

Increasing Beach Recreation Benefits by Using Wetlands to Reduce Contamination

SEBASTAIN N. AWONDO

University of Georgia

KEVIN J. EGAN

DARYL F. DWYER

University of Toledo

Abstract *The public swimming beach at Maumee Bay State Park (MBSP) on Lake Erie is often posted for occurrences of unsafe levels of bacteria. The main source of bacteria derives from a drainage ditch that discharges near the beach. We have conducted a comprehensive study to determine the feasibility of using a constructed wetland to filter the ditch water, prior to its entry into Maumee Bay. As part of this study, we administered an on-site non-market valuation survey of beach visitors, in which observed and contingent trips to the beach were used to estimate the potential welfare benefits of the restored wetlands. The data were analyzed using three versions of the multivariate Poisson-lognormal (MPLN) model, a random effects count data model. We conclude version one, with flexible covariance structure and vehicle costs of \$0.25 per mile, is the preferred version and use it to estimate an average annual willingness to pay (WTP) of \$166 to construct wetlands and improve water quality. The aggregate annual benefit to an estimated 37,300 annual beach visitors is estimated as \$6.19 million. The robustness of this estimate to a variety of alternative assumptions is examined.*

Key words Count data model, Poisson lognormal, on-site sampling, recreation demand, wetland, simulated maximum likelihood.

JEL Classification Code Q51.

Introduction

Wetlands are complex dynamic systems providing a wide range of ecosystem services, including water purification, filtration, retention of nutrients, ground water recharge, flood control, and habitat for a variety of plants and animal species. Wetlands have historically been considered as unhealthy and unproductive (Vileisis 1997). As a result, over 50% of all wetlands were lost through urbanization and agriculture in the lower 48 states (Boyer and Polasky 2004). In Ohio, close to 90% of the original wetlands have disappeared;

Sebastain N. Awondo is a graduate student, Department of Agricultural & Applied Economics, University of Georgia, 309 Conner Hall, Athens, GA 30602 USA (email: sawondo@uga.edu). Kevin J. Egan is an assistant professor, Department of Economics (MS 922) and Daryl F. Dwyer is an associate professor, Department of Environmental Sciences (MS 604), University of Toledo, 2801 West Bancroft St., Toledo, OH 43606–3390 USA (email: kevin.egan@utoledo.edu and daryl.dwyer@utoledo.edu, respectively).

The authors thank two anonymous reviewers for numerous helpful comments. This is contribution #2010-08 from the University of Toledo, Lake Erie Center. The authors acknowledge funding under award NA06NOS4190185 from the National Oceanic and Atmospheric Administration, U.S. Department of Commerce through the Ohio Department of Natural Resources, Office of Coastal Management, and the Toledo Metropolitan Area Council of Governments.

reduced from 5,000,000 acres in the 1780s to about 483,000 acres in the 1980s (Dahl 1990). Much of the reduction occurred in northwest Ohio due to the tiling and draining of the Great Black Swamp; only 5% remains (Andreas and Knoop 1992).

Because water quality and biodiversity are linked to healthy wetland ecosystems, people have begun to recognize the value of wetland protection and restoration. Indeed, the Ohio Department of Natural Resources has stated that, “wetlands are almost unequalled in their benefits to humans...and unequalled in biological productivity.”¹ The focus of the study reported here was to determine the monetary value of restoring wetlands in Maumee Bay State Park (MBSP), focusing solely on the resulting MBSP beach recreation benefits due to the ability of restored wetlands to eliminate high levels of bacteria and thus eliminate the need for posting swimming advisories. MBSP is a major recreational destination in northwest Ohio for swimming, boating, fishing, and observing wildlife. An estimated 37,300 individuals visit the beach each season to swim.² From 1999–2004, densities of *Escherichia coli* (*E. coli*) at the beach have exceeded state standards (greater than five-day geometric mean standard of 126 colonies per 100 milliliters) for 148 days out of 546 seasonal recreation days. This indicates a potential health risk for recreational users of the beach. Research initially was conducted to determine the source(s) of bacterial contamination. Francy *et al.* (2005) concluded that Berger Ditch, which discharges 75 meters east of the MBSP beach, was a major source of *E. coli* (figure 1). A committee consisting of researchers and stakeholders prepared a study to determine the feasibility of restoring wetlands within MBSP to remove bacteria from the ditch water prior to its entering Maumee Bay. The wetland valuation study that is reported here was undertaken as part of this feasibility study.

