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Measuring the Benefits of Improvements in Water Quality: The Chesapeake Bay

N. E. BOCKSTAEL
K. E. McCONNELL
I. E. STRAND

Department of Agricultural and Resource Economics
University of Maryland
College Park, MD

Abstract *Federal, state, and local government agencies have joined forces in the ambitious and expensive task of improving the water quality of the Chesapeake Bay. Clean-up efforts will be devoted to three major problems: nutrient over enrichment, toxic substances, and the decline of submerged aquatic vegetation. Although the beneficiaries are ultimately human, criteria for judging the Bay's water quality have been primarily biological and physical. This paper addresses the question of the human values from the Bay. How do people use the Bay and how much are they willing to pay for the changes in water quality that improve their use? With a variety of methods and data sources, we estimate the annual aggregate willingness to pay for a moderate improvement in the Chesapeake Bay's water quality to be in the range of $10 to $100 million in 1984 dollars.*

Introduction

Over the past decade, the Chesapeake Bay has been the focus of an impressive amount of research and the beneficiary of numerous environmental programs. Concentrated efforts began in 1976 when the Congress directed the U.S. Environmental Protection Agency to conduct a five-year study of the Bay's resources and water quality. The study focused on three major problems of the Bay—nutrient overenrichment, toxic substances, and the decline of submerged aquatic vegetation. In 1983 the three surrounding states, the District of Columbia, and the federal government signed a pact, the Chesapeake Bay Agreement of 1983, committing them to improve and protect water quality of the Chesapeake Bay through coordinated activities.

The first plan of the Chesapeake Bay Commission was the Chesapeake Bay Restoration and Protection Plan of September 1985. The plan states the goals:

> Improve and protect the water quality and living resources of the Chesapeake Bay estuarine system (in order) to restore and maintain the Bay's ecological integrity, productivity, and beneficial uses and to protect public health.[1]

The goals of the Restoration and Protection Plan are broad, and include general reference to ecological and human health issues, as well as productive use by humans.

However, there is no clear connection between the goals of the Bay program and the way people who pay for it are expected to benefit.

To accomplish the goals, specific objectives and implementation strategies have been developed. Many of these strategies are designed to reduce or control nutrients. Major strategies to control point sources of nutrients include plans to provide grants to design, construct, operate, and maintain sewage treatment facilities, and plans to support phosphorous removal projects at treatment plants. The primary strategy for controlling nonpoint sources of nutrients to the Bay has been the subsidy of management practices to reduce runoff from urban, forested, and, in particular, agricultural lands. More recently, the governors of Maryland and Virginia agreed to reduce nutrient loads by 40%. The plan enacted a series of additional policies to reduce or control the level of toxic materials in the Bay. Lastly, the Chesapeake Bay Restoration and Protection Plan instituted a series of policies designed directly to "provide for the restoration and protection of living resources and their habitats and ecological relationships"[2] in the Chesapeake.

In this article, we estimate the value of a moderate improvement in water quality in the Bay. This task is tackled given the typical limitations on research. We rely on a variety of different sources of data, gathered by others for different purposes. We assume untestable relationships between human behavior and physical and biological water quality changes. Finally, our results depend on a variety of maintained hypotheses about the estimated models, including error distributions, functional forms, and estimation approaches. Our results aid in understanding both the benefits of improving the Chesapeake Bay and the value of nonmarket benefit techniques.

There are two motives for this study. First it helps us understand how people use the Bay, the ways in which they derive enjoyment from it, and the paths through which environmental quality affects them. The Restoration and Protection Plan is notably vague in defining how individuals benefit from environmental improvements. Whereas human use is emphasized in a broad context, objectives are defined in scientific (chemical, biological) terms. A better understanding of human use and perceptions of the Bay can help focus clean-up efforts in ways that would generate the greatest payoff.

Programs to improve the Bay cost society in various ways, providing a second motive for our study. For example, agricultural best management practices impose restrictions on farmers and require taxes from the general population. These programs are undertaken in part because the Bay provides valuable services to people. The amount people are willing to pay for the services of a cleaner Chesapeake Bay is one reasonable measure of the value of those services. We are interested in what people are willing to pay for access to recreational activities of the Bay, and how their willingness to pay changes as water quality improves.

Consequently, this is not an article about nonmarket methods. Rather it is a paper that uses methods in an attempt to address the larger question: what is the monetary worth of pursuing the programs suggested by the Chesapeake Bay Restoration and Protection Plan? We focus on the recreational benefits because we believe that most of the increase in well-being accrues to recreationists. Whereas there is considerable discussion about the benefits to commercial fishing, it is not clear that society gets any long-run benefits there in the absence of well-defined property rights. We employ both the contingent valuation technique and indirect or behavior-based techniques. Only the contingent valuation approach allows insights into the value of Bay improvements to nonusers. We report the results of this analysis first.

Using Contingent Valuation to Measure the Economic Benefits of Improved Water Quality

In this section, contingent valuation is used to value improvements in water quality in the Chesapeake Bay. We consider a hypothetical change of the Bay's water quality from its current condition to an improved condition, which the respondent considers acceptable for swimming. Because individuals' perceptions of water quality are not easily linked to objective measures and because individuals do not easily understand these scientific measures, the gauge of acceptability in this analysis rests with the individual.

