**Omitted Downstream Attributes and the Benefits of Nutrient Reductions: Implications for Choice Experiments**

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## Abstract

Discrete choice experiments have been used extensively to value environmental quality; however, some important attributes are often omitted due to design challenges. In the case of quantifying the values of water quality improvement programs that bring transboundary impacts, existing studies predominantly focus solely on local benefits. Using a statewide survey of Iowa residents, we provide one of the first estimates of willingness-to-pay for both local and downstream water quality improvements—Gulf of Mexico hypoxic zone reduction—stemming from nutrient reductions. Using a split-sample design, we find that excluding hypoxic zone reduction as an attribute significantly reduces the total economic value of nutrient reduction programs. Moreover, we find evidence showing that such exclusion, in line with the theoretical prediction, only changes the preferences of respondents who are aware of the transboundary impacts of nutrient reductions. Conversely, our results also show that providing information about the downstream water quality benefits of nutrient reductions increases support for water quality improvement plans among local residents who are unaware of the connection 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

## 1. Introduction

Nutrient pollution from agricultural non-point sources is one of the most critical global water resource issues today (Diaz and Rosenberg 2008, Hallegraeff et al. 2021, Keiser et al. 2019, Rabalais et al. 2007). In particular, the elevated nutrient runoff from crop and livestock production has resulted in an increase of harmful algal blooms and hypoxic zones in many regions across the globe (Carpenter et al. 1998, Hallegraeff 1993), including China (Liu et al. 2011), Europe (Karlson et al. 2021), and the United States (Liu et al. 2020, Rabalais and Turner 2019, Scavia et al. 2017). Recently, Africa also reported disruptive algal blooms of brown tide species (Gobler and Sunda 2012), and the Caribbeans saw a sharp increase in the Great Atlantic Sargassum Belt (Wang et al. 2019). Within the United States, this issue is even more prevalent in the Mississippi/Atchafalaya River basin (MARB), which encompasses many of the top agriculture-producing states, whose excessive nutrients have resulted in the second largest coastal hypoxic zone in the world in the northern Gulf of Mexico (Rabalais and Turner 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 2020, USDA invested nearly $14 billion in voluntary working lands conservation programs in the 12 MARB states (USEPA 2022).

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). Researchers have often used stated preference methods such as choice experiments and contingent valuation to quantify economic benefits of water quality improvements. Van Houtven et al. (2014) and Nelson et al. (2015) respectively use contingent valuation to study the benefits of nutrient reductions from improving local water quality in eight southeastern states and the state of Utah. Using a discrete choice experiment, Zhang and Sohngen (2018) link the economic benefits of improved recreational fishing opportunity with nutrient reduction efforts in the Lake Erie basin. However, the economic benefits of reducing nutrient pollution in the MARB are thus far rarely studied. To the best of our knowledge, Parthum and Ando (2020) is the only study that focuses on the benefits of nutrient reductions in the MARB, but they only quantify the benefits of nutrient reductions in one single HUC8 watershed in Illinois.

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.[1] If some respondents care about the downstream impacts of local water quality improvement programs, the omission of downstream water quality would underestimate the total values of water quality programs with transboundary impacts. Moreover, any reduction in local water pollution is likely to lead to improvement in downstream water quality; in case the downstream attributes excluded from studies are perceived as correlated with those included local attributes, the omission of downstream water quality can further lead to biased welfare estimates for changes in local water quality. Although the decision of excluding downstream water quality impacts may be justified if such impacts are negligible (at least from the perspective of the respondents), it is empirically unknown what the effects of omitting the downstream impacts of nutrient reductions are.

This issue of omitted attributes extends beyond studies on water quality. Choice experiment studies often exclude relevant attributes from the choice profiles for the sake of limiting respondents' cognitive burden (Hoyos 2010). 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). However, 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 omitted attribute problem is also relevant for other stated preference methods: Bishop et al. (2017) show in a contingent valuation study of BP oil spill that only focuses on economic injuries of oil spill on birds while ignores impacts on dolphins, corals and sea turtles could lead to an underestimate of economic benefits.

[1] For example, in the survey instrument of Parthum and Ando (2020), although about half of the background information is on describing the hypoxic zone in the Gulf of Mexico and its link with local nutrient pollution, but their choice experiment did not include any impacts on the hypoxic zone as an attribute. Instead, similar to what most existing studies did, asked the respondents to focus on the changes in the local watershed. Interestingly, their study is premised on the conjecture that the local benefits are "overlooked" when quantifying the benefits of programs primarily concerned about water quality in the Gulf of Mexico.

Using a statewide survey with choice experiments of 853 residents in Iowa on their knowledge of and preferences for the Iowa Nutrient Reduction Strategy (INRS), we assess the impacts of omitted downstream benefits on respondents' willingness-to-pay (WTP) for water quality, and provide one of the first empirical estimates for the economic benefits of nutrient reductions at the state level in the MARB. Specifically, we estimate citizens' WTP for four local water quality attributes—algal toxins and nitrate in drinking water sources, lake beach closures due to harmful algal blooms, lake water clarity—and a non-local water quality attribute: changes in the size of hypoxic zone in the Gulf of Mexico. Understanding these local benefits of nutrient reductions is crucial, because many associated local policies, such as state-level cost-share conservation programs, could be important funding sources. By including both local and downstream water quality impacts of nutrient reduction programs, this study, to our knowledge, is also the first that quantifies the values of improving downstream water quality for residents in the upstream states. 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).

To assess the extent to which the exclusion of downstream water quality benefits would affect the total values of nutrient reduction programs and citizens' valuation of the local benefits, we develop a split-sample information experiment. Specifically, we experimentally remove the downstream water quality attribute—changes in the size of the 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). Moreover, we also explore if the 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 the effects of respondents' beliefs and knowledge on their valuation from those of preferences (e.g., Cameron, DeShazo, and Johnson 2011; Howard et al. 2020; Lusk, Schroeder, and Tonsor 2014).

Leveraging our split-sample experiment, we further test the effects of providing information of downstream impacts on local citizens' valuations for nutrient reduction programs. Therefore, we join the literature on information provision in stated preference studies (e.g., Bateman and Mawby 2004; Needham et al. 2018; Tienhaara et al. 2022).

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 excluding information on the hypoxic zone and the associated attitudinal questions. We also investigate if information heterogeneously affects respondents with different levels of awareness or knowledge 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 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. 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, 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.

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

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.[2] 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 (Rabotyagov et al. 2014).

