4
	Downstream Information	Full	Downstream Information	Full	Downstream Information	Full	Downstream Information + Full
Means	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)
Toxin (-50%)	0.9703***	0.7278***	1.0594***	0.6050**	0.8632***		0.8491***
	(0.2772)	(0.2733)	(0.2767)	(0.2451)	(0.2000)		(0.1963)
Nitrate (-25%)	0.4840***	0.6606***	0.5619***	0.5976***	0.5946***		0.5912***
	(0.1666)	(0.1633)	(0.1558)	(0.1506)	(0.1183)		(0.1176)
Closure (-50%)	0.5345*	0.7069***	0.6327**	0.6368***	0.6387***		0.6464***
	(0.2730)	(0.2596)	(0.2527)	(0.2486)	(0.1927)		(0.1918)
Clarity (+10%)	0.2846*	0.6548***	0.4106***	0.5941***	0.5085***		0.5061***
	(0.1596)	(0.1559)	(0.1549)	(0.1397)	(0.1146)		(0.1141)
Hypoxia (-10%)		0.4016***		0.3551**		0.3704**	0.335***
		(0.1516)		(0.1430)		(0.1501)	(0.124)
Status Quo	-1.7995***	-0.9012***	-1.3567***		-1.4944***	-1.0849***	-1.3094***
	(0.3983)	(0.3975)	(0.2996)		(0.3097)	(0.3205)	(0.291)
Cost	-0.2292***		-0.2310***		-0.2293***		-0.2292***
	(0.0208)		(0.0214)		(0.0216)		(0.0211)
Standard Deviations (for normally distributed random parameters)							
Clarity	0.0069	0.1787	0.3504	0.2573	0.2448		0.2402
	(1.6985)	(0.8393)	(0.5167)	(0.6272)	(0.4802)		(0.5132)
Status Quo	3.3488***	2.8258***	3.099***		3.3930***	2.7939***	3.0744***
	(0.3457)	(0.3485)	(0.282)		(0.3573)	(0.3457)	(0.2782)
AIC	1866.41		1863.42		1858.15		1857.71
Log Likelihood	-917.2		-917.71		-918.07		-919.85
K	16		14		11		9
Observations	1804		1804		1804		1804

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Toxin, nitrate, closure, hypoxia, and cost are assumed to be zero-bounded triangular distributed, and their spread coefficients equal to the mean coefficients. Standard errors are robust and clustered at the respondent level.

Table 5. Willingness-to-Pay and Compensating Variations

WTPs	Coeff.	s.e.
Toxin (-50%)	4.6680	(0.6810) ***
Nitrate (-25%)	2.8390	(0.4100) ***
Closure (-50%)	3.1434	(0.6540) ***
Clarity (+10%)	1.9232	(0.3895) ***
Hypoxia (-10%)	1.3817	(0.5267) ***
Status Quo (Baseline)	-0.2630	(1.0747)
Status Quo (Downstream Information and Full)	-5.1447	(0.9348) ***

Notes: Willingness-to-pay are calculated using the Delta method; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6. Models with Familiarity Interactions

	Model 1		Model 2	
	Baseline	Downstream Information	Downstream Information	Full
Means	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)
Toxin (-50%)	1.1874 *** (0.2101)		0.8388 *** (0.1963)	
Nitrate (-25%)	0.6027 *** (0.1267)		0.5647 *** (0.1161)	
Closure (-50%)	0.6954 *** (0.1985)		0.6181 *** (0.1912)	
Clarity (+10%)	0.2770 ** (0.1152)		0.4983 *** (0.1138)	
Hypoxia (-10%) Unfamiliar				0.3483 * (0.2030)
Hypoxia (-10%) Familiar				0.3925 * (0.2067)
Status Quo Unfamiliar	0.3868 (0.3184)	-0.8051 ** (0.3317)	-0.8388 *** (0.3231)	-0.8116 ** (0.3567)
Status Quo Familiar	-1.1212 *** (0.3724)	-2.0791 *** (0.3739)	-2.0843 *** (0.3657)	-1.2802 *** (0.3692)
Cost	-0.2219 *** (0.0228)		-0.2210 *** (0.0213)	
Standard Deviations (for normally distributed random parameters)				
Clarity	-0.0649 (0.7320)		-0.1403 (0.8161)	
Status Quo Unfamiliar	4.2133 *** (0.5127)	-3.1122 *** (0.4124)	3.0364 *** (0.4020)	2.0830 *** (0.4249)
Status Quo Familiar	3.7341 *** (0.6417)	3.6795 *** (0.5500)	3.5992 *** (0.5437)	3.3781 *** (0.4720)
AIC	1864.1484		1861.0198	
Log Likelihood	-918.0742		-914.5099	
K	14		16	
Observations	1868		1804	

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Toxin, nitrate, closure, hypoxia, and cost are assumed to be zero-bounded triangular distributed, and their spread coefficients equal to the mean coefficients. Standard errors are robust and clustered at the respondent level. "Familiar" and "Unfamiliar" refer to respondents who consider themselves at least somewhat familiar with the hypoxic zone issue in the Gulf of Mexico or not all familiar, respectively.