The individuals in the contingent valuation experiment are a subset of a telephone survey of the Baltimore-Washington SMSA. Each of the randomly selected households was asked "Do you consider the water quality in the Chesapeake to be acceptable of unacceptable for swimming and/or other water activities?" In the context of this question, we can think of "acceptable" of "unacceptable" as proxies for "good" or "bad." Many users judged the water "unacceptable." Of the 959 respondents, more than one-half (57%) found the water quality unacceptable. Those who so responded were asked whether they would be willing to pay an amount ($A) in extra state or federal taxes per year, providing the water quality was improved so that it was acceptable for swimming. The amount of money ($A) was varied randomly from $5 to $50 per year over the sample. About 65% of the population who found water quality unacceptable were willing to pay an amount up to $20 if it were made acceptable. If the amount of the tax were raised to between $25 and $35, the percent of respondents who were willing to pay dropped to 54%. Finally, about 49% of those who answered that water quality was unacceptable were willing to pay between $40 and $50 a year. The percent responses by cells are given in Table 1.

The yes or no responses can be used to estimate willingness to pay via the referendum model (Hanemann 1984). The respondent derives utility from the water quality, money income (y), and a vector (x) of individual characteristics. Utility is given by u(1,y;x) when the water quality is acceptable and u(0,y;x) when it is not. Utility is composed of a deterministic element v and a stochastic element θ.

Table 1
Percent of People Willing to Pay Additional Taxes for Acceptable Water Quality for Swimming by Amount of Tax

Amount of Tax Increase ($)	Respondents Offered the Increase Who Are Willing to Pay (%)
5	64
10	66
15	63
20	70
25	58
30	46
35	57
40	47
45	47
50	53

$$u(j,y;x) = v(j,y;x) + \theta_j \qquad j = 0,1 \tag{1}$$

where θ_j are i.i.d. random variables with mean zero.

When offered swimmable water at a tax of \$A, the individual will accept if

$$v(1,y-A;x) + \theta_1 \geq v(0,y;x) + \theta_0 \tag{2}$$

and decline otherwise. The probability of an individual's response is

$$\Pr[\text{accept tax to get swimmable water}] = \Pr[v(1,y-A;x) - v(0,y;x) \geq \eta)$$

where $\eta \equiv \Theta_0 - \Theta_1$. Let $F_\eta(\cdot)$ be the cumulative distribution function of η. Then the probability of accepting the tax to get swimmable water equals $F_\nu(\Delta v)$ where Δv is just the difference in the deterministic portion of equation (2).

To complete the analysis, we choose a linear function for $v(\cdot)$ and a logistic function for η.

$$v(j,y) = \alpha_j + \beta y \qquad \beta > 0. \tag{3}$$

The arguments of x are suppressed into the constant α_j. The difference (Δv) is $(\alpha_1 - \alpha_0) - \beta A$, which gives a probability model of the form

$$F(\eta) = \prod_{i \epsilon S_1} F(-\alpha_0 + \alpha_1 - \beta A_i)] \prod_{i \epsilon S_0} [1 - F(-\alpha_0 + \alpha_1 - \beta A_i)] \tag{4}$$

where i is an index of individuals, S_0 is the set of individuals who prefer the unimproved state, and S_1 is the set who prefer the improved state with tax \$A.[4] $F(\cdot)$ is the logistic distribution.

Welfare analysis can proceed with a measure of central tendency of willingness to pay. Define A* as the amount of money that makes the individual indifferent between the improvement and the tax ($j = 1$) and no improvement ($j = 0$). At this level of the tax, utility is equal under each setting, implying

$$v(1,y-A^*;x) + \nu_1 = v(0,y;x) + \nu_0. \tag{5}$$

Combining (3) and (5) yields

$$A^* = [(\alpha_1 - \alpha_0) - \eta]/\beta$$

where η is random. To evaluate the individual's willingness to pay for the "acceptable" water quality, take the expected value of the random variable A*, treating α_0, α_1, and β as constants:

$$E[A^*] = (\alpha_1 - \alpha_0)/\beta. \tag{6}$$

In the application, we modify equation (3) in two ways. One modification makes $(\alpha_1 - \alpha_0$ depend on whether someone in the household had used or intended to use the Chesapeake Bay in 1984. A summary variable ($D_1 = 1$ for users) is included to reflect use. This approach allows users to value the change in the Bay's water quality more than nonusers, *ceteris paribus*. The other modification makes the income coefficient, β, depend on socioeconomic characteristics. We find race to be the most significant variable in explaining bid. However, the race variable is likely to reflect not only cultural differences but income differences, since there was a wide disparity in mean income between whites and nonwhites ($40,000 annually vs. $25,000) in the sample. The coefficient on the tax variable, β, represents the marginal utility of income. Since the socioeconomic variable we have identified is linked with income, it makes sense that this factor will alter β. We estimate

$$v(1,u) - v(0,u) = \alpha_1 - \alpha_0 + \alpha_2 D_1 - \beta_1 A - \beta_2 D_2 A.$$

Table 2 reports results. The observations include only those who found the water "unacceptable." Hence, aggregating the results will ignore those households who believe the water to be "acceptable" but nevertheless gain from improvements. The amount of the tax reduces the probability of a respondent's willingness to pay the annual tax increase in exchange for water quality improvement. Users are significantly more likely to pay the tax increase for water quality improvements. Being white also makes one more likely to pay for water quality improvements.

