2016

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Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, July 31 - August 2

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Version: May 25, 2016

Preliminary draft. Please do not cite without permission.

Abstract

Benefit estimates of water pollution control policies rely heavily on water quality indices. Since the 1970s, these measures of water quality have been used extensively in stated preference surveys to estimate willingness to pay for water quality that is suitable for recreational use. However, there is little empirical evidence of how well these indices correspond to observed recreational behavior. This paper utilizes a unique micro-dataset of individual household recreational use and water quality in a revealed preference framework to explore how well several major water quality indices explain water-based recreational use.

JEL Codes: Q51, Q53, Q57

[1]The authors gratefully acknowledge support provided by the USDA National Institute of Food and Agriculture, award number 2014-51130-22494 and USDA National Institute of Food and Agriculture, Hatch Multistate project 231641.

1 Introduction

For several decades, water quality indices have played a central role in studies that measure the benefits of water pollution control policies [Carson and Mitchell, 1993, Van Houtven et al., 2007, Ge et al., 2013]. As with other indices, water quality indices are attractive to policy makers and researchers because they combine multiple determinants of water quality into a single value. This measure is often translated into a description of supported uses, such as boatable, fishable and swimmable waters [Vaughan, 1986]. However, nearly all studies that use these measures of water quality rely upon stated preference surveys. To date, there is very little empirical evidence of how well these indices correspond to observed recreational behavior.

In this paper, we utilize a unique recreation and water quality dataset from Iowa to directly investigate the relationship between several water quality indices and water-based recreational use. Specifically, we consider three primary research question. First, how does the effect of water quality on recreational use vary across different indices, different ways of constructing these indices, and different sampling years? Second, how do estimated effects of these indices compare to other individual measures of water quality that have featured more prominently in revealed preference studies (e.g., Secchi depth, total phosphorus)? Lastly, what are are the implications of these finding for welfare analyses of water quality improvements?

To answer these questions, we use a unique dataset on recreational trips to lakes from a repeated random sample of households in Iowa. These data provide information on individual lakes that households visit within the state, the number of trips taken to each lake within a year, and socioeconomic characteristics of the respondents. These data are matched to a unique, long-term water quality monitoring program at lakes throughout the state. To measure the effects of water quality on recreational use, we use these data in a random utility maximization (RUM) model with heterogeneous preferences [Herriges and Phaneuf, 2002].

We explore a number of different methods of constructing a final water quality ranking. These include arithmetic mean, geometric mean, unweighted harmonic square mean and minimum operator based water quality indices. In addition, we compare our findings to specifications that use individual water quality parameters including Secchi depth, total phosphorus, total nitrate, total solids, and turbidity. We apply our specifications to five years of data separately in addition to pooling all data. As is common with many recreational demand studies today, we repeat these specifications with alternative specific constants (ASC) [Murdock, 2006].

Our results show mixed effects of water quality on recreational use. Many of our specifications with water quality indices show a significant, positive effect of improved water quality. However, the magnitude of these effects often vary by year and depend on how the index is constructed. In addition, in two years of our data, we find negative, significant effects of water quality on recreational use. In specifications that use ASCs, we generally find insignifcant effects of water quality on recreational use for both individual water quality parameters as well indices. Secchi depth is one exception.

The remainder of the paper is organized as followings. The methodology and empirical modeling strategies are discussed in Section 2. We explain the data in Section 3. Section 4 provides estimation results. Section 5 concludes.

2 Methodology

2.1 Water Quality Indices

The development of modern water quality indices can be traced several decades to Horton [1965]. Since then, there have been various efforts to improve these indices and to address specific regional needs. A handful of examples include the National Sanitation Foundation water quality index, the Canadian Council of Ministers of the Environment water quality index [CCME, 2001], and an Oregon water quality index [Dunnette, 1979]. Water quality indices differ in three fundamental steps used to construct them:

1. the individual water quality measures used to construct the index (e.g., total phosphorus, pH, etc.)

2. sub-index curves that translate physical units to sub-indices

3. aggregation methods that compile sub-indices into one overall index value

For example, there are nine individual water quality indicators in the NSF WQI. Table **??** shows these nine indicators. For each indicator, Brown et al. [1970] proposed a sub-index curve to translate physical units to a number between 0 and 100, where 0 is poor water quality and 100 is excellent. Taking pH as an example, Figure **??** shows the sub-index curve that translates the observed pH value to a score between 0 and 100. The curve shows that the sub-index of pH peaks at a ph value between 7 and 8 (slightly alkaline). With these sub-index values, a final water quality index is constructed with a certain aggregation method. One of the most common methods, a weighted arithmetic mean formula (A-WQI), is used in the NSF WQI. We use this approach as well as other proposed methods such as the geometric mean index (G-WQI), an un-weighted harmonic square mean index (H-WQI) and a minimum operator index (M-WQI).