Massive federal and state funding has been devoted to incentivizing 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 $4 billion in total obligations in 2020. 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 by 41% and phosphorus load by 45% in Iowa's waterways (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

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

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 (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 being additive benefits and an error term:

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

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:

$$U_{ij} = \boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}\boldsymbol{\beta}_{\boldsymbol{i}}^{\boldsymbol{L}} + z_{ij}^{D} + \beta_{i}^{SQ}SQ_{ij} + \mu_{ij} \tag{2}$$

where $z_{ij}^{D}$ is the value stemming from the perceived improvement in downstream water quality for individual $i$, which we assume to be a linear function of the local water quality improvement in scenario $j$. That is, $z_{ij}^{D} = \boldsymbol{f}(\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}, SQ_{ij}) = \boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}\boldsymbol{\alpha}_{\boldsymbol{i}}^{\boldsymbol{L}} + \gamma_{i}^{SQ}SQ_{ij} + \nu_{ij}$, where $\boldsymbol{\alpha}_{\boldsymbol{i}}^{\boldsymbol{L}}$ captures the downstream benefits determined by the changes in $\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}$; because in theory $\boldsymbol{f}(\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}, SQ_{ij} = 0) \geq \boldsymbol{f}(\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}, SQ_{ij} = 1)$, $-\gamma_{i}^{SQ}$ captures the downstream benefits from solely knowing that a nutrient reduction plan is implemented. Equation (2) can be rewritten as:

$$U_{ij} = \boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}\widetilde{\boldsymbol{\beta}_{\boldsymbol{i}}^{\boldsymbol{L}}} + \widetilde{\beta_{i}^{SQ}}SQ_{ij} + \varepsilon_{ij} \tag{3}$$

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

When $x_{ij}^{D}$ is not accounted for in the model, it is not immediately clear the degree to which $\boldsymbol{\beta}_{\boldsymbol{i}}^{\boldsymbol{L}}$ would be biased. The first extreme case is when, given $\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}$, a respondent has a clear perception of the (positive) correlation between $\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}$ and $x_{ij}^{D}$ and could determine the exact changes in $x_{ij}^{D}$ based on the perceived correlation with $\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}$.[3] That is, an individual can determine their $z_{ij}^{D}$ solely based on $\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}$ and not rely on $SQ_{ij}$, which would result in $\widetilde{\boldsymbol{\beta}_{\boldsymbol{i}}^{\boldsymbol{L}}}$ being

[3] Note that we focus on the perceived correlation instead of the actual correlation between local and downstream water quality, $\text{cor}(\boldsymbol{x}_{\boldsymbol{ij}}^{\boldsymbol{L}}, x_{ij}^{D})$, 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.

an upward biased estimator for $\boldsymbol{\beta_i^L}$; however, $\widetilde{\beta_i^{SQ}}$ is still an unbiased estimator for $\beta_i^{SQ}$. 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 $\beta_i^{SQ}$, 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 $\widetilde{\boldsymbol{\beta}_i^{\boldsymbol{L}}}$ 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 $\boldsymbol{\alpha}_i^{\boldsymbol{L}}$ and $\gamma_i^{SQ}$. 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 awareness or knowledge 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 $\boldsymbol{x}_{ij}^{\boldsymbol{L}}$, hypothesis one will be rejected so $\widetilde{\boldsymbol{\beta}_i^{\boldsymbol{L}}} \neq \boldsymbol{\beta}_i^{\boldsymbol{L}}$ 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 $\boldsymbol{x}_{ij}^{\boldsymbol{L}}$ 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 $\widetilde{\boldsymbol{\beta}_i^{\boldsymbol{L}}} = \boldsymbol{\beta}_i^{\boldsymbol{L}}$. Lastly, for those who are not at all aware of downstream water quality issues, in theory we will fail to reject both of the hypotheses with $\boldsymbol{\alpha}_i^{\boldsymbol{L}} = \gamma_i^{SQ} = 0$.

## 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 binary-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. Such a binary-choice format can better ensure that stated preference questions are incentive compatible (Carson and Groves 2007; Vossler and Evans 2009; Vossler et al. 2012). Figure 1 is an example choice scenario in the full version, with both the hypoxia zone information and attribute included.[4]

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 the 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

[4] See question 20 to 23 of the complete survey instrument of the full version in Appendix C.

water quality attributes are summarized in table 1.[5] The payment vehicle is designed as a monthly surcharge to the household water bill. 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.

To create the choice experiment design, we first ruled out likely implausible scenarios (e.g., 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 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 freshwater lakes, but hypoxic zones in marine water are 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. Therefore, we do not explicitly design the choice profiles to incorporate the complex and uncertain correlations between the water quality attributes.

[5] 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 base the current condition of hypoxia on the size of the 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.

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 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, as well as a comparison to a statistically-representative survey of visitors to Iowa lakes in 2019 (Wan et al. 2021) and general population statistics from the 2019 American Community Survey and Current Population Survey (US Bureau of Labor Statistics 2023; US Census Bureau 2023). 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.[6] The statistics show that the randomization is successful, and our sample is qualitatively comparable to the Iowa general public, especially those who have visited Iowa lakes in the previous year.

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 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 increase the

[6] 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?"

consequentiality, 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" (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 5.6% of the respondents answered "definitely not" to either the policy or payment consequentiality question.[7] 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). As we discuss later in the results section, we find the results are insensitivity to the exclusion of respondents who consider the survey to be either policy or payment inconsequential.[8]

## 5. Econometric Model

Following the current standard discrete choice experiment literature built on the random utility maximization model (Hanemann 1984; 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:

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

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

[7] The policy and payment consequentiality questions are "[D]o you think the information gathered in this survey will affect decisions about water quality management and policies in Iowa?" and "[D]o you think you will be sharing or paying the costs of implementing water quality projects to reduce excessive nutrients?"

[8] We also note that some respondents, such as those primarily rely on private wells or renters whose utilities are included in rent, may consider an increase in their water bill to be impossible and thus see the survey to be (payment) inconsequential. Still, among the 15.3% respondents who primarily rely on private wells, only 5.0% of them consider the survey definitely not payment consequential. Later in the results section, we also probe the robustness of our results by excluding respondents who rely on private wells.

but are unobservable to the researcher and follows IID Type-I extreme value distribution. We assume $\boldsymbol{\beta}_i$ being single-modal continuously distributed and model the choice probability using random parameter logit (also 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 for the probability of the series of choices, $y_i$, made by individual $i$ across all $S$ scenarios:

$$\Pr(y_i|\boldsymbol{x}_{js},\boldsymbol{\beta}_i) = \prod_{s=1}^{S}\frac{\sum_v\left(\beta_{iv}^{t}T_{j'sv}+\beta_{iv}^{n}N_{j'sv}+\beta_{iv}^{s}S_{j'sv}+\beta_{iv}^{r}R_{j'sv}+\beta_{iv}^{SQ}SQ_{j'sv}\right)+\beta_i^{c}C_{j'sv}}{\sum_{j=1}^{J}\sum_v\left(\beta_{iv}^{t}T_{jsv}+\beta_{iv}^{n}N_{jsv}+\beta_{iv}^{s}S_{jsv}+\beta_{iv}^{r}R_{jsv}+\beta_{iv}^{SQ}SQ_{jsv}\right)+\beta_i^{c}C_{jsv}} \quad (5)$$

where subscript $v = \{v_{baseline}, v_{downstream}\}$ indicates the survey version; $T$, $N$, $S$, and $R$ are toxin, nitrate, (beach) closure, and (lake water) clarity; $SQ$ and $C$ are respectively the status quo alternative constant and cost attribute.