Using equation (6), we calculate the benefits of a representative individual in each group. These results are found in Table 3. Users are willing to pay, on average, about three times as much in extra taxes as nonusers. But nonusers are willing to pay a positive amount. Both user and nonuser groups exhibit higher average willingness to pay bids among white (or higher income) individuals. Among users, the mean willingness to pay is $183 for whites and $34 for nonwhites. The corresponding figures are $48 and $9 for nonusers. In the conclusion, we aggregate these benefits for the population of the Baltimore-Washington SMSA.

Using Indirect Market Methods to Measure Water Quality Benefits

The contingent valuation approach covers a range of uses of the Bay. To gain insight into specific uses and to buttress the broad results, we exploit behavior-based methods. Of the various methods available, we choose two versions of the travel-cost model: the

Table 2
Logistic Model Estimates Related to the Probability a Respondent Will Accept a Tax Increase

Variable	Coefficient	Estimated Coefficient	Standard Error	t-ratio
Constant	$(\alpha_1 - \alpha_0$	.385	.222	1.73
D_1[1]	α_2	1.084	.202	4.77
Amount of Tax	$-\beta_1$	−.043	.009	−5.37
D_2[1] · tax	β_2	.035	.007	4.78
Chi-squared = 47.10				

[1] D_1, D_2 represent binary variables taking the value of one for the use of the Bay and white racial characteristics, respectively.

Table 3
Mean Willingness to Pay Tax Increase to Make the Bay "Acceptable" by Users and Nonusers, 1984 Dollars

	Respondents (%)	Mean Willingness to Pay ($)
Users in 1984	43	121
Nonusers in 1984	57	38

varying parameter model and the pooled model. These approaches have shortcomings, but they suit our data and are relatively easily applied.

To formalize the model, let the individual maximize constrained utility as a function of number of trips taken to the n quality-differentiated sites, the quality characteristics of each site, and a Hicksian good. Thus

$$\max u(x,q,z) \qquad \text{s.t. } px + z = y \tag{7}$$

where x is an n-dimensional vector of trips to the n sites, p is a corresponding vector of costs of accessing the sites where q_i, $i = 1, \ldots, n$ is the water quality at the i^{th} site, z is the Hicksian good, and y is income.

Problem (7) defines n demand functions, each of which may be a function of all n prices, n quality levels, and income:

$$x_i = g_i(p,q,y) \qquad i = 1, \ldots, n. \tag{8}$$

Under most circumstances, however, this model cannot be estimated. Imagine having observations on S individuals who visit site i. The quality characteristic at site i (q_i) is constant across the S individuals. The coefficients of the q_i's cannot be estimated when there is no variation in the q_i's across observations.

There are several methods for resolving this dilemma. Some of them build on the model presented in (8) (these are described in Bockstael et al. 1987a), whereas others rely on discrete choice models (see Bockstael et al. 1987b). The varying parameters model falls in the former category and follows similar methods applied by Vaughan and Russell (1982a, b) and Smith and Desvousges (1985).

To motivate the varying parameters model, consider a linear demand function for the i^{th} site:

$$x_i = \beta_{0i} + \beta_{1i}p_i + \beta_{si}p_s + \beta_{yi}y + \epsilon \qquad i = 1, \ldots, n. \tag{9}$$

where p_i is the own price and p_s is the price of the nearest substitute. This is a linear, parsimonious version of (8). Let the demand parameters be determinisitic functions of the quality characteristics at the site. For example, the β's might be linear functions of the q's:

$$\beta_{0i} = \gamma_0 + \gamma_1 q_i$$
$$\beta_{1i} = \alpha_0 + \alpha_1 q_i$$
$$\beta_{si} = \theta_0 + \theta_1 q_i$$
$$\beta_{yi} = \delta_0 + \delta_1 q_i \tag{10}$$

The model in (9) and (10) implies that variations in demand parameters across sites (i.e., variations in the β_{0i}'s, β_{1i}'s, etc.) correspond to variations in own-site attributes (q_i). Together, (9) and (10) imply:

$$x_i = \gamma_0 + \gamma_i q_i + (\alpha_0 + \alpha_1 q_i)p_i + (\theta_0 + \theta_1 q_i)p_s$$
$$+ (\delta_0 + \delta_1 q_i)y + \epsilon. \tag{11}$$

Although the model can be collapsed into one expression as in (11), the estimation procedure usually involves two steps: estimate the model of trips to each site depending on prices and income (e.g., n separate models) and regress the coefficients from the first n regressions on the quality characteristics of the n sites. In practice, not all parameters are allowed to vary. For the beach equations, there are eight parameters. We have used only the most important economic parameters. Further, we have excluded parameters that show no significant effects. The second step requires the application of generalized least-squares because of the properties of the error structure implicit in the estimation of (10), which must use estimated parameters (β's) in place of the true β's.

In estimating the demand functions, one must account for the censored nature of trips to sites. Some people take positive trips, others zero. Several estimation methods handle this problem. We estimate the Tobit, although it has some weaknesses:

$$x_i = \begin{cases} \beta_0 + \beta_1 p + \beta_s p_s + \beta_y y + \epsilon \\ \beta_0 + \beta_1 p + \beta_s p_s + \beta_y + \epsilon > 0 \\ 0 \end{cases} \tag{12}$$

otherwise,
where ϵ is $N(0,\sigma^2)$. The likelihood function is given by

$$L = \prod_{x>0} \left(\frac{1}{\sigma}\right) \phi \left(\frac{x - z\beta}{\sigma}\right) \prod_{x=0} \Phi \left(\frac{-z\beta}{\sigma}\right) \tag{13}$$

where $z\beta$ is the right-hand side of (12) and ϕ and Φ are the density function and the distribution function of the standard normal.