Similar to Walsh and Wheeler [2012], the parameters and sub-index curves proposed by the NSF serve as the basis to construct four different versions of water quality indices used in this paper. Due to data limitations, we only have six of the original nine water quality indicators used in Brown et al. [1970]. We adjust the water quality index calculation by focusing on these remaining six indicators and adjust their weights accordingly (See Table **??**). Summary statistics for these indicators and the four water quality indices are discussed in the data session.

2.2 Recreation Modeling

The recreation modeling framework is based on a repeated (mixed) logit model [Morey et al., 1993, Herriges and Phaneuf, 2002]. In this framework, an individual $i, i = 1, 2, \ldots, N$ chooses to visit one site $j, j = 0, 1, \ldots, J$ at the t, $t = 1, 2, \ldots, 52$ choice occasion.[2] The utility of visiting a site is characterized as the following:

$$U_{ijt} = V(X_{ij}, \beta) + \eta_{ijt} \tag{1}$$

where the conditional utility of U_{ijt} consists of $V(X_{ij}, \beta_i)$, a function of individual and site-specific variables with unknown parameter vector β_i, and the error term η, identically and independently distributed Extreme Value Type One random errors.

Given β_i, the probability for researchers to observe the individual to choose site j is given in a logit form as

$$Pr(y_{ij\bullet} = 1 | X_{ij}, \beta_i) = \frac{exp(V_{ijt})}{\sum_{r=0}^{J} exp(V_{irt})} \tag{2}$$

Thus, for a given set of observed trips to J sites $\{y_{ij}\}, j = 0, 1, \ldots, J$, the probability, from the researchers' perspective, is

$$L(X_{ij}, \beta_i) = \prod_{j=0}^{J} Pr(y_{ij\bullet} | X_{ij}, \beta_i)^{y_{ij}} \tag{3}$$

If there are some random parameters in the parameter vector β, the unconditional probability becomes

$$L(X_{ij}) = \int L(X_{ij}, \beta_i) f(\beta | \theta) d\beta \tag{4}$$

where θ are super-parameters characterizing the distribution of random parameters in β.

Water quality measures enter this framework as site-specific attributes in X usually in

[2] $j = 0$ stands for the stay-at-home option. Choosing 52 as the number of choice occasions in a given year is a common approach to model this type of data as in Egan et al. [2009] and Herriges and Phaneuf [2002].

linear form, i.e.

$$V(X_{ij}, \beta_i) = [\alpha_j] + \beta_i X_{ij}$$

where αs are alternative specific constants(ASC). Recently, the inclusion of these constants has become a common modeling practice as a way to address site-specific and time-invariant omitted variable bias concerns [Murdock, 2006]. However, the inclusion of ASCs does not come without a cost. In particular, all coefficients of site-specific attributes such as on-site facilities and water quality measures are no longer separately identified from ASCs. This greatly reduces the sample size in a second stage regression to recover coefficients on water quality variables. In addition, water quality is still treated as exogenous and perfectly measured. If either assumption is violated, the estimated coefficients on water quality will be biased.

In this paper, two sets of models, with and without ASCs, will be evaluated to test whether there exists significant impacts of water quality on lake related recreation behavior. In both sets of models, a dummy variable, with value 1 for all the lake sites except the stay-at-home option, is included in the utility function to mimic the nested logit structure.[3]

3 Data

3.1 Iowa Lakes Project Data

The lake visitation data comes from the Iowa Lakes Valuation Project which is an ongoing effort to study the use and value of water quality at approximately 130 lakes in the state of Iowa. Survey questionnaires were sent out to several thousand randomly selected, rep-

[3]Although the contract mapping method is proposed by Murdock [2006] in the maximum likelihood estimation framework, a direct simulated maximum likelihood estimation approach is adopted in this paper to estimate these ASCs. The reason not to use contracted mapping method is that the underlying mean-fitting property is violated in the mixed logit model [Klaiber and von Haefen, 2008, Abidoye et al., 2012], and the direct approach does not impose unacceptable computation cost given the size of our application. The contract mapping method could still be appealing when the size of problem becomes too large to be handled with the direct estimation method.