Few studies have focused on valuing the recreational swimming benefits attained by improving water quality via restored wetlands. This study seeks to estimate the beach recreation benefits from reducing densities of *E. coli* below the threshold levels for swimming advisory postings. Respondents are told that wetlands would be restored in size and quality to eliminate the high bacteria levels at MBSP and hence eliminate the need for swimming advisories. The survey did not include any uncertainty as to the effectiveness of the restored wetlands.³ An appendix includes the survey language for the key elements of the scenario.⁴

The non-market valuation survey also briefly described other potential benefits from the restored wetlands, such as increased bird watching opportunities, but we focus only on the beach recreation benefits, as our sample of respondents were directly intercepted at the beach and asked about their current and future beach trips, under current conditions, or given the improved water quality due to the absence of any posted swimming advisories. The data obtained from the survey were analyzed using a recreation demand model that incorporated the observed trips (revealed preferences) and contingent trips (stated preferences), where the contingent trips to the beach were contingent on improved water quality. Throughout the remainder of this article, when we refer to the beach water quality improvement, we are referring specifically to the absence of posted swimming advisories. We utilized a random effects count data model, the multivariate Poisson-lognormal model, to analyze the pseudo-panel data.

¹ “Ohio Wetland Restoration and Mitigation Strategy Blueprint,” Ohio DNR, Ohio EPA, USEPA Wetland Grant Program, Federal Grant NO. CD985853-01-0, September 1999.

² Estimate provided by the Maumee Bay Regional Manager.

³ Note that we are not saying that the *E. coli* will be eliminated from the beach, just that it will always be reduced below the threshold for posting a swimming advisory. The State of Ohio does not close swimming beaches at its state parks, instead posts swimming advisories when high *E. coli* are measured.

⁴ The complete survey instrument is available from the second author at <<http://homepages.utoledo.edu/kegan2>>.