We estimate the Tobit model for three activities: beach use, boating, and fishing. The data sets are different in their purpose, their year, and their coverage, but they are the best sources of information about recreational activities on the Bay.

Beach Use

The beach model is estimated from a survey of 484 people at 11 public beaches on the western shore of Maryland in the summer of 1984. The 484 individuals were randomly selected from sample beaches and days. The design is a two-stage stratified sample in which a probability sample of beaches and days was selected and then a random sample of persons was interviewed at each sample site.

Demand functions for 10 beaches are estimated using the Tobit model in equation (12). In practice we find that income is insignificant but ownership of stock variables (boat, recreational vehicle, swimming pool) is important. Further, we have enough information to estimate time costs using information on labor market participation (see Bockstael et al. 1987b). Demand coefficients are in Table 4. The estimated coefficients on own-price (travel cost) are all negative and most statistically significantly less than zero. Collinearity among the price and time variables may cause the large standard errors for Miami, Morgantown, and Rod and Reel. In some instances, the collinearity is sufficiently troublesome so that only the own-price and own-time variables are included.

To complete the second stage, we need to choose a measure of water quality (q in equation (1)). Our choices are limited by the absence of complete data covering all areas of the Bay. Our measure of water quality is the product of nitrogen and phosphorus, TNP_j. The measure of TNP_j is for the location nearest the beach. The measurement is the mean level for summer months in 1977, the last year for which complete data are available. A good case can be made for using this variable. Studies of the Bay conducted by the U.S. Environmental Protection Agency indicate that perhaps the most significant problem facing Bay restoration and protection efforts is nutrient overenrichment of Bay waters. Both nitrogen and phosphorus contribute to enrichment. Excessive nutrient levels may be the partial cause of decreased submerged aquatic vegetation, which in turn has adverse effects on the food chain and on the habitat for many fish species. Further, overenrichment leads to lower dissolved oxygen levels, which have additional adverse effects on fish stocks, degrading the appearance of the water as well. High collinearity between nitrogen and phosphorus readings prevents separate inclusion of both variables in the analysis. The product of nitrogen and phosphorus is used to avoid this problem and to capture the interactive nature of these nutrients.

The results of the second-stage estimation, equation (10), are based on weighted least-squares in which the weights were $1/\sigma_{\hat{\beta}}$, the inverse of the standard error of the coefficients for each beach. The estimated equations for the observations are

$$\begin{aligned} \text{own-price:}\quad \beta_{1j} &= \underset{(.04)}{-.0308} - \underset{(-2.22)}{.0002TNP_j} \\ \text{constant:}\quad \beta_{0j} &= \underset{(-1.1)}{-2.66} - \underset{(-.001)}{.00016TNP_j} \end{aligned} \tag{14}$$

where t-statistics are in parentheses.

The estimated effect of an increase in TNP is to make the demand function less steep and the constant term lower. (To see the effect on the demand slope, recall that price is on the vertical axis, quantity on the horizontal.) An increase in TNP increases the amount a given price change reduces quantity, thus flattening the curve.

Boating

The boating analysis is based on a 1983 survey of boaters sponsored by the University of Maryland Sea Grant Program and the Maryland Coastal Zone Management Program. The mail survey covered 2,515 registered boat owners in Maryland. The design of the

Table 4
Tobit Estimates for Beach Demand Model, by Beach[1]

Beach	Constant	Beach Access Costs	Beach Access Time	Substitute Beach Access Costs	Substitute Beach Access Time	Ownership Boat	Ownership Rec. Veh.	Ownership Swim. Pool	σ	Nonlimit/ Limit Observations
Sandy Point	8.17	−.35	−4.85	.24	2.47				14.85	243/139
	(2.83)[2]	(−4.07)	(−3.61)	(2.86)	(1.15)				(57.59)	
Fort Smallwood	.16	−.53	−4.24	.34					9.52	41/198
	(.05)	(−2.96)	(−2.58)	(1.14)					(11.61)	
Rod & Reel	−10.44	−.10	−1.51	.29					9.72	22/201
	(−2.28)	(−.84)	(−1.28)	(1.25)					(5.47)	
Rocky Point	10.29	−.47	−5.63					3.55	12.41	87/66
	(2.04)	(−1.45)	(−2.38)					(1.36)	(19.00)	
Chesapeake Beach	−3.96	−.18	−1.19	.19			3.23		6.16	46/272
	(−1.89)	(−2.19)	(−1.76)	(1.80)			(2.58)		(10.00)	
Porter's New Beach	−.70	−.29	−1.28	.31		1.54		−2.04	3.43	25/118
	(−.31)	(−2.21)	(−1.28)	(1.10)		(1.32)		(−1.31)	(5.15)	
Point Lookout	−3.49	−.05	−1.72	.12	4.55	2.19	2.98	−1.76	5.96	82/262
	(−2.72)	(−5.62)	(−4.72)	(3.35)	(5.41)	(1.69)	(2.50)	(−1.21)	(15.14)	
Miami	−2.20	−.09	−1.27				4.37		7.42	50/121
	(−1.45)	(−1.35)	(−1.18)				(2.46)		(10.06)	
Bay Ridge	−6.98	−.78	−9.63	.83	7.40	−6.19	7.55	−5.67	18.06	61/292
	(−1.16)	(−4.90)	(−3.50)	(3.19)	(1.96)	(−1.00)	(1.50)	(−1.13)	(17.56)	

[1]No coefficients were significantly different from zero for Morgantown site.
[2]t-ratios in parentheses.

sample provided equal representation to owners of boats kept in slips and owners who trailered their boats. The survey, which sought a variety of information about the household and its boating activity, achieved a response rate of approximately 70%. In our analysis, we use a sample of 496 boaters who trailer their boats. We cannot easily analyze the choices of boats kept in slips because boat owners cannot choose the location of their trip once they have chosen their marinas. Whereas owners of boats in marinas may well benefit from improved water quality, those benefits are excluded from our analysis.