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. Specifically, in our main analysis, we estimate one unrestricted and three restricted models to examine the potential heterogeneity across the two versions:

1. Unrestricted heterogeneity model: this model allows unrestricted heterogeneity of all water quality attributes and status quo parameters across different versions.
2. Homogenous status quo effect model: this model allows all preference parameters of water quality attributes to be heterogenous across versions but imposes the equality restriction on the status quo parameter.
3. Homogenous water quality preference model: this model imposes the equality restrictions on the water quality attribute parameters across versions but allows status quo parameters to be different.

4. No version heterogeneity model: this model imposes the equality restrictions on all parameters across the two versions, which in essence assumes that the treatment has no effect on respondents' preferences.

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:

$$\Pr(y_i|\boldsymbol{x}_{js}, \boldsymbol{\beta}_i) = \prod_{s=1}^{S} \frac{\sum_v (\beta_{iv}^t T_{j'sv} + \beta_{iv}^n N_{j'sv} + \beta_{iv}^s S_{j'sv} + \beta_{iv}^r R_{j'sv} + \beta_{iv}^{SQ} SQ_{j'sv}) + \beta_{iv}^h H_{j'sv} + \beta_i^c C_{j'sv}}{\sum_{j=1}^{J} \sum_v (\beta_{iv}^t T_{jsv} + \beta_{iv}^n N_{jsv} + \beta_{iv}^s S_{jsv} + \beta_{iv}^r R_{jsv} + \beta_{iv}^{SQ} SQ_{jsv}) + \beta_{iv}^h H_{jsv} + \beta_i^c C_{jsv}} \quad (6)$$

where subscript $v = \{v_{downstream}, v_{full}\}$, and $H_{jsv} = 0$ if $v = \{v_{downstream}\}$. A positively significant $\beta_i^h$ therefore indicates significant omitted downstream benefits. We again use likelihood ratio tests between the unrestricted and three restricted (with $\beta_{iv_{downstream}}^{\cdot} = \beta_{iv_{full}}^{\cdot}$) models described above to test if the marginal utilities of local water quality attributes are biased or the status quo effects are changed 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 ($\beta_{iv}^t$, $\beta_{iv}^n$, $\beta_{iv}^s$, and $\beta_{iv}^h$) follow zero-bounded triangular distribution. The marginal utility of increasing clarity ($\beta_{iv}^r$), 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). The status quo effect is assumed to be normally distributed: while some respondents may tend to stay with the current status, others might prefer a plan with changes. Lastly, to ensure the cost parameter has the theoretically correct sign, we use zero-bounded triangular distribution to model its distribution. Note that, with little reason to expect that the treatment would affect the marginal utility of cost/income, we assume that the cost parameters are equal across all versions. Later in the results section, we also conduct checks to probe the sensitivity of our results with respect to this assumption of homogenous cost parameter. All estimations are performed using `mlogit` (version 1.1-1) in `R` (Croissant 2020). We estimate the models with 2,000 Halton draws.

## 6. Empirical Results

### *6.1 WTPs for Water Quality Improvements and the Effects of Downstream Impacts*

Table 3 presents the estimation results of the model pooling the baseline and downstream information versions, i.e., equation (5).[9] All the estimates in the unrestricted heterogeneity model (model 1) 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. The likelihood ratio test of the homogenous status quo effect model (model 2) against the unrestricted heterogeneity model strongly rejects the null hypothesis that the two status quo coefficients are equal (p-value = 0.006). The increased Akaike information criterion (AIC) in the homogenous status quo effect model also indicates that the model fit deteriorates from the unrestricted heterogeneity model.

Model 3 in the table presents the results based on the homogenous water quality preference model. The likelihood ratio test of this model against the unrestricted heterogeneity model 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 the homogenous water quality preference model is the preferred specification.[10] However, the likelihood ratio test of the no version heterogeneity model (model 4) against the homogenous water quality preference model rejects the hypothesis that the status quo effects are the same (p-value = 0.005). Furthermore, the AIC of the no

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

[10] The status quo by construction captures the unobserved effects. Comparing the results of the unrestricted heterogeneity and homogenous water quality preference model therefore shows that the unobserved effects can be well modeled by simply allowing for the heterogeneity in the status quo parameter.

version heterogeneity model increases from that of the homogenous water quality preference model suggesting an inferior model fit.[11]

Our results therefore show 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. 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.

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). Based on the unrestricted heterogeneity model (model 1), 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 respectively the homogenous status quo effect, homogenous water quality preference, and no version heterogeneity models parallel to those in table 3.[12] The no version heterogeneity model, however, is now the preferred specification based on AIC, and the likelihood ratio tests of the no version heterogeneity model against all three other models do not reject the hypothesis that the parameters are different across the two versions.[13] Although we cannot reject the

[11] Figure B1 in online 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 the homogenous water quality preference model in table 3. To test if the results are sensitive to answers from respondents who consider the survey to be policy or payment inconsequential or who primarily rely on private wells for drinking water, we run the models by excluding those responses and present the results in tables A1 (excluding respondents who consider the survey policy or payment inconsequential) and A2 (excluding respondents who consider the survey policy or payment inconsequential or who primarily rely on private wells) in appendix A. The results are robust to the sample exclusions.

[12] Note that, in the no version heterogeneity model (model 4), the hypoxia attribute dummy is set to zero for respondents who took the downstream information version.

[13] Figure B2 in online appendix B presents the kernel density plots of the WTPs of each attribute based on the no version heterogeneity model in table 4. We again run two models by (1) excluding those answers from respondents who consider the survey policy or payment inconsequential and (2) excluding respondents who consider the survey to be inconsequential or who are private well users. We present the results in tables A3 and A4 in appendix A. The results are again insensitive to the exclusions.

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 (in the unrestricted heterogeneity and homogenous water quality preference models) 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 status quo (the p-value of the likelihood ratio test between the homogenous water quality preference and no version heterogeneity models 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.[14]

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:

$$\Pr(y_i | \boldsymbol{x}_{js}, \boldsymbol{\beta}_i) = \prod_{s=1}^{S} \frac{\boldsymbol{X}_{j'sv}\boldsymbol{\beta}_i + \sum_v (\beta_{iv}^{SQ} SQ_{j'sv})}{\sum_{j=1}^{J} [\boldsymbol{X}_{jsv}\boldsymbol{\beta}_i + \sum_v (\beta_{iv}^{SQ} SQ_{jsv})]} \tag{7}$$

where $\boldsymbol{X} = \{T, N, S, R, H, C\}$ and $v = \{v_{baseline}, v_{downstream}, v_{full}\}$. That is, the marginal utility parameters of water quality attributes are homogenous across versions. We use the same assumed parameter distributions 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 with the Delta method that accounts for the parameters' randomness (Greene 2018). Table A6 in Appendix A presents the full estimation results.

[14] As pointed out in our econometric model section, to test if our results are sensitive to the assumption of homogenous cost parameters across all three versions, we also estimate models with samples of each version and present the results in table A5 in appendix A. With the cost parameters being similar across all three models, the results overall resemble those in the unrestricted heterogeneity model (model 1) of tables 3 and 4.