Table 7. Models with Correlation Interactions

	Model 1		Model 2	
	Baseline	Downstream Information	Downstream Information	Full
Means	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)
Toxin (-50%)	1.3325*** (0.2430)		0.8810*** (0.2039)	
Nitrate (-25%)	0.6202*** (0.1418)		0.6237*** (0.1212)	
Closure (-50%)	0.7400*** (0.2226)		0.6413*** (0.1942)	
Clarity (+10%)	0.3060** (0.1298)		0.5240*** (0.1173)	
Hypoxia (-10%) Uncorrelated				0.3785 (0.2543)
Hypoxia (-10%) Correlated				0.3833** (0.1836)
Status Quo Uncorrelated	0.8316** (0.4113)	-0.1061 (0.3898)	0.0370 (0.3601)	-0.4861 (0.3775)
Status Quo Correlated	-2.0809*** (0.4466)	-2.6159*** (0.4186)	-2.3656*** (0.3673)	-1.3553*** (0.3617)
Cost	-0.2545*** (0.0270)		-0.2335*** (0.0220)	
Standard Deviations (for normally distributed random parameters)				
Clarity	0.0912 (0.7635)		0.1917 (0.5978)	
Status Quo Uncorrelated	3.0369*** (0.5885)	3.6212*** (0.5538)	3.4783*** (0.5350)	3.9110*** (0.6497)
Status Quo Correlated	4.0975*** (0.6825)	3.2873*** (0.4358)	3.0522*** (0.4125)	2.1794*** (0.3732)
AIC	1842.76		1844.63	
Log Likelihood	-907.38		-907.31	
K	14		16	
Observations	1868		1804	

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Toxin, nitrate, closure, hypoxia, and cost are assumed to be zero-bounded triangular distributed, and their spread coefficients equal to the mean coefficients. “Correlated” and “Uncorrelated” refer to respondents who consider the nutrient in Iowa’s waterways and the size of hypoxic zone in the Gulf of Mexico as positively correlated or not, respectively.

Figures

Figure 1. Example Choice Experiment Scenario

Scenario 1 (Please pick ONE between plan 1 and plan 0)

	Plan 1 (Proposed Plan)	**Plan 0** (Current Condition)
Number of days algal toxins are detected in source water	No change	Current Level (varies across Iowa)
Nitrate concentrations in source water	No change	Current Level (varies across Iowa)
Average number of days of beach closures due to algal blooms	Reduce by 50%	6 days per year
Average water clarity in Iowa's lakes	Increase by 20%	5 feet deep
Average size of hypoxic zone in the Gulf of Mexico	No change	7,000 square miles
Monthly surcharge on your water bill	$5	$0
24. Which plan do you prefer?	**Plan 1**	**Plan 0**

Appendices

Appendix A. Supplementary Tables

Table A1. Baseline and Downstream Information Model Versions (Excluding "Inconsequential" Respondents)

	Model 1		Model 2		Model 3		Model 4
	Baseline	Downstream Information	Baseline	Downstream Information	Baseline	Downstream Information	Baseline + Downstream Information
Means	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)
Toxin (-50%)	1.4304 ***	1.0264 ***	1.1359 ***	1.2986 ***	1.2273 ***		1.2362 ***
	(0.3118)	(0.2957)	(0.2835)	(0.2943)	(0.2224)		(0.2220)
Nitrate (-25%)	0.7322 ***	0.5405 ***	0.5780 ***	0.7056 ***	0.6450 ***		0.6388 ***
	(0.1874)	(0.1758)	(0.1619)	(0.1659)	(0.1323)		(0.1312)
Closure (-50%)	0.9048 ***	0.3856	0.7029 ***	0.6066 **	0.6554 ***		0.6609 ***
	(0.2838)	(0.2797)	(0.2624)	(0.2651)	(0.2032)		(0.2035)
Clarity (+10%)	0.3171 *	0.3461 **	0.1448	0.5698 ***	0.3507 ***		0.3530 ***
	(0.1680)	(0.1663)	(0.1523)	(0.1610)	(0.1197)		(0.1200)
Status Quo	0.1439	-1.9013 ***	-0.8677 ***		-0.1564	-1.5508 ***	-0.8655 ***
	(0.3900)	(0.4213)	(0.2945)		(0.3027)	(0.3308)	(0.2941)
Cost	-0.2279 ***		-0.2249 ***		-0.2278 ***		-0.2264 ***
	(0.0238)		(0.0238)		(0.0238)		(0.0238)
Standard Deviations (for normally distributed random parameters)							
Clarity	0.1251	0.0943	0.0885	0.1748	-0.0915		-0.0835
	(1.3843)	(1.6581)	(1.5154)	(1.0198)	(1.2998)		(1.3019)
Status Quo	4.2561 ***	3.4048 ***	3.8267 ***		4.1762 ***	3.4811 ***	3.8895 ***
	(0.4597)	(0.3772)	(0.3330)		(0.4455)	(0.3801)	(0.3321)
AIC	1769.58		1777.40		1762.45		1769.91
Log Likelihood	-869.79		-875.70		-871.23		-876.96
K	15		13		10		8
Observations	1784		1784		1784		1784

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Toxin, nitrate, closure, hypoxia, and cost are assumed to be zero-bounded triangular distributed, and their spread coefficients equal to the mean coefficients. Standard errors are robust and clustered at the respondent level.