Because we have a "second-hand" data set over which we had no control, a simpler version of the demand function is estimated. The variables included are own-price, substitute price (where the substitute is the county closest to the individual's home county) and the owner's estimate of the value of the boat. The cost of time is included in the individual's travel costs. The demand functions for each of the 12 county sites are presented in Table 5. The results are remarkably consistent across sites. The own-price coefficients are significantly less than zero at the 99% level of confidence. Substitute price coefficients are all positive and significantly different from zero for 8 of the 12 sites. The coefficient on boat value is significantly greater than zero for seven of the sites, suggesting that wealthier people or people with bigger boats take more boating trips, *ceteris paribus*.

In the second stage, there are as many equations as there are parameters from the first stage. With no expectations about which parameters might vary, we allow the test statistics to determine the outcome.

The second stage model is given by

$$\hat{\beta}_{kj} = \alpha_{ok} + \alpha_{ik}\,\mathrm{TNP}_j + v_j \tag{15}$$

where $k = 1, 4$ (the number of parameters in each equation) and $j = 1, 12$ (the number of sites). The regression of the own-cost coefficients from the linear first-stage model on these environmental variables produced good results. The coefficient is significantly less than zero. The negative sign suggests that the demand curve becomes less steep with increasing levels of pollutants. The estimated equations for the 12 observations are:

$$\begin{aligned}
&\text{own-price} \quad \beta_{1j} = \underset{(4.29)}{-.0887} - \underset{(3.54)}{.000102}\,\mathrm{TNP}_j \\
&\text{substitute price} \quad \beta_{2j} = \underset{(7.47)}{.0682} - \underset{(1.73)}{.000016}\,\mathrm{TNP}_j \\
&\text{constant} \quad \beta_{0j} = \underset{(4.14)}{-19.41} + \underset{(1.93)}{.007338}\,\mathrm{TNP}_j
\end{aligned} \tag{16}$$

No significant relationship was found for the income coefficient. The equations in (16) are used to calculate the benefits of reductions in TNP.

Striped Bass Fishing in Maryland

The 1980 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation (NSFHW) is the source data for analysis. Of the available data sets on Chesapeake Bay sportfishing, the portions of this survey relating to saltwater recreational fishing in Maryland, and by Maryland residents, offered the best prospects for modeling the ef-

Table 5
Estimated Tobit Demand Coefficients for Boating Data Set Maryland Counties, 1983

County	β_1 (cost/trip)	β_2 (substitute cost/trip)	β_3 (boat value \$1000's)	β_0 (constant)	Nonlimit Observations[1]
	Estimated Coefficients (Variable)				
Anne Arundel	−.13	.03	1.29	−2.21	142
	−(8.75)[2]	(3.42)	(5.94)	(−1.61)	
Baltimore	−.43	−.02	1.78	−1.94	75
	(−9.21)	(1.13)	(4.01)	(−.77)	
Calvert	−.14	.08	1.84	−27.14	44
	(−4.14)	(13.70)	(3.45)	(−7.21)	
Cecil	−.22	.04	2.12	−16.44	17
	(−4.84)	(1.54)	(3.09)	(−3.97)	
Charles	−.34	.07	2.75	.49	38
	(−8.41)	(3.77)	(6.79)	(.19)	
Dorchester	−.09	.08	.66	−34.39	30
	(2.98)	(2.69)	(.78)	(−6.69)	
Harford	−.15	.05	−1.51	−12.21	36
	(−5.55)	(2.63)	(−1.67)	(−3.74)	
Kent	−.25	.11	.14	−18.25	28
	(−4.94)	(3.57)	(.14)	(−3.45)	
Queen Anne's	−.27	.07	.12	−3.83	36
	(−6.17)	(2.89)	(−.19)	(−1.03)	
St. Marys	−.11	.05	1.25	−9.46	67
	(−6.4)	(3.12)	(2.94)	(−3.31)	
Somerset	−.12	−.03	2.81	−37.20	24
	(4.76)	(.58)	(3.13)	(−6.64)	
Wicomico	−.15	.05	1.02	−7.03	26
	(−6.93)	(1.58)	(1.71)	(−2.02)	

[1]Each equation is estimated with the 496 boaters who trailer their boats.
[2]Parenthesized numbers are asymptotic t-statistics under the null-hypothesis of no association.

fects of water quality improvements. This data set contained the essential variables for estimating recreational fishing demand functions.

