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How much is clean water worth? Valuing water quality improvement using a meta analysis

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Keywords
water, water quality, valuation

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1 Introduction

Since the passage of the Clean Water Act in 1972, protecting and improving water quality has been an important issue of U.S. national environmental policy. Numerous clean water projects and programs have been proposed since then. The cost of such a project depends on available technologies, but the benefit of it is, by a large extent, subject to judgment. Do people value clean water? This study attempts to find the answer in existing literature. Our research questions include: How much is clean water worth? What is peoples willingness to pay for a better water quality? Does willingness to pay for clean water estimates vary systematically by research methodologies, sample characteristics and site characteristics?

We conducted a meta-analysis on existing non-market valuations of water quality improvement [1]. We collected 332 valuations from 38 distinct studies for the analysis, after having examined more than 100 studies. Since different studies use different ways to quantify water quality, one of the challenges is to devise methods to convert different water quality indicators to a consistent water quality index. In Section 4, we will talk about that challenge in detail.

For any given region, our estimated valuation model enabled us to predict the mean willingness to pay for water quality improvement in a site of a certain size. For example, an average household living in the 50,000 square-mile region of the site might be willing to pay $115.14 for a water quality improvement of 5 points (e.g., from 40 to 45) in a one-square-mile aquatic site. The model is particularly useful when we need to evaluate the benefit of a project that aims at improving water quality, but collecting first-hand data is considered too costly or time consuming.

We will also test the null hypothesis that the three main approaches in non-market valuationthe hedonic model, the travel cost model, and the contingent valuation model have generated statistically consistent valuations in these data. Our test results reject the null hypothesis, and we conclude that, for any given site and water quality improvement, the hedonic model estimates are the highest, the travel cost model the second highest, and the contingent valuation model the third highest.

This report is structured as follows. First, we describe the three main approaches to valuing water quality improvement, followed by a brief introduction to meta-analysis as a research methodology. We then describe our approach to converting different water quality indicators from the various studies to a common metric which is essential for undertaking the meta

[1] An introduction to meta-analysis is presented in Section 3

analysis. After that, we move on to willingness-to-pay function and data specifications. We then display and discuss the regression results. Next, we compare this study with other meta-analyses. Last, we present conclusions.

2 The Three Main Approaches for Valuing Water Quality Improvement

Unlike most commodities, access to lakes, rivers, and streams is generally not traded in a market, so there is no market price for clean water. Three standard approaches to the valuation of non-market goods have been used to solve the problem. The first approach is the travel cost method. The idea is, although people do not pay direct fees to visit the aquatic site, they do spend time and other costs, such as cost of gasoline, to travel to the site. The opportunity cost of time and other costs are the price for access to clean water. Hence, we can use it to elicit the value of clean water.

The second approach is the hedonic method. This approach recognizes that housing prices depend on water access and water quality. A house on a lake or river is usually more expensive than a similar one not on an aquatic site. Likewise, a house on a very clean lake or river is usually more expensive than one on a not-so-attractive lake or river. Thus, the differences in the housing price reflect peoples valuation of clean water.

One common feature of the two approaches is that they both use actual behavioral data, be it people's visitation to a site or transaction in the property market. Both approaches indirectly infer people's valuation of clean water from their behavior. The third approach, however, is not based on what people do, but what people say they will do under certain scenarios. The third approach, the contingent valuation method, directly elicits the maximum willingness to pay for better water quality in a survey.

The first two approaches, the travel cost and the hedonic method are revealed preference methods, because economic values are indirectly "revealed" from behavior. The third approach, the contingent valuation method, is a stated preference method because people directly state their preference (in a survey for example). Researchers have also combined stated and revealed preference methods for the same sample. In short, all three approaches have been widely used and have become standard tools in the non-market valuation literature. Since valuations of clean water have important policy implications, one purpose of this paper is to test if the three approaches generate the same statistical valuation. And, since the methods are likely to be applied to different types of resources and different populations of users, we do not necessarily expect the values generated by them to be the same, but understanding the source of difference in valuations will be valuable.

3 What is a Meta Analysis and Why Use Meta Analysis?

Meta-analysis is a research method that collects results from existing studies by independent researchers . It is widely used in psychology, epidemiology, sociology, educational research, and evidence-based medicine. More recently, it has become more common in economic research as well [23]. It serves as a base to achieve one or more of three purposes: research synthesis, hypothesis testing, and benefit transfer.

The first purpose, research synthesis, is to provide a quantitative review of the existing literature. The second purpose, hypothesis testing, is to test hypothetical patterns that might exist in the results from existing studies. The third purpose, benefit transfer, is to construct a valuation model from estimates in existing studies. The valuation model can then be used to derive benefit estimates in different settings.

In this paper, we will conduct a meta-analysis that serves all three purposes. We will provide a quantitative summary of existing literature in non-market valuation of water quality changes in lakes and streams. We will test the null hypothesis that the three standard non-market valuation approaches generate equal valuations. We will also develop a valuation model of peoples willingness to pay for clean water. The valuation model can be used to perform benefit transfer on any site in any region.

There are several advantages of using a meta-analysis as opposed to collecting first-hand data. First, it takes much less money and time to do a meta-analysis. Projects usually come under strict time and budget constraints and benefit estimates may be needed promptly. For example, a contingent valuation (CV) survey can last a year or more from survey design, to implementation, to data analysis. Additionally, primary data collection can cost thousands of dollars, depending on the scale of the survey. In short, collecting primary data for the purpose of study is costly and time consuming, if possible at all. On the contrary, a meta-analysis can be done with a fraction of the time and money. Moreover, once a meta-analysis is done, the resulting valuation model can be used to evaluate other projects.