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 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 increase the total welfare estimate of the plan, which is predominantly 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).[15] These results highlight that the omission of key downstream impacts will not bias the marginal utilities of local water quality attributes but can result in underestimation of the total program benefits.

To calculate the total benefits 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

[15] 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.

the provision of downstream information and $319 million by further including the benefit from reducing the hypoxic zone in the Gulf of Mexico.[16] In terms of the total annual costs for all nutrient reduction efforts in Iowa, the estimated average annual funding for INRS-related effort between 2017 and 2019 is $503 million (INRC 2020). The numbers suggest that, with only the five types of water quality benefits included in our study alone, the nutrient reduction efforts may not pass the benefit-cost test. We note that, the above back-of-envelope benefit estimates do not include any benefits that residents in the downstream states would accrue from the nutrient reduction efforts in Iowa; moreover, we have yet to quantify many other ecological benefits such as improvements in aquatic ecosystem and reduction in greenhouse gas emissions (Del Rossi et al. 2023). Therefore, our cost-benefit analysis is by no means comprehensive and should be interpreted with caution.

Lastly, we note that, with the use of zero-bounded triangular distributions to ensure the preference parameters to have the theoretically correct signs, our models do not allow for correlation between preference parameters. Recent studies have demonstrated the use of mixed logit model with correlated parameters to more fully account for unobserved heterogeneity (e.g., Hess and Train 2017, Mariel and Artabe 2020). We therefore estimate models with correlated parameters to probe the robustness of our main findings showing that the inclusions of downstream information and attribute do not significantly change preferences for local water quality attributes but only change the status quo effect. Specifically, we estimate our unrestricted heterogeneity and homogenous water quality preference models with correlated parameters that allow water quality attribute and status quo parameters within the same version to follow some normal distributions and cost parameter to be log-normally distributed.

The estimation results, presented in table A7 in the appendix, and likelihood ratio tests still show that neither the provision of downstream information or inclusion of hypoxia attribute significantly affect the preferences for local water quality attributes. We also present the kernel density plots and means of individual WTPs for each water quality

[16] 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.

attribute in figure B3 in the appendix. We find that, while the mean WTPs for water quality attributes are not sensitive to whether the correlations between parameters are explicitly accounted for, non-negligible shares of respondents have negative WTPs for water quality improvements based on the models with correlated and normally distributed parameters. Therefore, we acknowledge the importance of accounting for unobserved preference heterogeneity with correlated parameters but consider using zero-bound triangular distributions to be more plausible in our case.[17]

### *6.2 The Heterogeneity by Respondents' Awareness and Knowledge*

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 (self-reported) awareness 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.

Model 1 of table 6 presents the estimation results of the model paralleled to the homogenous water quality preference model 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 with p-value = 0.0140 and -1.1212 vs. -2.0791 with p-value = 0.0373), and such effect is stronger among respondents who are unfamiliar with

[17] We attempted to estimate models that can simultaneously allow for correlations between parameters and ensure all of the parameters to have the theoretically correct signs: i.e., models that assume the marginal utilities of reducing toxin, nitrate, closure, and hypoxia, as well as (negative) costs to be log-normally distributed, while those of clarity and status quo to follow normal distributions. However, such models with full covariance matrix failed to converge. In addition, we tried to estimate models in WTP space, which can bound the WTPs to have the correct signs and allow for correlated parameters (Carson and Czajkowski 2019, Scarpa et al. 2008). Those models still have clear convergence issues in our case. Therefore, we acknowledge that our findings, showing no significant treatment effects on the marginal WTPs for local water quality attributes, may not hold with larger sample sizes allowing the estimation of more flexible models.

the hypoxia issue.[18] 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, it is widely acknowledged that individuals are more likely to respond to surveys on topics of interest to them (Groves, Presser, and Dipko 2004), so our respondents were 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 observation 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 quo (than those who are unfamiliar with the hypoxia issue do).

Although we do not find that the effect of omitting downstream attributes for all respondents is significant, such an effect, as noted in our theoretical illustration, can be different across respondents with different awareness or knowledge 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.

By comparing the coefficients of status quo effects across two versions by whether a respondent is at least slightly familiar with the hypoxia issue (-0.8388 vs. -0.8116 with p-value = 0.2871 and -2.0843 vs. -1.2802 with p-value = 0.0495), the exclusion of the hypoxia attribute only affects the tendency of moving away from the status quo for those who are more informed about the hypoxia. The result suggests that, when downstream impacts are not included in the attribute set, the status quo effect would capture some of the benefits of perceived downstream water quality improvement—i.e., $\gamma_i^{SQ}$ in equation (3)—for people

[18] We again use the likelihood ratio tests by estimating models with equality constraints on each parameter of interest and test against the corresponding unrestricted models. For example, to test if the status quo effects are equal among respondents who are unfamiliar with the hypoxia issue across the two versions, we estimate a model that assumes the parameters of "status quo unfamiliar" are homogenous across versions and use the log-likelihood ratio to test for the equality of the status quo effects.

who are aware of the downstream impacts.[19]

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." Given the fairly well-established scientific evidence that the correlation between upstream nutrient concentrations and downstream hypoxia to be positive, we use the answer to this question as a measure of respondents' knowledge level on the hypoxia issue. Specifically, 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 and are more knowledge about the hypoxia issue. Respondents who answered otherwise are classified as those who consider downstream water quality and nutrient pollution in Iowa is "uncorrelated" and less knowledge about the hypoxia issue. We then estimate the hypoxia and status quo parameters for these two types of respondents separately.

Table 7 presents the estimation results, which show consistent implications with 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 the marginal utility of choosing the status quo (0.8316 vs. -0.1061 with p-value = 0.0390 and -2.0809 vs. -2.6159 with p-value = 0.1308). However, the effect is only significant for those who do not believe the local and downstream water quality positively correlate.[20] This finding suggests that the information has stronger effects on the preferences of respondents who are more knowledgeable about the issue of the hypoxic zone in the Gulf of Mexico than on those less knowledgeable.

In model 2, the inclusion of the hypoxia attribute has a stronger effect on the preferences of those who are more knowledgeable. 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 (p-value

[19] This can also be observed by directly comparing the status quo effects between those who are unfamiliar and familiar under the downstream information version (-0.8388 vs. -2.0843) in model 2.

[20] 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.

= 0.0160). This is again consistent with our theoretical predictions and what we find from model 2 in table 6. Overall, the heterogeneity presented above 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 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 improving both local and downstream water quality when we provide the associated information.

Leveraging a split sample design, we also show that omitting downstream water quality attributes does not significantly change the marginal WTPs for local water quality attributes; however, it can lead to a noticeable underestimate of the total benefits of nutrient reduction programs. Our results suggest that such an 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. We further 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. Omitting important downstream water quality benefits, such as hypoxic zone effects, or by extension other co-benefits to nutrient reductions, 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.

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 investigated the issue of attribute non-attendance, when respondents ignore one or more of the attributes in a 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. Moreover, as many dimensions of a choice experiment design, including the amount of information and number of attributes, are found to be associated with attribute non-attendance behaviors (for a recent review, see Lew and Whitehead 2020), future studies should explore how the inclusion/exclusion of non-local attributes affects the pattern of both stated and inferred non-attendance to local attributes, especially those being perceived as correlated with the non-local ones, as well as the associated welfare estimates.