The survey consisted of two parts. The first was a telephone screening of households, predominantly by telephone interviews, to determine the hunting, fishing, and nonconsumptive recreation activities that household members took during 1980 and certain demographic characteristics of the household. The second part was a detailed questionnaire administered (typically in person) to selected individuals who indicated they had hunted or fished in 1980, collecting information on activities and expenditures. Of the 30,300 fishermen and hunters and 6,000 nonconsumptive users interviewed nationwide, 760 pursued some of these activities in Maryland. Of these 760, 184 fished for striped bass in the state in 1980.

For recreational fishing, the quality variable is assumed to be the number of fish caught per trip. From the survey we have information on individual catch rates so that quality varies across individuals. The NSFHW defines three large sites for Maryland. But almost all anglers fished at only one site out of the three. Hence we used a pooled model rather than a varying parameters model. The demand function is specified as:

$$x_i = f(p_i, q_i, y_i, IB_i, OB_i)$$

where x_i is striped bass days in 1980 (a trip measure was not available), p_i is the i^{th} individual's cost of striped bass fishing, q_i is the catch rate (fish/day), y_i is the recreational fishing/hunting budget, and IB_i and OB_i are (0,1) variables representing ownership of inboard or outboard boats. Catch rate variables are not available for individuals who did not fish in 1980. We use an estimate of catch rate, based on fishing experiences and capital stock, for nonfishing persons. The demand function estimates are shown in Table 6.

Calculating Benefits of Improvements in Water Quality

Parameter estimates for each activity described the recreational choices made by the representative user. From these estimates and information on the number of users, we can estimate the benefits of improved water quality to the average user and then expand to the total population. Indirect methods pose the most problems in calculating benefits, and so they are addressed first.

We choose to analyze a 20 percent reduction in TNP and a 20 percent improvement in catch rates. This requires the calculation of consumer surplus before and after the change. When the demand function is linear, individual i's consumer surplus from site j is

$$CS_{ij} = (x_{ij})^2/(-2\beta_{j1}), \tag{17}$$

where x_{ij} is i's demand for trips to j and β_{j1} is the coefficient on cost of access in the j^{th} site demand function. The weighted average change in consumer surplus over the sample for the j^{th} site, where the change is from q^0 to q^1, is

Table 6
Tobit Estimates of the Demand for Striped Bass Fishing, 1980

Effect	Coefficient	Estimate	Asymptotic t-statistic
Constant (C)	β_0	−10.60	−5.79
Own price (p)	β_1	−.34	−7.52
Catch rate (q)	β_2	.34	2.13
Inboard Motor (IB)	β_3	12.65	4.49
Outboard Motor (OB)	β_4	6.66	3.47
Recreational Budget (y)	β_5	1.40	3.04

$\hat{\sigma}^2 = 18.3$; N = 760; Nonlimit Observations: 184

$$\sum_{i=1}^{N} [(x_{ij}(q_j^1))^2/(-2\beta_{ji}(q_j^1)) - (x_{ij}(q_j^0))^2/(-2\beta_{ji}(q_j^0))]*k_i/N \tag{18}$$

where N is the sample size and k_i is the sampling weight determined by the sampling scheme and reflecting how representative of the population a given observation in the sample should be. The notation $x_{ij}(q_j)$ and $\beta_{j1}q_j)$ implies that both the quantity demand and the β coefficient are functions of the level of water quality. Calculating consumer surplus for hypothetical environmental circumstances thus requires values for $x^0 = x(q^0)$, $\beta^0 = \beta(q^0)$, $x^1 = x(q^1)$, and $\beta^1 = \beta(q^1)$.

The first step is to use the results of model (10) to predict β_{j1} after hypothetical changes in water quality. The coefficients are then used to determine values for the x^0 and x^1 variables. The Tobit predicting equation which adjusts for the censored dependent variable is

$$\hat{x}_{ij} = \Phi\left(\frac{\beta z}{\sigma}\right)\beta z + \sigma\phi\left(\frac{\beta z}{\sigma}\right) \tag{19}$$

where ϕ and Φ are the density and cumulative distribution functions for the standard normal.

There are two ways of obtaining the "before" and "after" x's for the consumer surplus functions. One way is to use the predicting equation (19) to calculate both $\hat{x}^0$ and $\hat{x}^1$ values. The second method is to accept the observed x as x^0 and then to adjust this x by $\hat{x}^1 - \hat{x}^0$ to reflect the hypothetical change in water quality to obtain the x^1 (see Bockstael and Strand, 1987, for details of the two approaches).

Because there is no clear theoretical reason to choose either of these approaches, we calculate the results both ways. Both methods use formula (18) to calculate the change in average consumer surplus. Method A calculates trip values as

$$\hat{x}_{ij}^0 = \Phi\left(\frac{\beta_j^0 z_{ij}}{\sigma}\right)\beta_j^0 z_{ij} + \sigma\phi\left(\frac{\beta_j^0 z_{ij}}{\sigma}\right) \tag{20}$$

$$\hat{x}_{ij}^1 = \Phi\left(\frac{\beta_j^1 z_{ij}}{\sigma}\right)\beta_j^1 z_{ij} + \sigma\phi\left(\frac{\beta_j^1 z_{ij}}{\sigma}\right) \tag{21}$$

Method B calculates these values in the following way:

$$x_{ij}^0 = \text{observed value of } x_{ij} \tag{22}$$

$$x_{ij}^1 = x_{ij}^0 + \hat{x}_{ij}^1 - \hat{x}_{ij}^0. \tag{23}$$

These mechanics, equations (17) through (23), the parameters in Tables (4) through (6), and equations (14) and (16), as well as the independent variables provide the ingredients for calculating benefits. Before we undertake this task, however, we suggest some limitations of the estimates.