Second, there are certain things that can only be learned in the context of multiple studies. Since each study is a snapshot, we need to combine many such studies to be able to identify any underlying trends and patterns within the existing literature. If we want to study the similarities and differences between valuations from travel cost, hedonic, and contingent valuation models, we need to look at multiple papers that cover the three methodologies. This is an important question that cannot be answered by any single study using only one of the three standard approaches.

Third, the meta-analysis provides a quantitative review of the literature in a way that identifies how differences in study design, resource characteristics, and sample characteristics translate into different economic values. This information can help identify weakness in the literature and where future research should best be targeted.

There are, however, critics of the methodology who cite its potential loss of accuracy. We are aware of these concerns and discuss some caveats in the conclusions.

4 Conversions Between Water Quality Indicators

4.1 Water Quality Indicator

To compare the willingness to pay for water quality across a range of studies, we need to identify a common unit of water quality change. Each study produces a willingness to pay in dollar value, which is the dependent variable. On the right hand side, we have water quality improvement, and other factors such as site characteristics, sample characteristics, and research methodologies.

In the studies we have collected for the meta-analysis, there are three common ways to quantify water quality: secchi depth, water quality index, and other water attributes. To conduct a meta-analysis, we need to find a way to convert all three types of water quality indicators to a consistent scale. Since a water quality index taking the form of a score from 1 to 100 is common, we have decided to convert all indicators to the water quality index. Before we do that, we will explain the three water quality indicators in turn.

The first indicator, secchi depth, is the deepest level that a secchi disk (a circular black and white disk) is visible in the water. It is used to measure the water transparency. The higher the secchi depth, the more transparent the water is, and the better the water quality.

The second indicator, referred to as index, uses an index or ladder to quantify water quality.

A score from 0 to 100 is an example of ladder, and good, fair, poor is another example. One commonly used ladder is the Resources For the Future (RFF) water quality ladder [47]. The RFF ladder identifies water quality by its suitable recreational use. From high to low, water quality can be identified as drinkable, swimmable, fishable, boatable, suitable for outings, and not suitable for any activities, with each corresponding to a score of 95, 70, 50, 25, 15, and 5, respectively.

The third indicator, referred to as water attribute, uses one or more of the nine water attributes to measure water quality. Those attributes include pH value, phosphorus level, oxygen level, and nitrogen level. The water quality index can be derived from these water attributes using the now standard method developed in 1970 by the National Sanitation Foundation [8].

The National Sanitation Foundation index ranges from 0 to 100 and reflects the composite influence of nine physical, chemical, and microbiological attributes of water quality [29]. The nine attributes are: dissolved oxygen, fecal coliform, pH, biochemical oxygen demand, temperature change, total phosphate, nitrate, turbidity, and total solids. Each attribute is given a different weight according to its importance. The National Sanitation Foundation water quality index is a weighted average of the quantile value (Q value) of the nine attributes. Specifically, the formula to construct the water quality index (WQI) is,

$$WQI = \prod_{i=1}^{9} {q_i}^{w_i} \tag{1}$$

where q_i is the quantile, or Q value of parameter i, and w_i is the weight for parameter i, $\sum_{i=1}^{9} w_i = 1$. The Q values are used instead of raw measurements so that the scale is consistent. Water quality parameters and weights are shown in Table 1.

Table 1: Water Quality Parameters and Weights (Complete)

Parameter	**Weight**
dissolved oxygen	0.17
fecal coliform	0.16
pH	0.11
biochemical oxygen demand	0.11
temperature change	0.10
total phosphate	0.10
nitrates	0.10
turbidity	0.08
total solids	0.07
Total	1.0

If all nine parameters are not available, a WQI can still be calculated based on parameters that are available. For example, if we only have M out of nine parameters ($M < 9$), WQI can be obtained by adjusting the weight for the available parameters proportionately, such as in the following equation,

$$WQI = \prod_{i=1}^{M} q_i^{w_i'} \tag{2}$$

where w_i' is the adjusted weight for attribute i, $w_i' = \frac{w_i}{\sum_{i=1}^{M} w_i}$, and $\sum_{i=1}^{M} w_i' = 1$.

The National Sanitation Foundation water quality index enables us to convert water attributes (the third indicator) to a water quality index (the second indicator). However, the first indicator, secchi depth, is not a parameter in the water quality index, although it is understood that the secchi measure is directly related to the individual components of the WQI. Hence, there is no readily available conversion between secchi depth and water quality index, and we must establish one ourselves. However, a conversion between secchi depth and water quality index can only be found if we have information for both indices on the same water body, such as in the National Lakes Assessment (NLA) [44].

The NLA is a survey conducted by the U.S. Environmental Protection Agency in 2007. It was designed to assess, without bias, the water quality of the nations lakes, ponds, and reservoirs. A total of 1,028 lakes were sampled from across the nation. Excluding missing data, the public data has a sample of 1094 observations over two years. The NLA data report five water attributes that are used in the National Sanitation Foundation water quality index: dissolved oxygen, total phosphate, nitrate, turbidity, and pH level, and it also provides secchi depth for each water body. We constructed the water quality index from the five attributes using the National Sanitation Foundation formula above. The available parameters and adjusted weights are presented in Table 2. The summary statistics of the NLA data: the Q values of dissolved oxygen, pH, total phosphate, nitrates and turbidiry, the secchi depth (in meter), and the constructed water quality index (wqi) are shown in Table 9 in the appendix. Now that we have the water quality index and secchi depth for the same lake, we can establish a link between the two.

Table 2: Water Quality Parameters and Weights (Adjusted)

Parameter	**Weight (Adjusted)**
dissolved oxygen	0.30
pH	0.20
total phosphorous	0.18
nitrates	0.18
turbidity	0.14
Total	1.0

4.2 Use of Eureqa to Find the Conversion

Since there is no scientific basis for a specific functional form between the water quality index and secchi depth, we would like to use a tool to help identify the best functional form as well as the parameter values. Although a more complex structure often means a better model fit, we do not want the model to be too complex. The tool we used to make this trade-off is "Eureqa" [1].