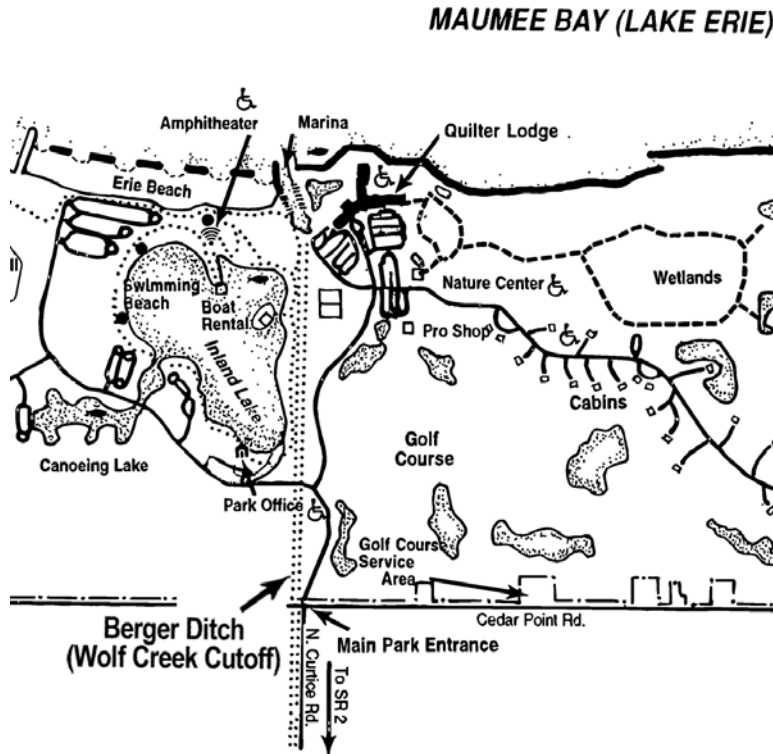


Figure 1. Aerial Sketch of Maumee Bay State Park

Literature Review

Several recreation demand papers utilize both observed and contingent trips to estimate the gains in consumer surplus that are attained by making improvements at swimming beaches. Most recently, Whitehead *et al.* (2008) report the additional consumer surplus from beach nourishment and parking improvements at 17 North Carolina beaches, utilizing a random population telephone sample and a random effects Poisson count data model (the multivariate Poisson-gamma mixture model (MPG), using Winkelmann's (2000) nomenclature). The reported average annual additional consumer surplus per person from beach nourishment was \$85.25 and \$392.97 for the improved parking.

Hanley, Bell, and Alvarez-Farizo (2003) estimated the value of coastal water quality improvements for visitors to seven south-west Scottish beaches. They cited epidemiological studies in the U.K. that demonstrate a link between pathogens in swimming beaches and gastroenteritis (Wyer *et al.* 1999). Their average additional consumer surplus per person estimates from perceived water quality improvements are \$8.53,⁵ with per trip estimates of \$0.70. However, their sample was collected on-site and they did not correct for the endogenous stratification, possibly leading to inflated annual values due to inflated trip counts (Egan and Herriges 2006). However, they correctly point out that their values may underestimate the welfare gains to the wider population, due to the exclusion of "new visitors" who would visit the beaches with the improved water quality.

⁵ A reported value of 5.81 pounds, converted to dollars using the exchange rate on April 11, 2009.

Whitehead, Haab, and Huang (2000) address this concern and show that with their population sample, a significant number of the current non-visitors state they will visit the resource given the hypothetical improved water quality. Their water quality improvement is broader, including improved wildlife habitat (60% higher fish catches and 25% more shellfish beds) and lower water pollution in the Albemarle and Pamlico Sound estuaries. They estimate the average additional consumer surplus per person to be \$34, where they average over many types of recreation participants (anglers, hunters, boaters, birders, campers, and beach visitors).

While Hanley, Bell, and Alvarez-Farizo (2003) did not control for the on-site sampling, they did control for the pseudo-panel nature of their data (each respondent provides multiple trip responses) by utilizing the same MPG as Whitehead *et al.* (2008) and Whitehead, Haab, and Huang (2000). Another paper using a sample collected on-site does the opposite, controlling for the on-site sampling but not for the correlated individual trips in their pseudo-panel data (Poor and Breece 2006). The data was analyzed using a pooled Poisson count data model in which the observed and contingent trips are assumed to be independent responses. Recreational angler's average additional consumer surplus for improved water quality in Chesapeake Bay was reported as either \$75 or \$44 depending on opportunity cost of time model specifications.

Recently, Egan and Herriges (2006) extended the existing univariate count data models corrected for on-site sampling to the multivariate case, where either a system of sites is modeled or each respondent provides multiple observed and contingent trip responses to one site. Therefore, it is possible to control for both on-site sampling and individual correlated trip responses. We follow Egan and Herriges (2006) and use the multivariate Poisson-lognormal random effects count data model (MPLN), as they found it fit the data better than the competing MPG.

Others have also concluded the Poisson-lognormal mixture model provides a better fit to the distribution of unobserved heterogeneity than the commonly used gamma distribution, possibly due to the appealing theoretical property that if the individual heterogeneity is due to many independent omitted factors, the central limit theorem justifies the normality of the heterogeneity term (Winkelmann 2000; Greene 2007). Moreover, Greene (2007) emphasizes the convenience of using the Poisson-lognormal mixture as a framework for several extensions he discusses, such as sample selection, zero inflation, and hurdle models. He concludes stating the Poisson-lognormal, "provides a unified framework that will accommodate other similar models with minimal change in the basic template" (Greene 2007, p. 37). Beyond panel data, the Poisson-lognormal distribution is also a flexible framework for a small system of demands as discussed in Shonkwiler (1995) and Moeltner and Shonkwiler (2010).