Table A2. Downstream Information and Full Version Models (Excluding “Inconsequential” Respondents)

	Model 1		Model 2		Model 3		Model 4
	Downstream Information	Full	Downstream Information	Full	Downstream Information	Full	Downstream Information + Full
Means	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)
Toxin (-50%)	1.0387 ***	0.8142 ***	1.1374 ***	0.6745 ***	0.9210 ***		0.9136 ***
	(0.2925)	(0.2819)	(0.2841)	(0.2510)	(0.2042)		(0.2011)
Nitrate (-25%)	0.5459 ***	0.6921 ***	0.6408 ***	0.6168 ***	0.6370 ***		0.6435 ***
	(0.1750)	(0.1691)	(0.1638)	(0.1547)	(0.1226)		(0.1222)
Closure (-50%)	0.4196	0.6698 **	0.5214 **	0.5861 **	0.5383 ***		0.5501 ***
	(0.2816)	(0.2646)	(0.2601)	(0.2519)	(0.1935)		(0.1931)
Clarity (+10%)	0.3476 **	0.6456 ***	0.4644 ***	0.5730 ***	0.5239 ***		0.5187 ***
	(0.1661)	(0.1603)	(0.1545)	(0.1419)	(0.1161)		(0.1143)
Hypoxia (-10%)		0.4311 ***		0.3765 ***		0.3988 ***	0.3435 ***
		(0.1557)		(0.1461)		(0.1525)	(0.1273)
Status Quo	-1.9357 ***	-0.9442 **	-1.4252 ***		-1.6658 ***	-1.0848 ***	-1.3801 ***
	(0.4148)	(0.4072)	(0.3080)		(0.3154)	(0.3240)	(0.2956)
Cost	-0.2368 ***		-0.2363 ***		-0.2330 ***		-0.2334 ***
	(0.0221)		(0.0218)		(0.0213)		(0.0210)
Standard Deviations (for normally distributed random parameters)							
Clarity	0.0152	0.2702	0.0140	0.3116	0.0256		-0.0405
	(1.4472)	(0.5980)	(3.1703)	(0.5313)	(1.9779)		(1.7657)
Status Quo	3.4385 ***	2.9186 ***	3.1574 ***		3.4159 ***	2.8387 ***	3.1468 ***
	(0.3621)	(0.3657)	(0.2873)		(0.3595)	(0.3488)	(0.2820)
AIC	1794.20		1792.24		1786.83		1786.02
Log Likelihood	-881.10		-882.12		-882.41		-884.01
K	15		13		10		8
Observations	1752		1752		1752		1752

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Toxin, nitrate, closure, hypoxia, and cost are assumed to be zero-bounded triangular distributed, and their spread coefficients equal to the mean coefficients. Standard errors are robust and clustered at the respondent level.

Table A3. All Three Version Models (Separated)

	Model 1	Model 2	Model 3
	Baseline	Downstream Information	Full
Means	Coefficients (s.e.)	Coefficients (s.e.)	Coefficients (s.e.)
Toxin (-50%)	1.4734 ***	0.9117 ***	0.7652 ***
	(0.3307)	(0.2867)	(0.2843)
Nitrate (-25%)	0.7369 ***	0.4543 ***	0.6918 ***
	(0.1966)	(0.1675)	(0.1719)
Closure (-50%)	0.8927 ***	0.4794 *	0.7451 ***
	(0.2891)	(0.2734)	(0.2732)
Clarity (+10%)	0.2864 *	0.2783 *	0.6822 ***
	(0.1677)	(0.1623)	(0.1681)
Hypoxia (-10%)			0.4082 ***
			(0.1580)
Status Quo	0.1184	-1.6859 ***	-0.9888 **
	(0.3796)	(0.4375)	(0.4207)
Cost	-0.2338 ***	-0.2114 ***	-0.2433 ***
	(0.0365)	(0.0293)	(0.0309)
Standard Deviations			
Clarity	0.0633	0.1051	0.3071
	(2.5359)	(1.3915)	(0.5860)
Status Quo	4.2559 ***	3.2934 ***	2.9272 ***
	(0.5174)	(0.3887)	(0.4093)
AIC	968.27	906.75	960.60
Log Likelihood	-476.14	-445.38	-471.30
K	8	8	9
Observations	980	888	916

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Toxin, nitrate, closure, hypoxia, and cost are assumed to be zero-bounded triangular distributed, and their spread coefficients equal to the mean coefficients. Standard errors are robust and clustered at the respondent level.