Eureqa (or Eureqa Formulize) is a scientific data mining software that searches for mathematical patterns and relationships hidden in data. Behind Eureqa is a method called symbolic regression [54]. The biggest difference between Eureqa and conventional regression is that Eureqa does not impose any prior structures or specific functional forms before the search, so it is very flexible. Eureqa also shows the complexity of each model, depending on the number of terms and order of terms, as well as mean absolute error or fitness of the model. We chose from a dozen candidate models provided by Eureqa to strike a balance between complexity and fitness, as shown in Figure 1.

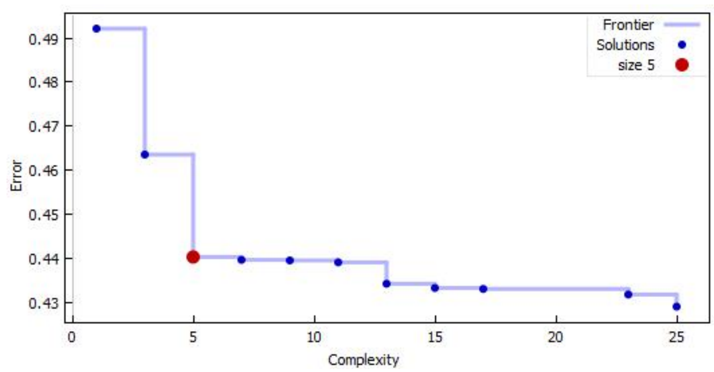

Figure 1: Complexity Versus Fitness Provided by Eureqa

Each dot in Figure 1 represents a functional form and parameter estimates. The "Error" of the model is defined as mean absolute error between fitted and actual data and is plotted for each model on the vertical axis. The "Complexity", or size, of a function is defined as the number of operations in the function and is plotted on the horizontal axis.

The model we chose to use for the conversion between water quality index and secchi depth is the one identified by the red spot. We felt this model had a relatively simple form and good fitness. The slightly more complex models (the three blue dots to the right of the red dot) are not very different from the selected one, so the results should not be sensitive to our choice of the conversion. The model we chose is,

$$WQI = 78.9 + S + \frac{1.95}{0.06 - S^2} \tag{3}$$

where S is secchi depth and WQI stands for water quality index. The raw plots from NLA and fitted plots using Eq 2 are shown in Figure 2 (We truncate the data at secchi depth less than or equal to five meters to give a better visualization of model fit). There is a positive relationship between WQI and secchi depth as expected. The mapping from secchi depth to water quality index takes the shape as shown in Figure 2. When the secchi depth is small, i.e. when the water is not clear, a small increase in the secchi depth will result in a relatively large increase in water quality index. As the secchi depth becomes bigger, the curve flattens out, meaning that an increase in the secchi depth will not lead to as much of an increase in the water quality index.

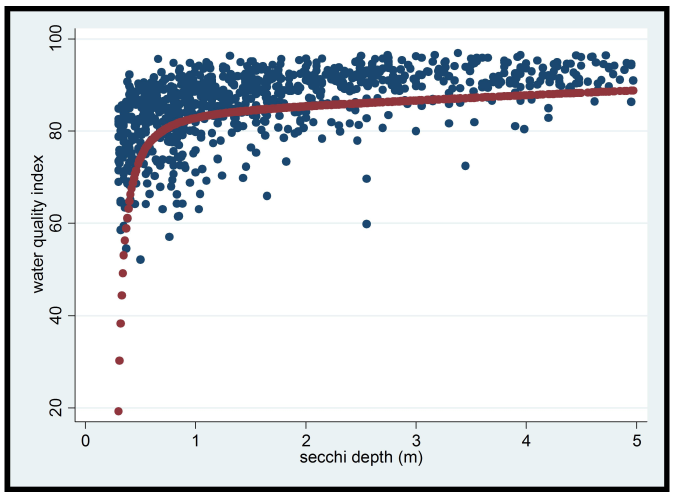

Figure 2: Mapping Secchi Depth To Water Quality Index

With the use of Eureqa, we now have the means to convert secchi to the water quality index. Each observation in our data set has a water quality index that was either taken from the original study, or converted from other indicators. In the next section, we describe the data and estimation of the willingness to pay function.

5 WTP Function and Data Specification

Following Van Houtven et al.[46], we define a WTP function to depend on initial water quality Q^0, the change in water quality ΔQ, and other characteristics (control variables) such as affected site, surveyed sample, and research methodology. A simple representation is

$$\text{WTP} = V(Q^0, \Delta Q; \text{control variables}) \tag{4}$$

To estimate Equation 4, we specify a linear regression model where the dependent variable is annual willingness to pay (WTP) per household in 2010 U.S. dollars. The independent variables include the initial water quality index (startingWQI) and the change in the water quality index (deltaWQI). We control for: (a) site characteristics, such as site size, type and location, (b) sample characteristics, such as income and sample regions, and (c) research methods, such as publication date, model approach, elicitation method, and water quality indicator. We use clustered robust regression, where each study is treated as a cluster [50].

Among the large body of papers on the valuation of aquatic resources, only those that meet three criteria are included in the metadata set. First, the studies must have considered changes in water quality. A paper that assesses the value of a lake without concerning any change in the lakes water quality, for example, will not be included. Second, even if the paper considers change in water quality, it must be measured in one of the three ways described in Section 4. In other words, it must be measured by secchi depth, the water quality index, or other water attributes; otherwise we cannot convert it to a consistent water quality index and include it in the data. For instance, some papers evaluate the value of implementing a specific management plan, but do not provide information on the water quality improvement. Another example is studies that use fish catch rate as the measure of interest. These papers focus more on the economic value of fishing or value of fishing as a recreational activity. Finally, we considered sites in the United States only.