The concern of this article is using the MPLN model while controlling for on-site sampling. Many non-market valuation studies use sample data collected on site to cheaply target the users of the resource. These data misrepresent the study population because the sampling procedures exclude non-users (truncation) and over sample individuals who frequently use the site (endogenous stratification). On-site sampling directly truncates observed trip responses and tends to indirectly truncate contingent trip responses because of its correlation with observed trips (Egan and Herriges 2006). Several authors have stressed the importance of correcting for on-site sampling (Haab and McConnell 2002; Englin, Loomis, and Gonzalez-Caban 2001; Moeltner and Shonkwiler 2005; Egan and Herriges 2006). Failure to do so results in remarkable upward bias in both average number of trips to the sites and corresponding welfare estimates. For example, Egan and Herriges (2006) in a valuation study of water quality in Clear Lake, Iowa, found that failing to correct for on-site sampling produced substantial bias in both the estimated average number of observed and contingent trips, overstating the population trip levels by a factor of 14.

Data

The survey was designed to collect visitor information on three trip responses to MBSP beach. These include observed trips during the current season (y_{i1}), contingent trips based on current water quality (y_{i2}), and contingent trips based on improved water quality following wetland restoration (y_{i3}). Socioeconomic information about respondents (education level, household income, gender, age, and household size) was also gathered. The final survey was administered at the MBSP beach from July 4th through the beginning of September, 2006, and also two days during the summer of 2007 to increase the number of responses. The surveys were completed on-site. The survey administrators approached all groups on the beach, with one person from each group asked to complete the survey. Return boxes were placed along the edge of the beach near the parking lot where the respondents could place their survey upon completion. The chosen days for interception included mostly weekend days when the weather was favorable, as few visitors were at the beach during the week or during inclement weather.

In all, 360 questionnaires were administered to potential respondents; 260 during the summer of 2006 and an additional 100 during the summer of 2007. A total of 269 (74.7%) were returned. Respondents who traveled more than three hours to visit the beach (20 observations deleted) and those who made more than 52 trips to the beach (four observations deleted) were considered atypical and dropped from the sample. In order to have a balanced panel, those who failed to report any of the three trips were also dropped (67 observations deleted).⁶ This resulted in a final sample of 178 completed surveys. Those who failed to state their household income, age, and household size were assigned the sample mean. Table 1 provides summary statistics for the 178 usable, completed surveys. The information contained in table 1 is corrected for the fact that individuals who visit the MBSP beach more frequently are more likely to be intercepted and are over represented in the sample. The assumption is that a visitor who takes y_i trips to MBSP beach is y_i times more likely to be intercepted than a visitor who only takes one annual trip (Shaw 1988). Therefore, the reported means in table 1 for all the variables are weighted by the inverse of actual trips taken (Corrigan, Egan, and Downing 2009; Bin *et al.* 2005).⁷ The reported travel cost is based on vehicle costs per mile of \$0.25.

When calculating the additional consumer surplus from the improved water quality, we use the expected trips next season as the base, compared to the expected trips next season given the improved water quality, since the respondents were asked, "How many additional trips would you take to this beach next year if conditions were improved as described above?" On average, respondents reported taking about three trips per year to MBSP beach during the current season. They expected to take slightly more trips (3.8), on average, for the next season under current water quality. The respondents could be reporting higher expected trips next season due to new information provided in the survey about the beach, or because they are optimistic about their future trips. With the proposed restored wetlands eliminating the beach advisories due to high bacteria counts, the respondents report, on average, expecting to take about 5.2 trips per season to the beach, which is a 37% increase in the average number of trips. Of the 178 respondents, 108 (60.7%) reported that they would not increase their number of trips, 38 (21.3%) reported an increase of between one and five trips, and 32 (18%) reported an increase of greater

⁶ Eight of these 67 observations were deleted due to individuals not answering the dichotomous choice contingent valuation question. The contingent valuation data is analyzed elsewhere in the final report to the granting agency (Egan and Dwyer 2008).