Table A4. Models with All Three Versions

<table>
<tr><th rowspan="3">Means</th><th colspan="2">Model 1</th></tr>
<tr><th>Baseline</th><th>Downstream Information + Full</th></tr>
<tr><th>Coefficients (s.e.)</th><th>Coefficients (s.e.)</th></tr>
<tr><td>Toxin</td><td colspan="2">0.8901***
(0.1461)</td></tr>
<tr><td>Nitrate</td><td colspan="2">0.5380***
(0.0906)</td></tr>
<tr><td>Closure</td><td colspan="2">0.6718***
(0.1402)</td></tr>
<tr><td>Clarity</td><td colspan="2">0.3773**
(0.0887)</td></tr>
<tr><td>Hypoxia</td><td></td><td>0.3265**
(0.1405)</td></tr>
<tr><td>Status Quo</td><td>-0.1976
(0.3396)</td><td>-1.0220***
(0.2656)</td></tr>
<tr><td>Cost</td><td colspan="2">-0.1996***
(0.0168)</td></tr>
<tr><td>Standard Deviations</td><td></td><td></td></tr>
<tr><td>Clarity</td><td colspan="2">0.1064
(0.1993)</td></tr>
<tr><td>Status Quo
Correlated</td><td>3.7463***
(0.3899)</td><td>2.8318***
(0.2233)</td></tr>
<tr><td>AIC</td><td colspan="2">2961.10</td></tr>
<tr><td>Log Likelihood</td><td colspan="2">-1469.5</td></tr>
<tr><td>K</td><td colspan="2">11</td></tr>
<tr><td>Observations</td><td colspan="2">2784</td></tr>
</table>

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; toxin, nitrate, closure, and cost are assumed to be zero-bounded triangular distributed. Standard errors are robust and clustered at the respondent level.

Appendix B. Supplementary Figures

Figure B1. Individual Specific WTPs (Baseline and Downstream Information)