As a result, we have collected 332 observations from 38 distinct studies, including 25 journal articles, one book chapter, six government agency reports, one Masters dissertation, four PhD dissertations, and one working paper. Some explanatory variables such as publication year, income, and site type are shared by all estimates reported in a study; other variables, such as elicitation method are only applicable to a certain type of study, or only applicable to contingent valuation studies. Table 3 summarizes the primary studies and willingness-to-pay estimates included in this study; Table 4 lists all 38 studies used in the meta analysis and provides some summary statistics about them; Table 5 contains the variable description; Table 6 is summary statistics of the variables. Finally Table 10 in the appendix lists all 332 willingness-to-pay estimates used in the meta-analysis.

Table 3: Summary Statistics for Studies Included in the Meta Analysis

	Studies(I=38) Number(Percent)	**WTP Estimates(N=332)** Number(Percent)
Type of Publication		
Peer-reviewed jornal/book	26(68%)	182(55%)
PhD/Mater's thesis	5(13%)	38(11%)
Other (working paper, report, etc.)	7(18%)	112(34%)
Year of Publication		
Before 1980	2(5%)	3(1%)
1980-1989	15(39%)	116(35%)
1990-1999	7(18%)	24(7%)
2000 or later	14(37%)	189(57%)
Type of Water Resource Affected		
Lake	13(34%)	168(51%)
River/stream	14(37%)	106(32%)
Estuary	9(24%)	42(13%)
Other	2(5%)	16(5%)
Regions Experiencing WQ Change		
Northeast	23(61%)	137(41%)
Midwest	11(29%)	166(50%)
South and West	2(5%)	18(5%)
Other	2(5%)	11(4%)
Valuation Method Used		
Contingent valuation and combined	22(58%)	153(46%)
Travel cost	6(16%)	52(16%)
Hedonic property value	10(26%)	127(38%)
WQ Indicator Used		
Ladder	18(47%)	137(41%)
Secchi depth	11(29%)	168(51%)
Water attributes	9(24%)	27(8%)

Table 4: Studies Used in the Meta Analysis

Study	Author	Affected Site	Methodology	Water Quality Indicator	#Est
1	Azevedo et al.(2001) [2]	Clear Lake, IA	Contingent Valuatoin (CV)	Secchi	5
2	Bockstael et al.(1987) [3]	Boston area beaches	Travel Cost (TC)	oil, turbidity, COD and fecal coliform	1
3	Bockstael et al.(1989) [4]	Chesapeake Bay, beaches in Maryland	CV, TC	RFF Ladder	4
4	Boyle et al.(1999) [6]	Lakes in Maine	Hedonic	Secchi	6
5	Boyle et al.(2003) [5]	Selected lakes in Vermont, New Hampshire, and Maine	Hedonic	Secchi	22
6	Brashares(1985)[7]	Lakes in southeast Michigan	Hedonic	Secchi, turbidity, and fecal coliform	7
7	Carson et al.(1993) [9]	National lakes rivers and streams	CV	RFF Ladder	3
8	Croke et al.(1987) [10]	Rivers in Chicago	CV	RFF Ladder	6
9	Cronin(1982) [11]	Potomac River, Washington D.C.	CV	dissolved oxygen, fecal coliform, nitrogen, phosphorus, turbidity and recreational activities	20
10	Desvousges et al.(1987) [13]	Monongahela River, PA	CV	RFF Ladder	16
11	Edward(1984) [15]	Salt pond lake, RI	CV	Score out of 100	3
12	Egan et al.(2009) [16]	Lakes in Iowa	TC	Improve from current to west Okoboji lake	20
13	Eppa et al.(1979) [17]	Rivers in Rural Pennsylvania	Hedonic	Secchi	1
14	Farber et al.(2000) [18]	River in Western Penssylvania	CV	3-level scale	18
15	Gibbs et al.(2002) [19]	Lakes in New Hampshire	Hedonic	Secchi	4
16	Gramlich et al.(1977) [20]	Charles River, MA, and National lakes rivers and streams	CV	RFF Ladder	2
17	Holly et al. (1996) [30]	Selected Maine lakes	Hedonic	Secchi	6

18	Huang(1986) [22]	Selected lakes in Minnesota	TC	Water quality index	22
19	Johnston et al.(1999) [38]	River in Rhode Island	CV	RFF Ladder	3
20	Krysel C. et al.(2003) [25]	Mississippi Headwaters Region, MN	Hedonic	Secchi	74
21	Leggetta et al.(2000) [26]	Chesapeake Bay	Hedonic	fecal coliform	1
22	Lipton et al.(2003) [27]	Chesapeake Bay	CV	5-step improvement	1
23	Magat et al.(2000) [48]	National lakes rivers and streams	CV	15% improvement	7
24	Matthews et al.(1999) [28]	Minnesota River, MN	CV, Combined	Phosphorous	3
25	Moore et al.(2001) [31]	Green Bay, WI	CV	Secchi	24
26	Mullen et al.(1985) [32]	Rivers in Adirondack, NY	TC	fishable	1
27	Holly et al.(1996) [30]	Lakes in Maine	Hedonic	Secchi	6
28	Ralph et al.(1989) [33]	Lake Okoboji, IA	Hedonic	Water quality index	2
29	Randall et al.(2001) [34]	Maumee River, OH	CV	Nitrate	3
30	Schuetz(2001) [39]	Maine's great ponds	CV	Secchi	3
31	Smith et al.(1983) [41]	Monongahela River, PA	CV	RFF Ladder	2
32	Smith et al.(1986) [40]	Monongahela River, PA	CV, TC	RFF Ladder	14
33	Steinnes (1992) [42]	Lakes in northern Minnesota	Hedonic	Secchi	2
34	Stumborg et al.(2001) [43]	Lake Mendota, WI	CV	Phosphorus	1
35	Walsh et al.(1981) [14]	South Platte River, CO	CV	RFF Ladder	12
36	Wey(1990) [49]	Great Salt Pond, RI	CV	1-6 scale	2
37	Whitehead(2005) [52]	Neuse River, NC	Combined	RFF Ladder	6
38	Young(1984) [53]	St. Albans Bay on Lake Champaign, VT	Hedonic	1-10 scale	2
				TOTAL:	332