⁷ The weighted means for any variable is calculated as: $weighted \bar{x}_i = \sum_{i=1}^n \left[x_i y_{i1}^{-1} \left(\sum_{i=1}^n y_{i1}^{-1} \right)^{-1} \right]$.

than five trips.⁸ Also, for the trip responses their standard deviation is at least twice the corresponding unconditional means; therefore, the unconditional variance is several times greater than the unconditional mean, indicating the problem of overdispersion in the sample.⁹ Our MPLN model allows for overdispersion.

Table 1
Summary Statistics for Weighted Data (n=178)

Variable	Mean	Std. Dev.	Minimum	Maximum
Observed trips (y_{1i})	3.02	7.72	1.00	40.00
Contingent trips under status quo (y_{2i})	3.81	8.40	0.00	40.00
Contingent trips with improved quality (y_{3i})	5.22	12.09	0.00	70.00
Travel cost (COST)	63.10	43.73	1.73	263.48
Income (INC)	83,382.95	44,523.71	7,500.00	200,000.00
Male dummy (MALE)	0.48	0.49	0.00	1.00
AGE	39.64	12.29	11.00	76.00
Education dummy (EDUC)	0.72	0.46	0.00	1.00
Household size (HH)	3.61	1.41	1.00	8.00

Table 1 also provides summary statistics on the respondent's socio-demographic characteristics. The "education" variable equals one if the respondent has attended some level of higher education and zero otherwise. Seventy percent of the sample has at least some college education, and the sample also has a relatively high average household income, indicating that more-educated, higher-income individuals are more likely to visit MBSP beach. The average age of the respondents is 40, and 40% of the respondents were male.

The travel cost (COST) variable represents the round-trip travel cost and was calculated using the formula, $COST_i = 2(g * \text{distance}_i + \frac{1}{3} \text{wage}_i * \text{travel time}_i)$, where wage is the average hourly wage rate calculated as the household's annual income divided by 2,000 (assuming 40 work hours per week for 50 weeks). The variable, g , is the vehicle cost per mile assumed to be either \$0.25 or \$0.33. As justification for these estimates, the American Automobile Association reports vehicle operating cost estimates (gasoline, maintenance, and tires) of \$0.17 per mile and depreciation estimates per year per mile of \$0.22, on average, assuming 15,000 annual miles, for a combined operating cost of \$0.39 per mile (AAA 2008). We follow Whitehead *et al.* (2008), and only include variable travel costs, but we use lower vehicle costs per mile, as we only consider a portion of the depreciation cost as a variable cost with the remainder being considered as a fixed cost for owning the vehicle. Our justification is that the vehicle depreciates every year regardless of how much it is driven. Since the estimated consumer surplus values from

⁸ We cannot rule out the possibility of respondents not answering truthfully, for example, by strategically inflating their contingent trips given the restored wetlands in order to increase the likelihood of them being built. However, Whitehead *et al.* (2010) and Jeon and Herriges (2010) provide evidence through convergent validity tests, and Grijalva *et al.* (2002) through construct validity tests, that respondents do not overstate trip-taking behavior for quality changes.

⁹ See Cameron and Trivedi (1998) who state, "if the sample variance is more than twice the sample mean, then data are likely to remain overdispersed after inclusion of regressors."

the recreation demand models are usually sensitive to the specification of the individual's travel costs, for the sensitivity analysis we report results assuming \$0.25 and \$0.33 vehicle cost per mile, due to the inclusion of 36 or 86% of the average vehicle depreciation cost. We estimate the opportunity cost of time at one-third the respondent's average wage rate.¹⁰ The software PC-Miler was used to calculate the distance and travel time from each household's zip code to the MBSP beach.