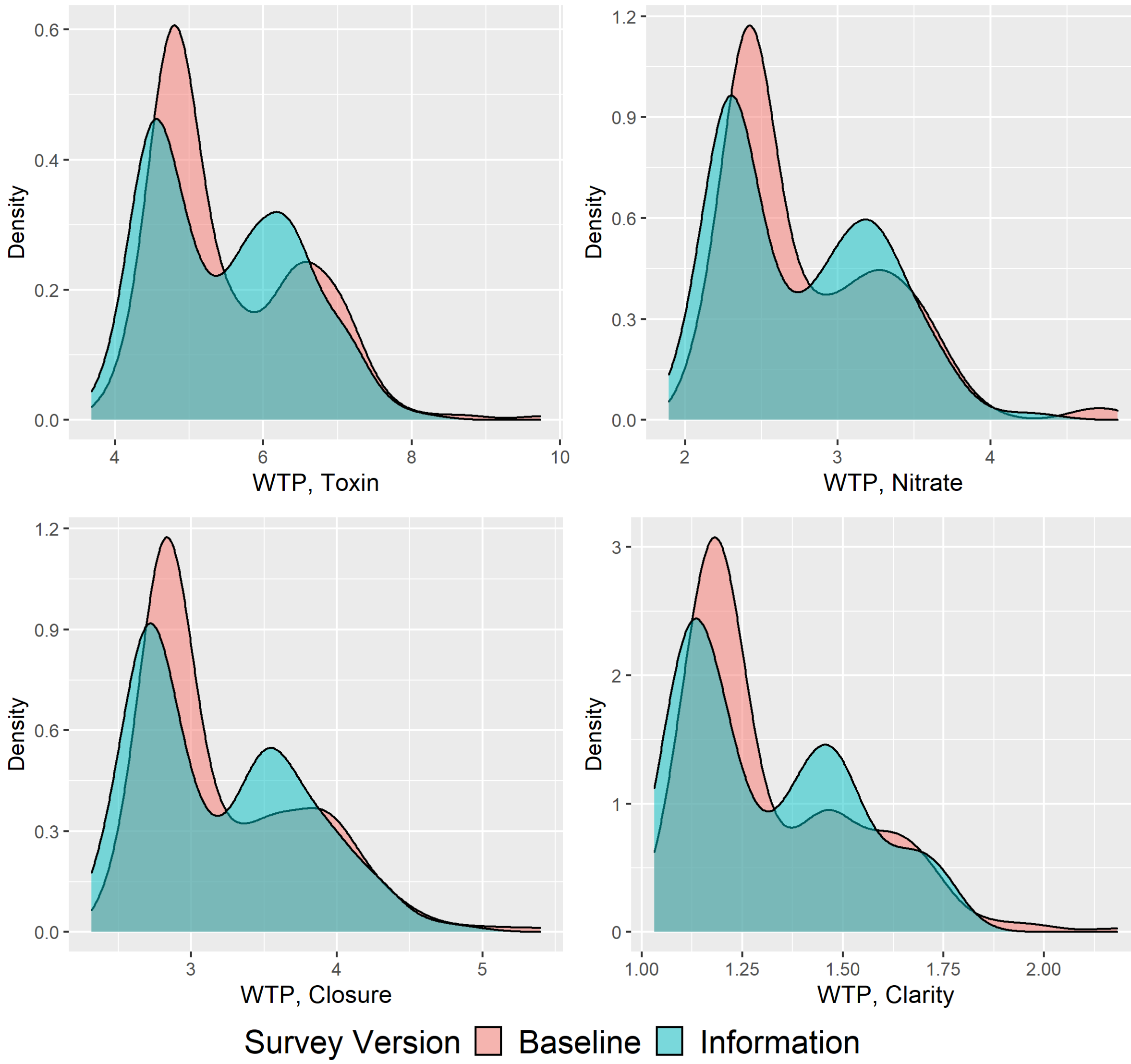
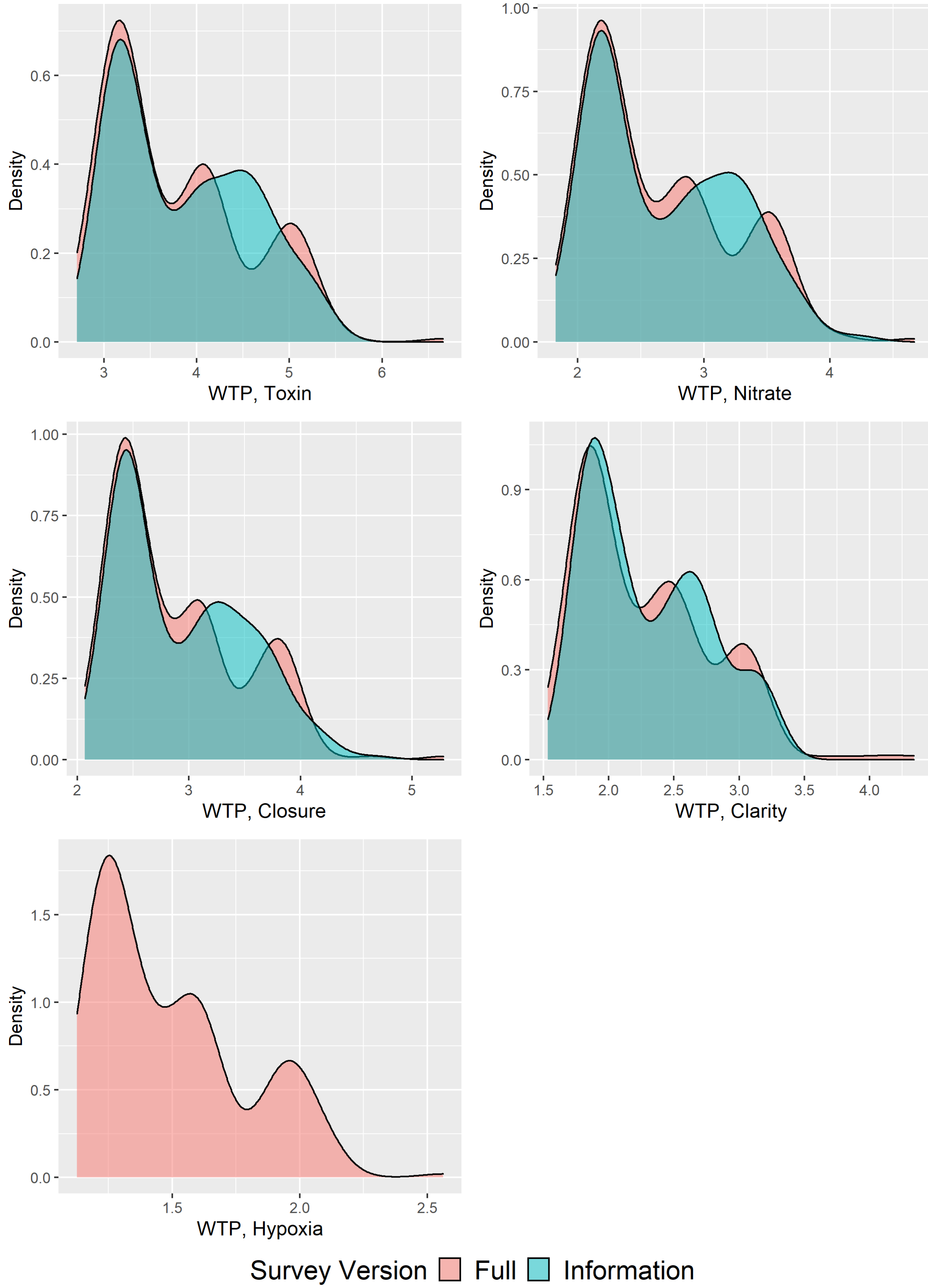


Figure B2. Individual Specific WTPs (Downstream Information and Full)



Appendix C. Survey Instrument (Full Version)

Iowa Waterways Survey

Thank you for your participation in this survey.