Table 5: Variable Description

Variable	Description
WTP	willingness to pay in 2010 dollars
D_NE	=1 if the affected water bodies are in the Northeast region of the U.S.
D_lakeEstuary	=1 if the affected water bodies are lakes and estuaries
pubDate	publication year, 0=year 1977
D_inPerson	=1 if the survey used in the study was administered with an in-person interview
income	average household income in 2010 dollars
D_totalValue	=1 if the original study estimates total value
D_improvement	=1 if the change in water quality is an improvement
D_index	=1 if the water quality indicator used in the original study is an index
startingWQI	starting water quality index of affected water bodies
deltaWQI	change in water quality index of affected water bodies
D_CV	=1 if the original paper uses contingent valuation method
D_hedonic	=1 if the original paper uses hedonic method
D_openended	=1 if elicitation method is open-ended
D_bidding	=1 if elicitation method is iterative bidding
D_elitmtdOther	=1 if elicitation method is not open-ended, bidding, or dichotomous choice (default)
sitesize	the size of the affected water bodies in square miles
regionsize	the size of the sampling region in square miles

Publication date, pubDate, is the year that the study was published, or for unpublished studies, the date it first became available. The base year is 1977, in which pubDate equals 0. Publication date may differ from when the data is collected. We used the latter to convert the value to 2010 dollars. Income is the median income of the state where the sampled households live. The state-level median income is only a crude measure of sampled households mean income. Since not all studies in the meta-base have reported the mean income of their sample, we used the state median income as a proxy [45]. The dummy variable for total value, D_totalValue, captures whether the valuations from the original studies include use value, non-use value only, or if they are total value (i.e. the sum of both use and non-use values). The variable D_totalValue takes the value 0 for all revealed preference papers, since use value is the only component that they can measure. Improvement dummy, D_improvement, equals 1 if the valuation is for water quality improvement and it equals 0 if the valuation is for avoiding water quality degradation. The three dummy variables D_openended, D_bidding, and D_elitmtdOther are elicitation methods in surveys. The default is dichotomous choice. The variable sitesize is the size of the affected water body, and the variable regionsize is the size of sampling region. We expect region size to have a negative effect on the willingness to pay, because peoples willingness to pay for a site depends on the accessibility of the site, and a bigger region means less accessibility on average.

Table 6: Summary Statistics (N=332)

Variable	Mean	Std. Dev.	Min.	Max.
WTP	312.14	679.54	3.08	5491.65
D_NE	0.41	0.49	0	1
D_lakeEstuary	0.63	0.48	0	1
pubDate	19.64	9.63	0	34
D_inPerson	0.22	0.41	0	1
income	51582.9	6606.17	39701	69047
D_totalValue	0.29	0.45	0	1
D_improvement	0.75	0.43	0	1
D_index	0.41	0.49	0	1
startingWQI	61.2	26.62	5	92
deltaWQI	16.3	19.18	0.42	85
D_CV	0.44	0.5	0	1
D_hedonic	0.38	0.49	0	1
D_openended	0.13	0.34	0	1
D_bidding	0.1	0.3	0	1
D_elitmtdOther	0.12	0.33	0	1
D_dichotomous	0.11	0.31	0	1
sitesize	7908.13	43873.87	0.22	256481.23
regionsize	119851.56	648653.95	0.22	3794101

6 Results

For most studies, more than one observation is included, and as a result, our data is naturally clustered. Observations from the same study may exhibit dependency not present in observations from different studies. One source of this dependence is the same observations or study from which the estimates are obtained. Other factors, such as author and journal effect, can also cause dependency. In short, observations from the same study may have different correlation structures than the ones from different studies. To take into account the clustered nature of the data, we use clustered robust regression where each study is a cluster instead of standard OLS [50].

Table 7 shows the clustered robust regression results with water quality index as the water quality indicator (the regression results with Secchi as the water quality indicator are shown in Table 11 in the Appendix). The column labeled Pooled 1 is the regression results using the full data, with all explanatory variables; the column labeled Pooled 2 is the regression results from the pooled data, with all explanatory variables except site size and region size; the column labeled CV is the regression results from the CV papers only; and the column labeled Hedonic is the regression results from the hedonic papers only. Only 52 observations fell into the travel cost category, so a regression on that sub-sample was not estimated due to its small size.

The results on the full (pooled) data (columns 1 and 2) show that peoples willingness to pay does depend on the (absolute) level of change in the water quality index. For a 10-point change (out of 100) in the water quality index, an average household is willing to pay around \$45. In addition, willingness to pay for given water quality improvement is higher for lakes and estuaries than for rivers. It is also higher when the survey is administered in person, or when water quality is indicated by secchi depth, as opposed to the water quality index. Moreover, people are willing to pay more for avoiding degradation than making an improvement; and people are also willing to pay more for an improvement in water bodies with bad initial condition than those with already good initial conditions, reflecting the declining marginal utility in water quality. The hedonic dummy is positive and significant, while the CV dummy is negative and significant. So the hedonic approach tends to produce larger valuations, followed by the travel cost approach (the default), which is followed by the contingent valuation approach.