Summarizing other data collected in the survey, the majority of respondents, 78.3%, had visited MBSP beach before. The average time spent at the beach is four hours. When respondents were asked the open-ended question, "What would you have done during this time if you had not come to this beach?", the largest number of responses could be categorized as other leisure activities (103 responses), such as gardening or activities at home. Another 40 respondents listed house or yard work. Only five respondents listed they would have instead visited another beach, highlighting MBSP beach as a unique destination and supporting our usage of a single-site model. Notably, a higher number, 11, listed swimming at a pool as their alternate use of time. A following question asked respondents to list any other beaches they visit, with East Harbor State Park being the site mentioned the most (16 respondents). No other site was mentioned by more than four respondents.

Estimation Methodology

Since the three collected trip responses, y_i , are nonnegative integers, we chose to use a count data model. To account for the overdispersion and expected correlation between the trip responses, we use the multivariate Poisson-lognormal mixture model (Egan and Herriges 2006). As in Egan and Herriges (2006), our data is collected on-site; therefore, we also correct for on-site sampling. The on-site sample joint probability distribution for the three trip responses is:

$$g_1(y_{i1}, y_{i2}, y_{i3} | x_{i1}, x_{i2}, x_{i3}) = \left(\frac{y_{i1}}{\tilde{\lambda}_{i1}} \right) \iiint \frac{\exp(-\tilde{\lambda}_{i1})(\tilde{\lambda}_{i1})^{y_{i1}}}{y_{i1}!} \frac{\exp(-\tilde{\lambda}_{i2})(\tilde{\lambda}_{i2})^{y_{i2}}}{y_{i2}!} \frac{\exp(-\tilde{\lambda}_{i3})(\tilde{\lambda}_{i3})^{y_{i3}}}{y_{i3}!} \frac{\exp(-\frac{1}{2} \varepsilon_i' \Omega^{-1} \varepsilon_i)}{(2\pi)^{q/2} |\Omega|^{1/2}} d\varepsilon_i, \quad (1)$$

$$y_{i1} = 1, 2, \dots; y_{i2} = 0, 1, 2, \dots; y_{i3} = 0, 1, 2, \dots,$$

where $x_{i,q}$ is the vector of explanatory variables for each q trip response, and $\tilde{\lambda}_{i,q}$ is the expected trip responses from the Poisson-lognormal distribution. The multivariate Poisson distribution with parameters, $\lambda_{i,q}$, becomes a multivariate Poisson-lognormal distribution by including a multiplicative error, $v_{i,q}$, from a multivariate lognormal distribution, so that for any trip response the conditional expected value is:

$$E[y_{i,q} | x_{i,q}, v_{i,q}] = \tilde{\lambda}_{i,q} = \lambda_{i,q} v_{i,q} = \exp(\beta' x_{i,q} + \varepsilon_{i,q}), \quad (2)$$

¹⁰ While some papers directly address the estimation of vehicle cost per mile (Hagerty and Moeltner 2005) or the opportunity cost of time (Lew and Larson 2008; Larson and Shaikh 2004) for the whole sample most assume a constant average vehicle cost per mile and constant average opportunity cost of time. A wide range of assumptions is made, with the cited papers in the References section making the following assumptions: Whitehead *et al.* (2008) assume \$0.37 vehicle costs per mile and one-third inclusion of the respondent's average wage rate; Hanley, Bell, and Alvarez-Farizo (2003) assume \$0.15 vehicle costs per mile and no opportunity cost of time; Whitehead, Haab, and Huang (2000) assume \$0.20 vehicle costs per mile and the full inclusion of the respondent's average wage rate; and Poor and Breece (2006) assume \$0.34 vehicle costs per mile and one-fourth the respondent's average wage rate.