Please read each question carefully and provide a response for each one.

1. Overall, how would you rate the water quality in Iowa's lakes?

Very Poor	Poor	Fair	Good	Very Good
1	2	3	4	5

2. How familiar are you with water quality issues in Iowa's lakes?

Not at all familiar	Slightly familiar	Somewhat familiar	Very familiar	Extremely familiar
1	2	3	4	5

3. Have you ever visited a lake in Iowa?

1 = Yes
2 = No, or not sure ➔ ***IF NO, GO TO NEXT PAGE.***

4. Did you visit any lakes in Iowa last summer, between May and September 2018?

1 = Yes
2 = No, or not sure

5. What recreational activities do you usually do when you visit Iowa's lakes?
Please circle ALL that apply.

1 = Fishing
2 = Swimming and/or beach use
3 = Boating with motor
4 = Jet skiing, water skiing, or tubing
5 = Canoeing, kayaking, or sailing
6 = Wildlife and/or scenery viewing
7 = Trail use (Hiking / running / walking / biking)
8 = Relaxing, picnicking, or barbequing
9 = Camping
10 = Something else; please specify: _______________

6. How familiar are you with the issue of excessive nutrients in Iowa lakes?

Not at all familiar	Slightly familiar	Somewhat familiar	Very familiar	Extremely familiar
1	2	3	4	5

Nutrients in waterways, such as nitrogen and phosphorous, are components that support aquatic life. Excessive nutrients can also lead to overgrown algae, which is sometimes referred as **algal blooms**. Algal blooms are dense layers of tiny green plants that occur on the surface of lakes and other bodies of water.

7. How aware are you of algal blooms in Iowa's lakes?

Not at all aware	Slightly aware	Somewhat aware	Very aware	Extremely aware
1	2	3	4	5

8. In your opinion, how harmful are algal blooms in Iowa's lakes?

Not at all harmful	Slightly harmful	Somewhat harmful	Very harmful	Extremely harmful
1	2	3	4	5

9. Based on your knowledge, which nutrient is more likely the cause of algal blooms in Iowa's lakes?

1 = Nitrogen 2 = Phosphorous 3 = Not sure

10. Have you ever seen algal blooms in person? If so, how many times?

1 = Yes, only once
2 = Yes, 2 or 3 times
3 = Yes, more than 3 times
4 = No, never seen algal blooms, no sure ➔ ***GO TO QUESTION 13***

11. Did you see algal blooms when you visited lakes in Iowa in 2018?

1 = Yes
2 = No, or not sure ➔ ***GO TO QUESTION 13.***
3 = Did not visit Iowa lakes in 2018. ➔ ***GO TO QUESTION 13.***

12. Please list the lake(s) and month(s) you saw the algal blooms in Iowa's lakes in 2018.

Name of Lake	Month
________________________________	______________
________________________________	______________
________________________________	______________

13. Based on your knowledge, what is the **number one source** of excessive nutrients in Iowa's lakes?

1 = Agriculture (e.g., animal manure, fertilizer applied to crops)
2 = Stormwater runoff (e.g., from rooftops, roads, and lawns)
3 = Municipal wastewater (e.g., from sewer and septic systems)
4 = Industrial wastewater
5 = Not sure
6 = Other; please specify: ______________________________

There are currently many programs in place to tackle environmental quality issues in the state of Iowa, including those dealing with excessive nutrients in water, such as nitrogen and phosphorous. The *Iowa Nutrient Reduction Strategy* is a program designed to **assess and reduce nutrients** and **enhance water quality** in Iowa's waterways.

14. How familiar are you with the *Iowa Nutrient Reduction Strategy*?

Not at all familiar	Slightly familiar	Somewhat familiar	Very familiar	Extremely familiar
1	2	3	4	5

15. In your opinion, which of the following is the most appropriate way to fund the Iowa Nutrient Reduction Strategy and similar programs for protecting lakes in Iowa?

1 = A fee on residential and business water bills.
2 = A recreational fee for use of parks, beaches, and lakes. (e.g., swimming, boating, fishing, hunting, camping, etc.)
3 = A special sales tax on fertilizer (for both agricultural and household uses).
4 = Another way; please specify: ____

16. What is the primary source of the public water system in your area?

1 = Surface water
2 = Ground water
3 = Not sure

17. Are nitrates in drinking water a concern in your home or neighborhood?

1 = Yes
2 = No
3 = Not sure

18. Does your household primarily rely on a private well for drinking water?

1 = Yes
2 = No

19. In your opinion, how important are the following potential improvements in Iowa's lakes?

	Not at all importan t	Slightly importan t	Moderatel y important	Very important	Extremely important
Increasing average water clarity in Iowa's lakes by 20%.	1	2	3	4	5
Reducing both nitrogen and phosphorous in Iowa's lakes by 45%.	1	2	3	4	5
No/minimal algal blooms or scum (no bright green water)	1	2	3	4	5

Some water in Iowa flows to the Mississippi River and eventually to the Gulf of Mexico. As a result, nutrients in Iowa's waterways can affect water downstream. One issue caused by excessive nutrients is a **hypoxic zone**, sometimes referred to as a "dead zone," an area of water with low levels of oxygen. Hypoxic zones have endangered marine life in the Gulf of Mexico and other places around the world.