Region and site size have significant impacts on the willingness to pay for water quality improvement. Site size, the size of the affected water bodies, has a positive effect. The willingness to pay for a given water quality improvement in an aquatic site will be \$0.60 higher if the site size increases by 10 square miles. Region size, the size of sampling region, has a negative effect. The willingness to pay, on average, will be \$4 lower if we expand the sampling region by 1,000 square miles. We conjecture that this is because the further away a household lives from the site, the less accessible the site is to the household, and the less important the quality of the site is to the household. The pooled results are robust to the inclusion of region and site size.

Columns 3 and 4 show the regression results for the CV and hedonic papers, respectively. Compared with the general population or local residents, from which the sample of most CV studies are drawn, homeowners, the sample of virtually all hedonic models, are more responsive to water quality change in the site on which their houses sit. For hedonic papers, the region size and site size are highly correlated, because most properties are on the site, we therefore included only site size in the regression. On-site property values respond positively to site size. A Chow test rejects the null hypothesis that the groups share the same coefficients. As noted below, existent meta-analyses only include CV papers. Yet, our study suggests that valuations from CV studies are, on average, the smallest among the three approaches. As a result, benefit transfers based only on CV studies could be biased downward.

Table 7: Clustered Robust Regression Results

	Pooled 1	Pooled 2	CV	Hedonic
	(1)	(2)	(3)	(4)
D_NE	27.94	-2.76	-72.62***	21.31
	(83.13)	(72.63)	(26.76)	(110.34)
D_lakeEstuary	287.23**	274.01**	268.11***	1507.93**
	(112.97)	(124.26)	(59.78)	(631.09)
pubDate	4.69	3.75	-2.95	-60.41
	(5.54)	(5.50)	(2.27)	(41.69)
D_inPerson	284.09***	283.37**	133.32***	
	(109.18)	(110.66)	(30.77)	
income	-.01	-.01	.003	-.009
	(.01)	(.01)	(.003)	(.02)
D_totalValue	78.96	92.80*	104.49***	
	(56.64)	(55.98)	(31.01)	
D_improvement	-212.50*	-193.56*	12.91	-272.56
	(110.19)	(106.33)	(33.34)	(181.26)
D_ladder	-208.04*	-142.73	-141.76*	-13773.26***
	(109.72)	(98.50)	(76.35)	(569.44)
startingWQI	-2.67*	-1.89	-.37	121.04***
	(1.38)	(1.31)	(.58)	(13.78)
deltaWQI	4.48*	4.62*	1.67***	142.94***
	(2.40)	(2.42)	(.50)	(18.18)
D_CV	-277.26*	-123.59		
	(146.45)	(125.98)		
D_hedonic	217.88*	349.16**		
	(120.53)	(136.81)		
sitesize	.06**		.003	29.88***
	(.03)		(.02)	(.62)
regionsize	-.004**		-.0002	
	(.002)		(.001)	
N	332	332	146	127
r^2	.13	.12	.46	.51
F	12.41	11.25	29.47	.

[a] *p=.10 **p=.05 ***p=.01

[b] Pooled 1 is the pooled regression with site and region size.

[c] Pooled 2 is the pooled regression without site and region size.

Table 8 shows the predicted annual willingness to pay per household (in 2010 dollars) for different levels of water quality improvement using the pooled results in Column 1 in Table 7 as a demonstration of the values that the meta regression generates. For example, for a small site that is only one square mile, (such as Little Spirit Lake in Iowa), a household living in 50,000 square mile area around the site is estimated to be willing to pay $115.14 for a 5-point increase (from 40 to 45) in the water quality index. Naturally, willingness to pay is larger for a big site than for a small one, and is also larger for a 10-point increase in water quality than for a 5 points increase.

Table 8: WTP for Water Quality Improvement

site type \ WQI change	40 to 45	40 to 50	70 to 75	70 to 80
small site (1 sq mi)	115.14	137.52	35.12	57.50
(Little Spirit, IA)	(143.84)	(141.78)	(142.33)	(139.9)
medium site (100 sq mi)	121.46	143.85	41.44	63.83
(Lake Winnibigoshish, MN)	(141.32)	(139.29)	(139.62)	(137.23)
big site (10,000 sq mi)	753.89	776.27	673.87	696.25
(Great Lakes)	(210.71)	(213.64)	(197.95)	(200.84)

[a] standard error in parenthesis
[b] in 2010 dollars
[c] sample region: 50,000 square miles

7 Comparison With Other Meta Analyses on Aquatic Sites

Two other meta analyses on the valuation of water quality improvement have been completed; one by Van Houtven, Powers and Pattanayak in 2007 [46], and the other by Johnston et al. in 2005 [23]. Our work differs from these in three important ways. First, neither Van Houtven et al. nor Johnston et al. controlled for site size and region size in the meta-regression of their papers.

Second, both Van Houtven et al. and Johnston et al. limit their analysis to contingent valuation (CV) studies, so papers using hedonic and travel cost approaches are excluded. When doing meta-analysis, we make a trade-off between including more studies and having a bigger sample size and consistency across studies. Van Houtven et al. and Johnston et al. include only CV papers in their meta-database to ensure consistency across studies. However, there is no evidence that not including papers using the other two approaches is the optimal trade-off. One benefit is, of course, a larger sample size: we obtain 332 observations from 38 unique studies, compared with 81 observations from 34 studies in the Johnston et al. paper, and 131 observations from 18 studies in the Van Houtven et al. paper. Moreover, it enables us to compare valuations from different approaches. If the hedonic and travel cost studies systemically produce larger valuations than the CV papers, benefit transfer based only on CV papers does not fully use the knowledge in existing literature, and is likely to be biased downward.

Third, both Van Houtven et al. and Johnston et al. limit their input to only studies using the RFF water quality ladder. Although this ladder is often used, other indicators such as Secchi depth are also used by a large number of studies. Our study appears to be the first one to estimate a link between Secchi depth and the water quality index.