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**Tables**

Table 1. Attributes and Levels in Choice Experiment

| Attribute | Levels of change | Current condition described |
|---|---|---|
| **Toxin**:<br>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**:<br>nitrate concentrations in source water | Reduce by 25%<br>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**:<br>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**:<br>average water clarity in Iowa's lakes | Increase by 10%<br>Increase by 20% | The current average water clarity in Iowa's lakes is about five feet. |
| **Hypoxia**:<br>average size of hypoxic zone in the Gulf of Mexico | Reduce by 10%<br>Reduce by 20% | The current size of hypoxic zone in the Gulf of Mexico is about 7,000 square miles. |
| **Cost**:<br>monthly surcharge on water bill | $5<br>$10<br>$20 | There is no additional surcharge on monthly water bill. |

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

| | Sample Demographics | | | | | Population Demographics | |
|---|---|---|---|---|---|---|---|
| Variables | Baseline (N = 285) | Downstream Information (N = 278) | Full (N = 290) | P-value* | Total | Iowa Lake Survey 2019 | ACS & CPS 2019 |
| Age (Years) | 60.35 | 58.27 | 57.72 | 0.1211 | 58.78 | 61.24 | 50.0[e] |
| Female (%) | 41.91% | 42.53% | 43.46% | 0.9333 | 42.65% | 35.72% | 50.4% |
| Household income above 60K (%) | | | | | | 61.97% | 60.3%[f] |
| Some College and above (%) | 77.94% | 79.01% | 77.03% | 0.8572 | 77.97% | 78.91% | 61.6% |
| Employed (%) | 54.58% | 57.95% | 59.36% | 0.5063 | 57.32% | 57.44% | 70.9%[g] |
| Visited lakes in 2018 (%) | 55.36% | 57.91% | 53.66% | 0.5932 | 55.62% | 65% | n.a. |
| Water quality rating[a] | 3.17 | 3.07 | 3.09 | 0.3152 | 3.11 | 3.22 | n.a. |
| Water quality issue familiarity[b] | 2.48 | 2.54 | 2.48 | 0.6846 | 2.50 | n.a. | n.a. |
| Awareness of algal blooms[c] | 2.60 | 2.71 | 2.67 | 0.5031 | 2.66 | 56.45%[d] | n.a. |

[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).
[d]: This denotes the percent of respondents to the 2019 Iowa Lakes Survey who have heard of harmful algal blooms (Wan et al. 2021).
[e]: Average age for people 18 years or older according to the 2019 American Community Survey (US Census Bureau 2023).
[f]: This represents the percent of households with annual household income of $60,000 or above according to the Current Population Survey (USBLS 2023).
[g]: This represents the percent of employed civilian non-institutional labor force according to the 2019 Current Population Survey (USBLS 2023).
*: 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** | 0.3350*** |
| | | (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*** | | 0.8810*** | |
| | (0.2430) | | (0.2039) | |
| Nitrate (-25%) | 0.6202*** | | 0.6237*** | |
| | (0.1418) | | (0.1212) | |
| Closure (-50%) | 0.7400*** | | 0.6413*** | |
| | (0.2226) | | (0.1942) | |
| Clarity (+10%) | 0.3060** | | 0.5240*** | |
| | (0.1298) | | (0.1173) | |
| Hypoxia (-10%) Uncorrelated | | | | 0.3785 |
| | | | | (0.2543) |
| Hypoxia (-10%) Correlated | | | | 0.3833** |
| | | | | (0.1836) |
| Status Quo Uncorrelated | 0.8316** | -0.1061 | 0.0370 | -0.4861 |
| | (0.4113) | (0.3898) | (0.3601) | (0.3775) |
| Status Quo Correlated | -2.0809*** | -2.6159*** | -2.3656*** | -1.3553*** |
| | (0.4466) | (0.4186) | (0.3673) | (0.3617) |
| Cost | -0.2545*** | | -0.2335*** | |
| | (0.0270) | | (0.0220) | |
| Standard Deviations (for normally distributed random parameters) | | | | |
| Clarity | 0.0912 | | 0.1917 | |
| | (0.7635) | | (0.5978) | |
| Status Quo Uncorrelated | 3.0369*** | 3.6212*** | 3.4783*** | 3.9110*** |
| | (0.5885) | (0.5538) | (0.5350) | (0.6497) |
| Status Quo Correlated | 4.0975*** | 3.2873*** | 3.0522*** | 2.1794*** |
| | (0.6825) | (0.4358) | (0.4125) | (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 Policy 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. Baseline and Downstream Information Model Versions, Excluding Payment 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%) | 1.4769 *** | 1.0997 *** | 1.2510 *** | 1.3379 *** | 1.2909 *** | | 1.2807 *** |
| | (0.3077) | (0.2939) | (0.2851) | (0.2936) | (0.2204) | | (0.2195) |
| Nitrate (-25%) | 0.6827 *** | 0.5482 *** | 0.5648 *** | 0.6948 *** | 0.6334 *** | | 0.6274 *** |
| | (0.1851) | (0.1758) | (0.1632) | (0.1660) | (0.1317) | | (0.1309) |
| Closure (-50%) | 1.0263 *** | 0.4215 | 0.8551 *** | 0.6128 ** | 0.7158 *** | | 0.7141 *** |
| | (0.2877) | (0.2803) | (0.2625) | (0.2647) | (0.2036) | | (0.2033) |
| Clarity (+10%) | 0.3165 * | 0.3680 ** | 0.1577 | 0.5606 *** | 0.3483 *** | | 0.3481 *** |
| | (0.1677) | (0.1668) | (0.1527) | (0.1570) | (0.1186) | | (0.1184) |
| Status Quo | -0.0047 | -1.7740 *** | -0.8470 *** | | -0.2741 | -1.4621 *** | -0.8513 *** |
| | (0.3744) | (0.4173) | (0.2885) | | (0.2966) | (0.3246) | (0.2883) |
| Cost | -0.2286 *** | | -0.2255 *** | | -0.2254 *** | | -0.2226 *** |
| | (0.0235) | | (0.0233) | | (0.0231) | | (0.0228) |
| Standard Deviations (for normally distributed random parameters) | | | | | | | |
| Clarity | -0.0179 | -0.0131 | -0.0367 | -0.0464 | 0.0023 | | -0.0037 |
| | (2.3708) | (3.5940) | (2.1756) | (2.8049) | (2.0815) | | (2.1886) |
| Status Quo | 4.0024 *** | 3.4415 *** | 3.7280 *** | | 3.9682 *** | 3.5104 *** | 3.7693 *** |
| | (0.4370) | (0.3665) | (0.3186) | | (0.4279) | (0.3704) | (0.3174) |
| AIC | 1758.92 | | 1761.61 | | 1753.10 | | 1756.96 |
| Log Likelihood | -864.46 | | -867.80 | | -866.55 | | -870.48 |
| K | 15 | | 13 | | 10 | | 8 |
| Observations | 1760 | | 1760 | | 1760 | | 1760 |