20. How familiar are you with the hypoxic zone issue in the Gulf of Mexico?

Not at all familiar	Slightly familiar	Somewhat familiar	Very familiar	Extremely familiar
1	2	3	4	5

21. In your opinion, if nutrients in Iowa's waterways were reduced by 50%, how would that affect the hypoxic zone in the Gulf of Mexico?

1 = The hypoxic zone would be **much smaller**
2 = The hypoxic zone would be **slightly smaller**
3 = There would be **little or no effect** on the hypoxic zone
4 = The hypoxic zone would be **slightly larger**
5 = The hypoxic zone would be **much larger**
6 = I don't know

22. In your opinion, how important are the following potential improvements in water quality?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Reducing nutrients in Iowa's waterways	1	2	3	4	5
Not sending nutrients downstream to other states	1	2	3	4	5
Reducing the size of the hypoxic zone in the Gulf of Mexico	1	2	3	4	5

23. Please indicate how strongly you **agree** or **disagree** with the following statements.

	Strongly disagree	Somewhat disagree	Neutral or Don't know	Somewhat agree	Strongly agree
The *Iowa Nutrient Reduction Strategy* can help resolve the hypoxic zone issue.	1	2	3	4	5
The *Iowa Nutrient Reduction Strategy* is a feasible plan to reduce nutrients in Iowa's waterways.	1	2	3	4	5

On the following pages, there are four scenarios showing different options for managing water quality in Iowa. Each scenario shown in a table includes the current water quality condition and one proposed water quality improvement plan. **Each plan could result in water quality changes in the five following ways.**

- **Number of days algal toxins are detected in source water**
- **Nitrate concentrations in source water**
- **Average number of days of beach closures due to algal blooms**
- **Average water clarity in Iowa's lakes**
- **Average size of hypoxic zone in the Gulf of Mexico**

Each plan also comes with a cost for implementation. **The cost would be paid through a fee included in your household water bill each month**, similar to a stormwater surcharge. The descriptions and current conditions of the above five water quality characteristics are provided on the next page.

- **Number of days algal toxins are detected in source water**: Algal blooms can produce toxins and make water unsafe to drink. Most water treatment systems remove these toxins at a cost, but some treated drinking water may still contain them. In a year-long monitoring report, 15 out of 22 Iowa public water treatment plants using surface water detected algal toxins in their (before-treatment) source water, while six plants relying on ground water did not detect algal toxins. The actual number of days algal toxins are detected can vary across the state.
  - Some plans could reduce the number of days algal toxins are detected in source water of your drinking water by 50%, which would reduce both the cost of water treatment and the likelihood that toxins may still remain in your drinking water.
- **Nitrate concentration in source water**: Elevated nitrate concentrations can make water unsafe to drink. Water treatment systems treat source water to make sure the nitrate level is below the federal regulation level (10 mg/liter). In 2018, the average nitrate concentration in Iowa waterways was about 6.8 mg/liter. The actual concentration can vary across the state.
  - Some plans could reduce nitrate levels in source water, including that of public water systems and private wells, by 25%–50%, thereby reducing both the cost of water treatment and the nitrates that remain in treated drinking water.
- **Average number of days of beach closures due to algal blooms**: Currently, the average Iowa lake beach is closed for six days a year because of algal blooms.
  - Some plans could reduce the number of days of beach closures by 50%.
- **Average water clarity in Iowa's lakes**: The current average water clarity in Iowa's lakes is about five feet; that is, you can see things in the water as deep as five feet from the surface.
  - Some plans could increase the average clarity in Iowa lakes by 10%–20%.
- **Average size of hypoxic zone in the Gulf of Mexico**: Currently, the size of hypoxic zone in the Gulf of Mexico is about 7,000 square miles.
  - Some plans could reduce the hypoxic zone by 10%–20%.

Please note that, **although you will not actually pay more fees based on the decisions you make, we ask you to make the decisions as though it would result in a fee increase. We ask you to think carefully when making your choices.** You answer will be used by researchers and policymakers to design the most appropriate water quality management to suit the needs of Iowans.

For each scenario table, please circle the number of the plan you prefer.