8 Conclusions

This paper is an attempt to answer the important question: How much is clean water worth? We do so by developing and estimating a valuation model based on a meta-analysis on non-market valuations of water quality improvements. After reviewing more than 100 non-market valuation studies on aquatic sites, we have 332 valuations from 38 distinct existing studies in the meta-database. The valuation model estimated in this study can be used to predict the mean willingness to pay by households living in a given region for water quality improvement in a given site.

We first developed a link between water quality index and Secchi depth, based on national lakes assessment (NLA) data. Eureqa, a data-mining software, enabled us to search for a model that is extremely flexible in functional structure. What we found, through Eureqa, is a link between water quality index and Secchi depth that has a flexible, but relatively simple, function form and reasonably good model fit. We then used the link to convert Secchi depth to water quality index, so that all observations in the metadata set have consistent water quality measurement (i.e. water quality index), a key component in our model. This completes the data set for the meat-analysis.

We then used the completed data set to estimate a valuation model for water quality improvement. Some findings from estimation results included: for a 10-point (out of 100 points) additional change in water quality index, a households willingness to pay will increase by \$45. Willingness to pay is higher for lakes and estuaries than for rivers. It is also higher if the survey in the original study is administered in person. Willingness to pay is lower for making improvement than for avoiding degradation. It is also lower if we started with an already good initial water quality condition, probably reflecting the decreasing marginal utility of water quality. We found that both size of the affected site and size of sampling region have a significant effect on willingness to pay. Site size has a positive effect and region size has a negative one, perhaps due to less accessibility of the site as the region became bigger.

The valuation model we estimated in this study enables us to predict the mean willingness to pay in a given region for water quality improvement in a site of certain size. For example, an average household living in a 50,000 square mile region around a given site is willing to pay$115.14 for a 5-point water quality improvement (from 40 to 45) in a one-square-mile aquatic site. This tool is particularly convenient and useful when we want to evaluate the benefit of a project that aims at improving water quality, but a primary study is regarded as too costly or time consuming. We also test the null hypothesis that the three main approaches in non-market valuationthe hedonic model, the travel cost model, and the contingent valuation modelgenerate consistent valuation estimates. Our test results reject the null hypothesis. We found that, among the three approaches, the hedonic model tends to produce the largest valuation, the second-largest were produced by the travel cost model, and the third-largest were produced the contingent valuation model.

This paper is different from other meta-analyses, to which two were paid particular attention in three important ways: (a) this paper includes studies using all three dominant approaches in non-market valuation, while others only include contingent valuation paper; (b) this paper includes studies using different water quality indicator, like Secchi depth, while others only include studies using RFF water quality ladder; and, (c) in this paper we controlled for size of the affected site and size of sampling region, while others have not, and found both to have a significant effect.

There are critics of using meta-analysis for benefit transfer, and some doubt its accuracy. Others argue that studies used in meta-analysis should be very restrictive to ensure consistency, and both are valid concerns. After all, hedonic, travel cost, and contingent valuation models are very different approaches to the same problem. However, if all three models have been standing side by side in the non-market valuation literature for decades, and if the valuations they produce have important policy implications, maybe it is worth the effort to examine them on the same plate, and have a valuation model that is inclusive of all three approaches.

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Appendix

Table 9: Summary Statistics of Water Parameter (Q Value) from National Lakes Assessment

Parameter	Mean	Std. Dev.	Min.	Max.
dissolved oxygen	84.99	17.05	7.11	99
pH	70.49	17.61	14.4	93
nitrates	97.67	1.57	63.85	97.98
total phosphorous	95.3	11.03	12.54	98.98
turbidity	81.39	16.02	18.2	96.62
wqi	85.73	8.25	42.21	96.97
secchi (m)	2.26	2.55	0.11	36.71
N		1094		

Table 10: Table of All Estimates Used in the Meta Analysis

Study	Author	Number of Estimates	Willingness To Pay Estimate (in 2010 dollars)
1	Azevedo et al.(2001) [2]	5	137.28
			749.76
			112.20
			726.00
			561.00
2	Bockstael et al.(1987) [3]	1	55.38
3	Bockstael et al.(1989) [4]	4	263.78
			82.84
			618.18
			128.53
4	Boyle et al.(1999) [6]	6	1010.30
			3401.80
			295.55
			1992.96
			288.64
			3669.88
5	Boyle et al.(2003) [5]	22	97.72
			114.27
			636.77
			499.20
			218.20
			409.22
			92.37
			113.65
			457.99

			543.54
			315.37
			402.03
			786.77
			993.23
			372.14
			439.05
			198.71
			257.75
			157.62
			189.67
			570.17
			741.08
6	Brashares(1985)[7]	7	185.42
			79.74
			4.06
			153.62
			41.40
			4.30
			93.05
7	Carson et al.(1993) [9]	3	211.11
			158.90
			177.06
8	Croke et al.(1987) [10]	6	85.99
			87.32
			98.76
			64.64
			73.85
			91.06
9	Cronin(1982) [11]	20	67.03
			51.56
			85.99
			78.43
			81.27
			86.39
			58.76
			42.54
			34.93
			59.47
			84.11
			57.29
			96.58
			81.27
			56.68

			31.28
			73.21
			77.22
			41.88
			83.60
10	Desvousges et al.(1987) [13]	16	72.21
			39.59
			21.66
			62.50
			142.93
			91.88
			46.81
			149.90
			61.01
			43.82
			30.88
			77.69
			126.99
			72.96
			31.13
			106.82
11	Edward(1984) [15]	3	167.86
			189.66
			368.42
12	Egan et al.(2009) [16]	20	311.19
			256.47
			285.53
			237.99
			84.80
			19.24
			8.85
			14.63
			12.70
			3.77
			187.36
			154.05
			133.04
			185.80
			110.77
			13.41
			7.77
			6.82
			12.37
			11.58