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. Downstream Information and Full Version Models, Excluding Policy 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 A4. Downstream Information and Full Version Models, Excluding Payment 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%) | 1.1083 *** | 0.7205 ** | 1.1564 *** | 0.6335 ** | 0.9215 *** | | 0.9180 *** |
| | (0.2929) | (0.2800) | (0.2825) | (0.2524) | (0.2070) | | (0.2024) |
| Nitrate (-25%) | 0.5686 *** | 0.6665 *** | 0.6159 *** | 0.6155 *** | 0.6351 *** | | 0.6395 *** |
| | (0.1765) | (0.1693) | (0.1639) | (0.1570) | (0.1243) | | (0.1231) |
| Closure (-50%) | 0.4334 | 0.7060 *** | 0.5220 ** | 0.6563 ** | 0.5843 *** | | 0.5957 *** |
| | (0.2801) | (0.2677) | (0.2611) | (0.2560) | (0.1974) | | (0.1955) |
| Clarity (+10%) | 0.3768 ** | 0.6639 *** | 0.4468 *** | 0.6209 *** | 0.5447 *** | | 0.5361 *** |
| | (0.1668) | (0.1607) | (0.1583) | (0.1439) | (0.1199) | | (0.1160) |
| Hypoxia (-10%) | | 0.4552 *** | | 0.4214 *** | | 0.4285 *** | 0.3942 *** |
| | | (0.1568) | | (0.1480) | | (0.1561) | (0.1297) |
| Status Quo | -1.8409 *** | -1.0725 *** | -1.4321 *** | | -1.5928 *** | -1.1398 *** | -1.3675 *** |
| | (0.4120) | (0.4059) | (0.3066) | | (0.3200) | (0.3284) | (0.2966) |
| Cost | -0.2346 *** | | -0.2352 *** | | -0.2329 *** | | -0.2335 *** |
| | (0.0218) | | (0.0217) | | (0.0221) | | (0.0212) |
| Standard Deviations (for normally distributed random parameters) | | | | | | | |
| Clarity | -0.0205 | -0.1845 | -0.0225 | -0.2085 | 0.2460 | | 0.0634 |
| | (1.6118) | (0.8106) | (3.2072) | (0.7477) | (0.5358) | | (1.4176) |
| Status Quo | 3.4647 *** | 2.7605 *** | 3.1091 *** | | 3.4700 *** | 2.7463 *** | 3.0962 *** |
| | (0.3609) | (0.3519) | (0.2819) | | (0.3671) | (0.3476) | (0.2773) |
| AIC | 1765.58 | | 1766.47 | | 1759.71 | | 1759.47 |
| Log Likelihood | -866.79 | | -869.24 | | -868.85 | | -870.73 |
| K | 15 | | 13 | | 10 | | 8 |
| Observations | 1720 | | 1720 | | 1720 | | 1720 |

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 A5. 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 A6. Models with All Three Versions

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

Table A7. MXL Results w/ Correlated Parameters

| Panel A: Restricted | Baseline & Downstream | | | Downstream & Full | |
|---|---|---|---|---|---|
| Means | Coefficients | s.e. | | Coefficients | s.e. |
| Toxin | 2.2087 *** | (0.5316) | Toxin | 1.5692 *** | (0.4667) |
| Nitrate | 0.9959 *** | (0.2487) | Nitrate | 1.0345 *** | (0.2805) |
| Closure | 0.9749 *** | (0.3607) | Closure | 0.7870 ** | (0.3331) |
| Clarity | 0.4229 | (0.2593) | Clarity | 0.6616 *** | (0.2548) |
| | | | Hypoxia | 0.6760 * | (0.3465) |
| Status Quo - Baseline | -0.8126 | (0.6760) | Status Quo - Downstream Info | -2.9399 *** | (0.8268) |
| Status Quo - Downstream Info | -3.6041 *** | (1.1124) | Status Quo - Full | -2.1049 *** | (0.8033) |
| Cost | -1.2879 *** | (0.2242) | Cost | -1.4455 *** | (0.2067) |
| S.D. | | | S.D. | | |
| Toxin | 2.2113 ** | (1.0084) | Toxin | 2.1024 ** | (0.8842) |
| Nitrate | 1.0219 ** | (0.4415) | Nitrate | 1.4732 *** | (0.4215) |
| Closure | 0.3375 | (1.3072) | Closure | 0.7289 | (1.0257) |
| Clarity | 0.1437 | (1.6007) | Clarity | 0.7702 | (0.6154) |
| | | | Hypoxia | 0.4635 | (2.5997) |
| Status Quo - Baseline | 1.4246 | (2.0667) | Status Quo - Baseline | 0.4270 | (3.2294) |
| Status Quo - Downstream Info | 3.3814 | (2.5745) | Status Quo - Full | 1.7646 | (2.1894) |
| Cost | 0.2504 | (0.2663) | Cost | 0.2514 | (0.2097) |
| Log likelihood | -896.96 | | Log likelihood | -897.74 | |
| K | 34 | | K | 42 | |
| Observations | 1868 | | Observations | 1804 | |
| Panel B: Unrestricted | | | | | |
| Means | | | | | |
| Toxin - Baseline | 3.6406 *** | (1.3349) | Toxin - Downstream Info | 2.3520 *** | (0.8607) |
| Toxin - Downstream Info | 2.7450 *** | (1.0072) | Toxin - Full | 1.5205 * | (0.8196) |
| Nitrate - Baseline | 1.3948 ** | (0.5607) | Nitrate - Downstream Info | 1.0753 *** | (0.3996) |
| Nitrate - Downstream Info | 1.1574 * | (0.5921) | Nitrate - Full | 1.5273 *** | (0.5911) |
| Closure - Baseline | 1.9156 ** | (0.9287) | Closure - Downstream Info | 0.6543 | (0.6983) |
| Closure - Downstream Info | 0.5713 | (0.9768) | Closure - Full | 1.2036 * | (0.6440) |
| Clarity - Baseline | 0.4839 | (0.5113) | Clarity - Downstream Info | 0.2685 | (0.4943) |
| Clarity - Downstream Info | 0.0353 | (0.6784) | Clarity - Full | 1.0467 ** | (0.4981) |
| | | | Hypoxia | 1.0349 ** | (0.5249) |
| Status Quo - Baseline | -1.3039 | (1.0281) | Status Quo - Downstream Info | -4.5655 *** | (1.3917) |
| Status Quo - Downstream Info | -5.9521 *** | (2.1348) | Status Quo - Full | -2.0581 * | (1.1111) |
| Cost | -1.3672 *** | (0.4801) | Cost | -1.0870 *** | (0.2286) |
| S.D. | | | S.D. | | |
| Toxin - Baseline | 3.9993 * | (2.2517) | Toxin - Downstream Info | 2.6799 * | (1.3880) |
| Toxin - Downstream Info | 2.4623 * | (1.3903) | Toxin - Full | 3.8210 ** | (1.5768) |
| Nitrate - Baseline | 0.9118 | (0.9394) | Nitrate - Downstream Info | 1.1965 | (0.9365) |
| Nitrate - Downstream Info | 0.7463 | (1.0709) | Nitrate - Full | 2.4938 *** | (0.8881) |
| Closure - Baseline | 0.9041 | (2.1310) | Closure - Downstream Info | 0.0640 | (1.5943) |
| Closure - Downstream Info | 0.6338 | (2.1650) | Closure - Full | 0.0259 | (1.7754) |
| Clarity - Baseline | 0.0211 | (2.9662) | Clarity - Downstream Info | 0.7709 | (2.2397) |
| Clarity - Downstream Info | 0.9419 | (1.5422) | Clarity - Full | 0.2755 | (1.2153) |
| | | | Hypoxia | 0.6588 | (2.9244) |
| Status Quo - Baseline | 0.9508 | (2.5676) | Status Quo - Downstream Info | 1.9331 | (2.6141) |
| Status Quo - Downstream Info | 0.5634 | (3.2021) | Status Quo - Full | 2.5154 | (3.3036) |
| Cost | 0.0678 | (0.2439) | Cost | 0.0516 | (0.2708) |
| Log likelihood | -888.13 | | | -890.28 | |
| P-value of LR test | 0.4780 | | | 0.6688 | |
| K | 52 | | | 60 | |
| Observations | 1868 | | | 1804 | |