Scenario 1 (Please pick ONE between plan 1 and plan 0)

	Plan 1 (Proposed Plan)	**Plan 0** (Current Condition)
Number of days algal toxins are detected in source water	No change	Current Level (varies across Iowa)
Nitrate concentrations in source water	No change	Current Level (varies across Iowa)
Average number of days of beach closures due to algal blooms	Reduce by 50%	6 days per year
Average water clarity in Iowa's lakes	Increase by 20%	5 feet deep
Average size of hypoxic zone in the Gulf of Mexico	No change	7,000 square miles
Monthly surcharge on your water bill	$5	$0
24. Which plan do you prefer?	**Plan 1**	**Plan 0**

Scenario 2 (Please pick ONE between plan 2 and plan 0)

	Plan 2 (Proposed Plan)	**Plan 0** (Current Condition)
Number of days algal toxins are detected in source water	Reduce by 50%	Current Level (varies across Iowa)
Nitrate concentrations in source water	Reduce by 25%	Current Level (varies across Iowa)
Average number of days of beach closures due to algal blooms	No change	6 days per year
Average water clarity in Iowa's lakes	Increase by 20%	5 feet deep
Average size of hypoxic zone in the Gulf of Mexico	Reduce by 10%	7,000 square miles
Monthly surcharge on your water bill	$20	$0
25. Which plan do you prefer?	**Plan 2**	**Plan 0**

Scenario 3 (Please pick ONE between plan 3 and plan 0)

	Plan 3 (Proposed Plan)	**Plan 0** (Current Condition)
Number of days algal toxins are detected in source water	No change	Current Level (varies across Iowa)
Nitrate concentrations in source water	No change	Current Level (varies across Iowa)
Average number of days of beach closures due to algal blooms	No change	6 days per year
Average water clarity in Iowa's lakes	No change	5 feet deep
Average size of hypoxic zone in the Gulf of Mexico	Reduce by 20%	7,000 square miles
Monthly surcharge on your water bill	$20	$0
26. Which plan do you prefer?	**Plan 3**	**Plan 0**

Scenario 4 (Please pick ONE between plan 4 and plan 0)

	Plan 4 (Proposed Plan)	**Plan 0** (Current Condition)
Number of days algal toxins are detected in source water	No change	Current Level (varies across Iowa)
Nitrate concentrations in source water	Reduce by 50%	Current Level (varies across Iowa)
Average number of days of beach closures due to algal blooms	Reduce by 50%	6 days per year
Average water clarity in Iowa's lakes	No change	5 feet deep
Average size of hypoxic zone in the Gulf of Mexico	Reduce by 10%	7,000 square miles
Monthly surcharge on your water bill	$20	$0
27. Which plan do you prefer?	**Plan 4**	**Plan 0**

28. Which of the five water quality attributes listed in the previous scenario questions is the **LEAST** important to you?

    1 = Number of days of algal toxins in water
    2 = Nitrate concentrations in Iowa's water
    3 = Number of days of beach closures due to algal blooms
    4 = Water clarity in Iowa's lakes
    5 = Size of the hypoxic zone in the Gulf of Mexico

29. **If the nitrate levels in Iowa's water were reduced,** what do you think would happen to the hypoxic zone in the Gulf of Mexico?

    1 = The hypoxic zone would be **much smaller**
    2 = The hypoxic zone would be **slightly smaller**
    3 = There would be **little or no effect** on the hypoxic zone
    4 = The hypoxic zone would be **slightly larger**
    5 = The hypoxic zone would be **much larger**
    6 = I don't know

30. **If there were fewer days of beach closures due to algal blooms in Iowa's lakes,** what do you think would happen to the hypoxic zone in the Gulf of Mexico?

    1 = The hypoxic zone would be **much smaller**
    2 = The hypoxic zone would be **slightly smaller**
    3 = There would be **little or no effect** on the hypoxic zone
    4 = The hypoxic zone would be **slightly larger**
    5 = The hypoxic zone would be **much larger**
    6 = I don't know

	Definitely not	Probably not	Not sure	Probably will	Definitely will
31. Do you think the information gathered in this survey will affect decisions about water quality management and policies in Iowa?	1	2	3	4	5
32. Do you think you will be sharing or paying the costs of implementing water quality projects to reduce excessive nutrients?	1	2	3	4	5

Lastly, we would like to ask a few questions about you and your family.

33. What is your current age? ____________

34. What is your gender? 1 = Female 2 = Male

35. Including yourself, how many people currently live in your household? __________

36. How many **children under 12** currently live in your household? _________

37. How many **children between the age of 12 and 18** currently live in your household? _________

38. What is the highest level of education you have completed?

1 = Less than high school
2 = High school diploma or equivalent
3 = Vocational school, technical school, or some college
4 = Four-year college degree
5 = Post-graduate degree

39. What is your current employment status?

1 = Employed or self-employed (either full or part time)
2 = Unemployed
3 = Retired
4 = Caring for home or family
5 = Other; please specify: ______________________________

40. What was your total household income before taxes in 2018?

1 = Under $20,000
2 = $20,000 up to $40,000
3 = $40,000 up to $70,000
4 = $70,000 up to $100,000
5 = $100,000 up to $150,000
6 = $150,000 or more

41. Do you belong to any of the following types of groups or organizations? [Please select all that apply.]

1 = Environmental group or organization
2 = Farmer group or association
3 = Outdoor recreation group or organization

42. Please record any other comments you have about Iowa's water quality.