where ε_{iq} follows a multivariate normal distribution:

$$\varepsilon. \sim N(0, \Omega). \quad (3)$$

The solution to equation (1) requires multiple (Q) integration and has no closed form. However, this can be obtained using standard numerical procedures, such as Gauss-Hermite quadrature (Greene 2007), or simulation techniques. We follow Egan and Herriges (2006) and Munkin and Trivedi (1999) and use maximum simulated likelihood estimation.¹¹ Lastly, we marginally restrict the covariance matrix, Ω , from:

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 & \rho_{13}\sigma_1\sigma_3 \\ & \sigma_2^2 & \rho_{23}\sigma_2\sigma_3 \\ & & \sigma_3^2 \end{bmatrix}, \quad (4)$$

to

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho_1\sigma_1\sigma_2 & \rho_1\sigma_1\sigma_3 \\ & \sigma_2^2 & \rho_{23}\sigma_2\sigma_3 \\ & & \sigma_3^2 \end{bmatrix}, \quad (5)$$

by assuming that the correlation between the unobserved error component for the observed data (y_{i1}) and contingent data (y_{i2} or y_{i3}) is the same ($\rho_1 = \rho_{12} = \rho_{13}$).

As an alternative restriction to the above model, we replace the multivariate lognormal mixing distribution ($\varepsilon. \sim N(0, \Omega)$) with a univariate lognormal error ($\varepsilon_{iq} = \varepsilon_i \sim N(0, \sigma^2) \forall q$) so that $\sigma = \sigma_1 = \sigma_2 = \sigma_3$ and $\rho_1 = \rho_{23} = 1$. We call this restricted version the MPLN1 and seek to compare its parameter and benefit estimates with that from the more general MPLN. This restricted form mimics the MPG specification, except that a univariate lognormal error is utilized instead of a univariate gamma error (Whitehead *et al.* 2008; Hanley, Bell, and Alvarez-Farizo 2003; Whitehead, Haab, and Huang 2000). For the MPLN1 model the covariance matrix is simply:

$$\Omega = \begin{bmatrix} \sigma^2 & \sigma^2 & \sigma^2 \\ & \sigma^2 & \sigma^2 \\ & & \sigma^2 \end{bmatrix}, \quad (6)$$

showing that the unobserved heterogeneity for the three trip responses for each individual is perfectly correlated.

¹¹ The MPLN model is simulated using Halton draws, since fewer draws are needed compared to pseudo-random draws for any given simulation error level. We use 1,000 Halton draws in the simulation to ensure low simulation error. Gauss code for the simulated maximum likelihood estimation is available at: <<http://homepages.utoledo.edu/kegan2>>.

Completing the empirical specification, we specify the expected trip responses as:

$$\begin{aligned} \ln(\lambda_{i1}) &= \alpha_1 \text{CONSTANT} + \beta_{\text{COST},1} \text{COST}_i + \gamma' \text{DEMO}_i, \\ \ln(\lambda_{i2}) &= \alpha_2 \text{CONSTANT} + \beta_{\text{COST},2} \text{COST}_i + \gamma' \text{DEMO}_i, \\ \ln(\lambda_{i3}) &= \alpha_3 \text{CONSTANT} + \beta_{\text{COST},3} \text{COST}_i + \gamma' \text{DEMO}_i, \end{aligned} \quad (7)$$

where:

$$\gamma' \text{DEMO}_i = \gamma_{\text{INC}} \text{INC}_i + \gamma_{\text{AGE}} \text{AGE}_i + \gamma_{\text{AGE}^2} \text{AGE}_i^2 + \gamma_{\text{MALE}} \text{MALE}_i + \gamma_{\text{EDUC}} \text{EDUC}_i + \gamma_{\text{HH}} \text{HH}_i. \quad (8)$$

In equation (7), separate constant and travel cost coefficients are estimated for each of the three trip responses, but the coefficients on the socio-demographic variables are assumed to be equal.