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. The marginal utilities of toxin, nitrate, closure, and hypoxia are assumed to be normally distributed. The marginal utility of cost is assumed to follow lognormal distribution. Preference parameters in the unrestricted models are allowed to be correlated within the same version. Standard errors are robust and clustered at the respondent level. The P-values of LR test are against the restricted models.

## Appendix B. Supplementary Figures

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

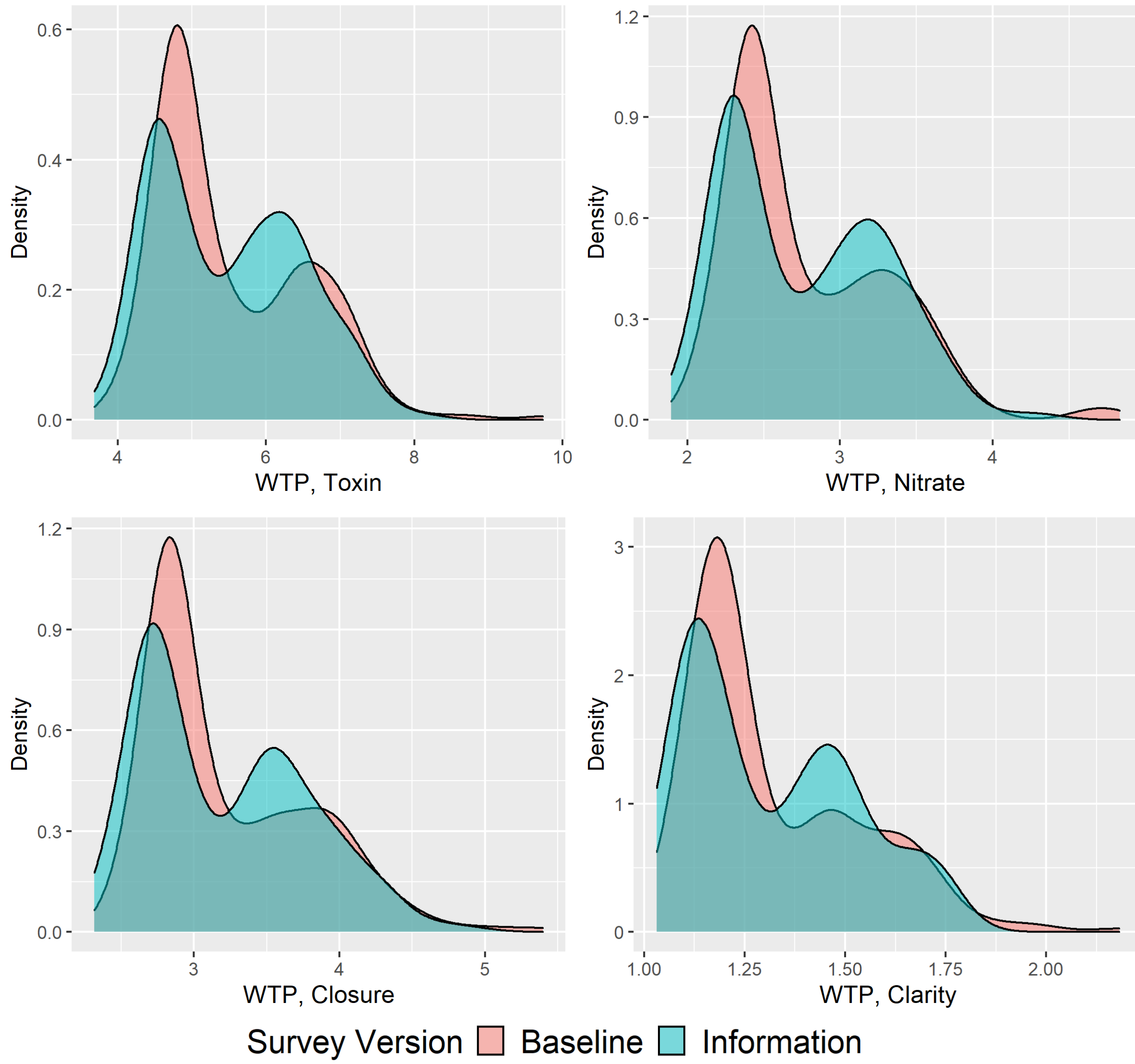


Figure B2. Individual Specific WTPs (Downstream Information and Full)