A review of the links between environmental policies designed to reduce pollution and the benefits of these policies gives a systematic view of the limitations. Policies influence effluents directly through regulations and indirectly through changes in incentives. Reductions in effluents will eventually improve the ambient water quality. Improvements in ambient quality when perceived by individuals eventually lead to changes in behavior toward the Bay, implying benefits. Further, when nonusers perceived improvements in the ambient water quality, they, too, may be better off. There is potential for error in our understanding of each link in this process.

Our analysis has concentrated on the connection between ambient quality and economic benefits. Logically, it rests on the relationship between environmental policy, effluents, and ambient quality. Even if we were able to capture the exact nature of the link between ambient water quality and behavior, there are honest differences about the connection between effluents and ambient quality. And little is known about the link between policy and effluents.

If the link between policy and ambient quality is ignored, the foremost uncertainty is between ambient quality and behavior. Recall briefly how this link was estimated. For boating and beach we used a varying parameters model to estimate the relationship between the product of the total phosphorus and nitrogen in 1977 and trips in 1983 or 1984. There is considerable room for error in this relationship. Since nitrogen and phosphorus are imperceptible, they serve as proxy measures of the aspects of ambient quality that can be perceived. It is not unreasonable to expect such a relationship to hold in principle, but empirical evidence is hard to come by.

For recreational fishing, the proxy used for water quality is the catch rate experienced by individuals in 1980, the year the trips were taken. There is a complex and uncertain chain of relationships between improvements in ambient quality and growth in the density of fish stocks. There is additional uncertainty in the connection between fish stocks and catch rates. And further, there is no connection between a 20% increase in catch rates and a 20% decrease in TNP.

In addition to the severe difficulties in inferring the relationships between ambient quality and willingness to pay, there are two other significant sources of error in computing aggregate benefits. First, there is the problem of sampling and nonsampling error associated with the measurement of the number of trips per participant and the number of participants in each activity, as well as measurements of exogenous variables such as costs per trip. The boating survey is a good example of nonsampling error for trips. This survey was by mail, so in a sense the respondents are volunteers. The return rate was 70%. We do not know whether those who completed their questionnaires were representative of the boating population as a whole.

We have also used only segments of the total population in our analysis of benefits. The boaters are limited to those who trailer their boats, the fishermen to those who fish for striped bass, and the beach users to those who use public-access western shore beaches. In the boating and fishing analysis, we exclude non-Maryland households. In the contingent valuation and beach analysis, only 20% of Virginia's population are sampled and about 80% of Maryland's households. In every instance, a major portion of users is excluded.

The second source of error comes from aggregating benefits across activities. There are two forms: doublecounting and aggregation bias. Doublecounting occurs because a substantial number of boaters also fish, and many fishermen have boats. The conceptual aggregation bia occurs because of the jointness of choice among sites for a given activity and among activities. For example, the choice of visiting Sandy Point versus Point Lookout may depend in part on water quality, but enhancing water quality at both sites may increase attendance at only one site, making the addition of benefits across sites incorrect.

Finally, we study only three activities: boating, fishing, and swimming. Cleaner water enhances the value of many other recreational and commercial uses of the Bay. We limit our analysis to boating, fishing, and swimming because we can obtain data of adequate quality only for these activities.

Mindful of these difficulties, we nonetheless estimate aggregate benefits of improving the Bay's water quality. We present low, middle, and high benefits for the beach use, boating, and fishing, and compare those with the total benefits derived from the contingent valuation experiment. Comparing the ranges of these independent sources of benefits helps us judge the magnitude of aggregate benefits.

The benefit estimates depend on the computational method and the proportionate change in the proxy for ambient quality and catch rate. The 20% reduction in nitrogen and phosphorus for boating and beach use and a 20% increase in the catch rate should be interpreted loosely as moderate improvements in the quality of the Bay. The change in nitrogen and phosphorus is a proxy for changes in most ambient determinants of water quality. In particular, we should *not* interpret the estimated effect of nitrogen and phosphorus as an "all else equal" effect. It is reasonable to suppose that most harmful pollutants decrease by about the same proportion. Further, to counteract the problem of aggregating across sites for a given activity, we select as a pessimistic estimate the lowest estimate of the benefits of improving the quality by 20% at the one, most important site.

Table 7 summarizes the estimates of aggregate benefits for boaters, sportsfishermen, and beach users. The range of estimates from pessimistic to optimistic is provided by two sources: variation induced by the method of calculating benefits (i.e., using actual trips versus predicted trips) and variation caused by choosing one site rather than the sum over all sites. The procedure is as follows. First, calculate benefits for each site by method A (predicted trips) and method B (actual trips). Find which method gives the larger benefit estimate and sum across sites. This is the optimistic estimate. The intermediate estimate is the smaller of these results summed across sites. The pessimistic estimate is the lower estimate (by method A or method B) for only the largest site.

For stripped bass fishing, the nature of the analysis does not allow disaggretation across sites. The pessimistic and optimistic estimates for fishing are the lower and higher estimates from the two methods of calculation. In this case, the intermediate estimate is simply the mean of the pessimistic and optimistic estimates.

The aggregate measures of willingness to pay for water quality improvements are revealing for several reasons. First, regardless of which benefit measure we use (pessimistic, intermediate, or optimistic), the returns to beach use are the greatest. This is primarily because a larger proportion of the population engages in some beach-going during a year than boating or fishing. and this group is no less sensitive to changes in water quality than the boating-fishing group.