resentative Iowa households in the years 2002 to 2005 and 2009. In the survey, households are asked to report the number of trips to around 130 identified lakes in Iowa along with demographic information.[4]

Table **??** shows the definitions and summary statistics of variables constructed from pooled survey samples. On average, households take about 7 lake trips in any sample year. The average travel cost to any lake is around \$200 per trip, ranging from almost nothing (the respondent lives near one of identified lake) to \$600 per trip.[5] Though the survey questionnaires were sent to randomly selected and representative Iowa households, the age distribution of returned survey samples suggest responses are skewed towards older respondents. The majority of respondents are male and have above high school education.[6] The average household size in our data set is around 2.5 people.[7]

Table **??** shows summary statistics of site attributes other than water quality measures. These attributes are the water area of the lake (in acres), the existence of a boat ramp at the site, whether a motor boat is allowed to create a wake, whether there are handicap facilities near the lake and whether the lake is designated as a state park or not.

3.2 Water Quality Data

The water quality data comes from the Limnology Lab at Iowa State University (Lab Link). The lake chemical and physical report provides a variety of water quality measurements at individual lakes. Among these parameters, there are six measures which are used in the NSF

[4]Due to availability of water quality measures and survey design change in these years, the final number of lake sites included in the model varies across years. Specifically, there are 129 lakes in 2002, 131 lakes in 2003, 130 lakes in 2004, 129 lakes in 2005 and 125 lakes in 2009.

[5]We use PCmiler software to calculate the reasonable travel routes from each household address to centers of lakes. Based on the simulated travel distance and time, we use per mile cost from AAA annual report and respondent's average hour wage rate to figure out the round-trip travel cost. The formula we used is $TC = 2 \times (fuelcost * one - waytraveldistance + 1/3 \times traveltimeinhours \times wagerate)$. The wage rate is obtained through dividing household annual income by 2000, if the respondent did not report household income, we use average wage rates from the state of Iowa.

[6]The above high school education here stands for some college education, professional education, undergraduate education and graduate education.

[7]We truncate the household size to be no more than 10 due to estimation concerns.

WQI: turbidity, dissolved oxygen saturation (%), total phosphate (phosphorus), total nitrate, pH value and total solids. We calculate sub-index values for each parameter and then use different aggregation schemes to aggregate these values into one overall water quality index.[8] The four aggregation schemes are listed in Table **??**.

Table **??** shows summary statistics of pooled water quality measures. Judging from either Secchi depth or WQIs, lakes surveyed in the Iowa Lake Project vary significantly in water quality. The NSF style of the WQI (an arthimetic mean index) has the highest value for each lake, followed by the geometric mean and unweighted harmonic mean indices. Unsurprisingly, the minimum operator index always has the lowest value for each lake. Another observation is that the sub-index conversion of raw measures of each indicator reduces the variation measured by the coefficient of variation (the last column of Table **??**). This observation is important since recovering coefficients of site-specific attributes in our ASC specifications could be affected due to reduced degrees of variation [Moeltner and Von Haefen, 2011].

4 Results

4.1 Model Specification

Water-based recreation studies, in general, find that individual water quality measures such as Secchi depth and total phosphorus affect households' recreation choices and overall number of visits [See Egan et al., 2009, Keiser, 2015]. However, there is no consensus on which set of water quality measures should be included in a recreational model and in which form these measures should be modeled. To investigate the correlation between households' recreation behavior and water quality measures with water quality indices we model a number of specifications in this paper. Table **??** shows the 13 basic specifications for each year's data.

[8] Individual indicators are translated into sub-index values via a water quality calculator excel sheet (download link) which is developed by Student Watershed Research Project of Portland State University's Environmental Sciences and Resources.

4.2 Estimation Results

4.2.1 Specification without ASCs

Table ?? shows the estimation results on coefficients of travel cost and household demographics in specification 1 with the 2002 data. The estimated coefficients are quite stable across model specifications. The pattern generally shows that compared with the youngest households, other age groups are more likely to choose the stay-at-home option.[9] Households with college (above high school) educated respondents tend to stay at home more often. Larger households also take less trips. We generally find no gender differences. For lake attributes other than water quality measures, all the coefficients are highly significant and suggest lake sites with larger area, boat ramp, wake allowed, handicap facilitates and state parks are more attractive.