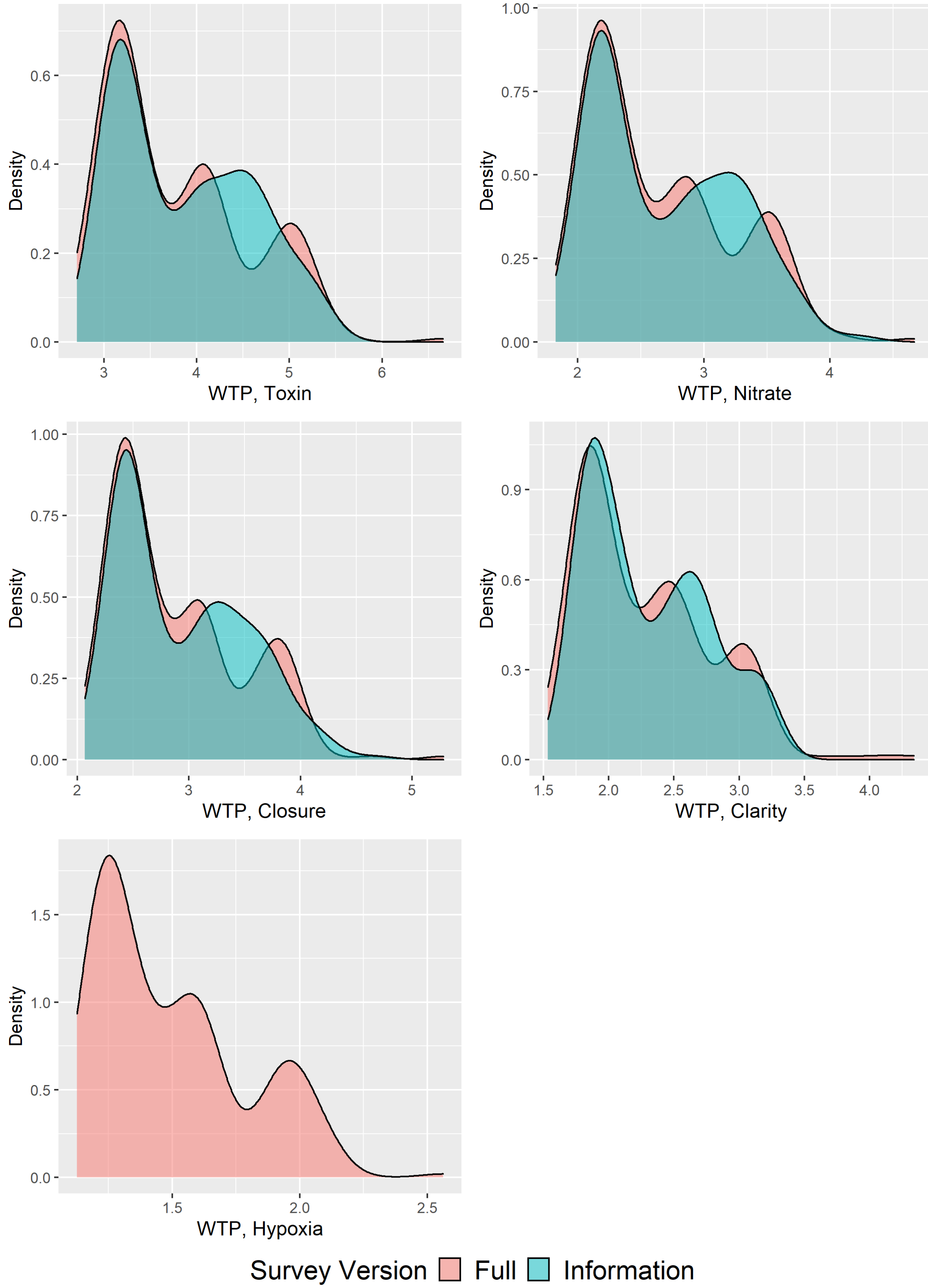
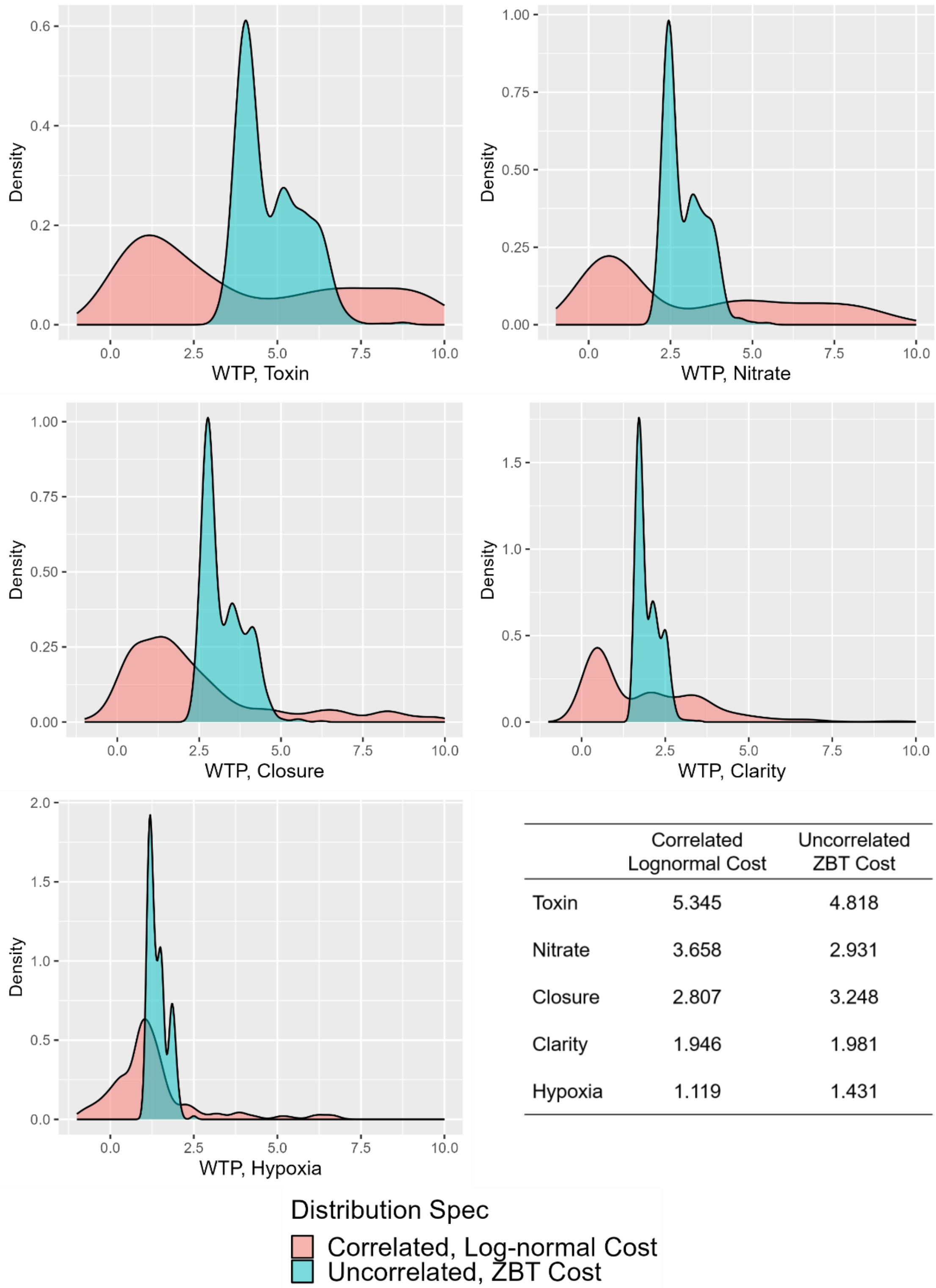


Figure B3. Individual WTPs by Distributional Assumptions of Parameters




| | Correlated Lognormal Cost | Uncorrelated ZBT Cost |
|---|---|---|
| Toxin | 5.345 | 4.818 |
| Nitrate | 3.658 | 2.931 |
| Closure | 2.807 | 3.248 |
| Clarity | 1.946 | 1.981 |
| Hypoxia | 1.119 | 1.431 |

Note: the figure presents the kernel density plots of individual-level WTPs by different parameter distributional assumptions based on the conditional-on-individual-taste approach. The table on the right-bottom corner shows the means of individual WTPs.

## 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 important | Slightly important | Moderately 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.** Your 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.