A second implication of the results is the importance of regional variation in water quality. If we were able to clean up the water only around Anne Arundel County, we would still go a long way toward satisfying some of the human needs for using the Bay. Whereas confining a water quality improvement program to a particular locality may not be technically, ecologically, or politically feasible, these figures suggest that we might be able to refine clean-up strategies by looking more closely at the regional variation in benefits.

Table 7

Aggregate Benefits for Three Water-Related Activities from a "20%" Improvement in the Chesapeake Bay's Water Quality (1987 dollars)

	Benefit Estimate		
Activity	Pessimistic	Average ($ Thousand)	Optimistic
Public western shore beach use (1984)[1]	16,853	34,658	44,950
Boating with trailered boat (1983)[2]	654	4,717	8,129
Striped bass sportfishing (1980)[3]	663	1,368	2,071

[1]From Table 4.8, Bockstael, et al. (1988). Pessimistic estimate is the method B value for Sandy Point, the average is the sum of method B values over all 10 sites, and the optimistic is the sum of method A values over all sites.

[2]From Table 5.13, Bockstael et al. (1988). All per boater estimates expanded to 80,000 boaters trailering boats. Pessimistic estimate is the low value (method A) for Anne Arundel County, the average estimate is the sum of low values (method A) across all counties, and the optimistic value is the sum of high values (method B) across all countries.

[3]From Table 6.2, Bockstael et al. (1988). Pessimistic value is the value using method B, average value is the average of the pessimistic and optimistic value, optimistic value is the value using method A.

The values shown in Table 7 help in assessing the contingent valuation estimates shown in Table 8. We might expect the CV estimates in our study to exceed any of the individual behavior-based estimates because the former is more inclusive. Comparing the $67 million estimate even to the pessimistic estimate for beach use suggests that the CV values are not vastly overstated. The lower bound behaviorally based benefit estimate for beach use at only one beach (Sandy Point) is about one-seventh the size of the all-inclusive CV value. The CV value does not appear to be out of line with the behaviorally based values.

Table 8

Aggregate[1] Benefits from Water Quality Improvements-Contingent Valuation (1987 dollars)

	Willingness to Pay for Improved Water Quality[2]		
Group	Pessimistic[3]	Average[3] ($ Thousand)	Optimistic[3]
User	47,254	67,582	87,870
Nonuser	18,446	23,555	28,733
Total	65,700	91,137	116,603

[1]Population is the Washington, D.C., and Baltimore SMSA's.

[2]Willingness to accept tax increase to raise Chesapeake Bay water quality from a level unacceptable for swimming and/or other related activities to a level acceptable for swimming.

[3]The average willingness to pay plus (optimistic) or minus (pessimistic) one standard error in estimate.

Conclusion

Tables 7 and 8 give estimates of the annual benefits of improving water quality in the Bay. The estimates range from slightly less than $10 million to more than $100 million. There are numerous errors in all estimates. Further, several activities and populations have been omitted. But based on these estimates, it seems plausible that the annual returns to cleaning up the Chesapeake lie somewhere in this range. This judgment is based on our limited analysis of existing surveys.

We recapitulate the meaning of the numbers in the tables. Society has undertaken an investment program. The nature of the program is the cleanup of the Chesapeake Bay. The costs of the program include construction of sewage treatment plants, funding of government programs to regulate and monitor agricultural effluents, subsidy of best management practice, installation of industrial waste disposal systems, and restrictions on housing development. The annual returns on the investment program are measured by what people are willing to pay for the improved services. This is the dividend yielded by the public's investment program. Our estimate of this divided is in the range of $10–$100 million, in 1984 dollars.

For several reasons, the long-run benefits may be higher than the estimates in Tables 7 and 8. First, as people learn that the Bay has become cleaner, they will adjust their preferences toward Bay recreation. This is especially true of people who do not currently use the Bay. These people have been largely excluded from the analysis. Second, the population and income of the area have grown since 1984 and are likely to grow more, increasing the demand for and value of improvements in water quality. Finally, the estimates (Table 8) ignore the existence value for households outside the Baltimore-Washington SMSA. The Chesapeake Bay is a nationally prominent resource. Its improved health is of value to many who will never use it.

The magnitude of the estimates raise two interesting issues. The first relates to the fact that indirect methods exploit behavior toward the Bay in its polluted state. The success of these measures relies on users' abilities to discriminate among sites of different quality even in its polluted state. To yield more returns to the public paying for improvements in the Bay, it would be useful to provide the public information on the actual state of regional variation in water quality. The substantial publicity on improving the Bay's water quality may obscure the fact that there are locations of clean water.

A second issue concerns the value of access. When the Bay's water quality is poor, the public's loss from having limited shoreline access is meager. But as water quality improves, the public stands to gain from improving conditions of physical access. Programs such as boat launching sites, fishing piers, and simply local beaches with adequate parking then become more attractive uses of public funds.

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Notes

1. Chesapeake Executive Council, *Chesapeake Bay Restoration and Protection Plan,* U.S. Environmental Protection Agency, Sept. 1985.

2. Chesapeake Bay Restoration and Protection Plan, Chapter 2, p. 1.

3. As is obvious from (3) and (4), the response and the function estimated are independent of income. We believe that the error in measuring income is too great to allow the proposed tax to give a separate effect.

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