13	Eppa et al.(1979) [17]	1	166.69
14	Farber et al.(2000) [18]	18	54.40
			51.14
			38.08
			72.96
			73.43
			55.18
			74.79
			70.96
			51.34
			95.38
			96.73
			79.31
			128.71
			125.02
			108.15
			157.19
			160.79
			132.65
15	Gibbs et al.(2002) [19]	4	94.48
			456.11
			328.65
			826.51
16	Gramlich et al.(1977) [20]	2	155.75
			282.69
17	Holly et al. (1996) [30]	6	841.14
			1464.21
			443.39
			847.67
			703.25
			1014.30
18	Huang(1986) [22]	22	11.07
			16.94
			13.72
			8.98
			5.69
			5.80
			6.60
			5.19
			5.19
			6.04
			5.29
			7.59
			7.94

			5.78
			16.31
			8.74
			4.32
			3.17
			3.22
			4.96
			5.80
			6.49
19	Johnston et al.(1999) [38]	3	19.84
			27.69
			54.82
20	Krysel C. et al.(2003) [25]	74	1778.88
			79.08
			225.00
			217.16
			130.37
			55.29
			73.36
			68.28
			40.76
			322.78
			20.11
			200.32
			89.01
			451.17
			39.58
			24.74
			18.87
			347.39
			51.69
			48.45
			26.48
			67.32
			4032.48
			84.92
			134.92
			242.35
			206.33
			287.02
			576.76
			340.05
			31.04
			1276.19

			4371.92
			205.89
			95.59
			273.07
			192.54
			4212.44
			105.23
			527.47
			276.09
			295.64
			70.12
			90.25
			87.21
			53.54
			435.34
			29.02
			245.70
			151.78
			586.40
			48.27
			36.82
			24.99
			426.92
			95.39
			60.00
			33.48
			87.74
			5656.40
			98.87
			172.65
			350.68
			300.30
			336.06
			782.15
			498.45
			36.95
			1833.69
			5629.00
			439.80
			134.52
			384.81
			414.82
21	Leggetta et al.(2000) [26]	1 395.49	
22	Lipton et al.(2003) [27]	1	72.18

23	Magat et al.(2000) [48]	7	316.18
			150.86
			233.52
			157.39
			141.97
			126.57
			674.47
24	Matthews et al.(1999) [28]	3	19.84
			27.69
			54.82
25	Moore et al.(2001) [31]	24	508.19
			600.59
			582.80
			457.83
			115.46
			247.70
			130.69
			53.19
			409.55
			450.91
			465.49
			363.37
			161.88
			224.56
			120.59
			46.81
			382.95
			520.77
			807.63
			421.67
			89.14
			144.32
			245.57
26	Mullen et al.(1985) [32]	1	79.20
27	Holly et al.(1996) [30]	6	841.14
			1464.21
			443.39
			847.67
			703.25
			1014.30
28	Ralph et al.(1989) [33]	2	1722.73
			911.78
29	Randall et al.(2001) [34]	3	89.08
			41.92

			61.57
30	Schuetz(2001) [39]	3	5.07
			11.37
			17.04
31	Smith et al.(1983) [41]	2	16.90
			35.49
32	Smith et al.(1986) [40]	14	52.74
			76.89
			10.48
			50.12
			520.83
			1269.00
			17.83
			77.64
			127.44
			26.22
			121.39
			1153.62
			2974.06
			71.86
33	Steinnes (1992) [42]	2	18.85
			21.96
34	Stumborg et al.(2001) [43]	1	452.52
35	Walsh et al.(1981) [14]	12	63.04
			134.68
			199.72
			441.58
			103.16
			198.68
			294.52
			591.59
			74.03
			152.24
			225.59
			482.50
36	Wey(1990) [49]	2	70.14
			63.23
37	Whitehead(2005) [52]	6	103.71
			105.26
			104.21
			16.86
			45.43
			45.26
38	Young(1984) [53]	2	587.50

		525.00
TOTAL:	332	

Table 11: Clustered Robust Regression Results (With Secchi As The Indicator)

	Pooled 1	Pooled 2	CV	Hedonic
	(1)	(2)	(3)	(4)
D-NE	81.73	57.37	-24.51	-269.67
	(72.56)	(62.51)	(22.70)	(372.93)
D-lakeEstuary	215.00*	215.83	252.66***	408.70
	(125.38)	(132.34)	(44.16)	(561.91)
pubDate	7.40	6.41	-3.62*	-66.50**
	(4.97)	(4.88)	(1.96)	(32.41)
D-inPerson	281.32**	273.50**	83.38***	
	(112.14)	(113.95)	(25.06)	
income	-.01	-.01	.002	-.02
	(.01)	(.01)	(.003)	(.02)
D-totalValue	75.51	92.14*	108.42***	
	(59.20)	(54.56)	(25.04)	
D-improvement	-246.40**	-228.94**	-73.10***	-355.87**
	(114.22)	(110.01)	(23.87)	(159.39)
D-ladder	-100.75	-53.25	-129.79**	-11466.95***
	(101.22)	(102.46)	(59.20)	(3048.98)
startingSecchi	-87.88**	-87.30**	-86.65***	-91.98**
	(36.92)	(35.92)	(16.62)	(35.76)
deltaSecchi	2.81	2.99	-.24	2262.46***
	(2.28)	(2.22)	(1.25)	(579.30)
D-CV	-218.02	-94.74		
	(137.41)	(114.70)		
D-hedonic	424.70***	537.73***		
	(144.22)	(152.51)		
sitesize	.06*		-.006	24.27***
	(.03)		(.02)	(6.17)
regionsize	-.004*		.0004	
	(.002)		(.001)	
N	332	332	146	127
r_2	.14	.13	.47	.49
F	23.31	18.52	68.46	.

[a] *p=.10 **p=.05 ***p=.01

[b] secchi is used as the water quality indicator instead of water quality index