Since the RUM model is highly nonlinear, the magnitude of water quality coefficients should be considered together with the price coefficient (travel cost coefficient here) to form meaningful welfare concepts such as compensating variation (CV). To get a general sense of the sign and significance of the water quality coefficients, we report the count of coefficients by their sign and signifance at the 5 percent level in Figure ??. We assign estimates into four categories: significant and expected sign, insignificant and expected sign, insignificant and unexpected sign and significant and unexpected sign. All of the coefficients of secchi belong to the first group in line with other studies that use the Iowa Lakes project data [See Egan et al., 2009, Abidoye et al., 2012, Abidoye and Herriges, 2012]. Other variables often used in revealed preference studies such as total phosphorus also have intuitive signs. Higher concentrations of total phosphorus often suggest the site is less attractive. However, we do find in some specifications, the sign is opposite and highly statistically significant. For water quality indices, we generally find the expected sign except in a few specifications in

[9] In the survey, two other age categories are also included, the group under 18 and the group between 19 and 25.

two years of data.

We also calculate welfare measures (compensating variation) for a 5 point change in water quality indices.[10] The results are shown in Figure **??**. There are several observations worth mentioning here. First, the variation of CV based on different water quality indices is quite large both within the same year and across years. For example, in 2003, the CV varies from approximately -$160 per year per household to positive values. Across years, the highest CV is $125 per household in 2004 with an arthimetic WQI. The lowest CV is around -$160 for the same arthimetic index in year 2003. Second, welfare changes using the minimum operator or harmonic mean index are much more stable than the arthimetic or geometric mean indices. The range of CV in dollars per household per year are: -$31.24 to $33.51 for the minimum operator index, -$19.74 to $58.03 for the harmonic mean index, -$89.52 to $99.17 for the geometric mean index and -$162.42 to $129.73 for the arthimetic mean index. The change scale of CV associated with the arthimetic mean index is more than 4 times larger than the minimum operator index. Third, these coefficients tends to move in the same direction. They are all positive in one year and then the sign flips in other years.[11]

4.2.2 Specification with ASCs

As is common with many recreational demand studies today, we estimate a set of regressions with alternative specific constants.[12] These constants are particularly helpful in addressing issues of omitted variable bias related to the individual, such as travel cost and demographics. However, problems may still arise when recovering estimates of site-specific attributes such as water quality [Moeltner and Von Haefen, 2011].

[10]The reason we do not calculate counterparts for an equivalent change in the individual water quality parameters is that it is difficult to compare a 5-point change in the WQI to changes in these indicators. The correlation between an individual parameter and its sub-index curve is non-linear, *i.e.,* more than one point in the curve has the same sub-index value (See Figure **??**).

[11]We suspect some unobserved year-specific factors drive this pattern and are further examining this issue.

[12]We use simulated maximum likelihood estimation method to estimate all the coefficients including ASCs. The reason is discussed before.

Since there is only one first stage estimation for each year, we compile the estimation results from all five years in Table **??**. Compared with the specifications without ASCs, the coefficient of travel cost is almost the same. Older households also tend to have fewer trips. We find much stronger differences in demographic coefficients.

Figure **??** shows a similar graph as in Figure **??**. In contrast with results from models without ASCs, there are only a few cases in which coefficients of water quality measures are statistically significant. The one exception is Secchi depth. It is found to be signification in 5 out of 10 cases when it is included. For other individual water quality measures, coefficients of turbidity, total solids and pH values are found to be significant in a few cases. For water quality indices, only the coefficient of the harmonic mean index is found to be marginally and negatively significant at the 10 percent level in one out of 20 cases. One potential reason for this finding is that the water quality indices have less variation compared with individual measures or even sub-indices. Another possibility is that omitted variable bias and/or measurement error could affect our coefficient estimates on water quality. The use of instrumental variables in the second stage regressions could potentially alleviate these issues [Keiser, 2015].

5 Conclusion

In this paper, we use data from the Iowa Lakes project to investigate whether water quality indices could be directly used in a revealed preference framework to establish the relationship between water quality and recreation behavior. We find mixed results regarding the applicability of water quality indices in our revealed preference application. In models without alternative specific constants, we generally find a positive and statistically significant correlation between water quality indices and the attractiveness of lake sites. This correlation agrees with the general findings in stated preference studies - better water quality leads to a higher willingness-to-pay payment. However, these effects are not entirely robust across years and generally disappear with the inclusion of alternative specific constants. These findings suggest that other research designs that address potential issues of omitted variable bias and measurement error could be helpful to better understand the relationship between water quality and recreational use.

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Appendix

Tables

We only have preliminary results at this stage and choose not to report Tables and Figures here. If interested, please contact authors for tables and figures.