Finally, the annual consumer surplus (CS) per person in each scenario, q , is calculated using the estimated travel cost coefficients ($\beta_{\text{COST},q}$) from the above model and the weighted mean number of beach trips from the corresponding scenario. That is:

$$CS_{iq} = \frac{\text{weighted } \bar{y}_{iq}}{\beta_{\text{COST},q}}. \quad (9)$$

The willingness to pay (WTP) for the beach's improved water quality, the elimination of swimming advisories due to high bacteria levels, can be calculated as the additional consumer surplus from the larger number of reported trips to MBSP beach:

$$\begin{aligned} WTP_i &= CS_{i,3} - CS_{i,2} \\ WTP_i &= \left(\frac{\text{weighted } \bar{y}_{i3}}{-\beta_{\text{COST},3}} \right) - \left(\frac{\text{weighted } \bar{y}_{i2}}{-\beta_{\text{COST},2}} \right), \end{aligned} \quad (10)$$

where $\text{weighted } \bar{y}_{i3}$ is the weighted mean of the contingent trips given improved water quality, $\text{weighted } \bar{y}_{i2}$ is the weighted mean of the status quo contingent trips, $\beta_{\text{COST},3}$ is the travel cost coefficient for the y_{i3} trip response, and $\beta_{\text{COST},2}$ is the travel cost coefficient for the y_{i2} trip response.¹² We follow Bin *et al.* (2005) in using the mean weighted actual trips in the consumer surplus and WTP estimations, as doing so controls for the endogenous stratification.

¹² It obviously would be incorrect to use the past observed trips, y_{it} , as the baseline, since the hypothetical scenario was forward looking, asking for trips next year given the water quality improvement.

Estimation Results

Estimation results of the MPLN model with three trip variances (σ_{iq}) and two correlation coefficients (ρ_1, ρ_{23}) evaluated at a vehicle cost per mile of \$0.25 (MPLN_\$0.25) and \$0.33 (MPLN_\$0.33) per mile are provided in columns 3 and 4, respectively, in table 2. Results of the MPLN with the three variance terms restricted to be equal and the correlation between the trips imposed as 1 (MPLN1) are shown in column 5 of table 2. The MPLN1 specification uses \$0.25 vehicle cost per mile. The corresponding parameter estimates across all three specifications are similar. The parameter estimates for travel cost are significant at the $\alpha < 0.01$ level across the three specifications. As expected, the travel cost parameters ($\beta_{cost,q}$) for all scenarios in all three specifications are negative, indicating that visitors living farther from the site are taking fewer trips due to higher travel cost. In general, observed trips (y_{i1}) appear to be more responsive to travel cost, while contingent trips (y_{i3}) assuming improved water quality are the least responsive to travel cost. Whitehead *et al.* (2008) found similar results, and we agree with their conclusion that this is evidence that the respondents are less sensitive to economic factors in a hypothetical situation.¹³ Also, the responsiveness to travel cost decreases as travel cost is more highly valued from \$0.25 to \$0.33 vehicle cost per mile. The trip variances are positive and significant at the $\alpha < 0.01$ level in all scenarios and models, thus indicating the presence of overdispersion in the data. The estimated variances for observed and contingent trips exhibit similar variability. The correlation coefficients for MPLN_\$0.25 and MPLN_\$0.33 are positive and close to one and significant at the $\alpha < 0.01$ level, indicating, as expected, high positive correlation between the unobserved factors of the observed and contingent trips. The estimated parameters on the male dummy and age are statistically significant at least at the $\alpha < 0.05$ level in all three models. The estimate on the male dummy is negative and high, indicating that males take fewer trips to the site than females. The parameter on age is positive (while the quadratic form is negative and insignificant), indicating that people take more trips as they get older.

Comparing the log-likelihood values indicates that using either \$0.25 vehicle cost per mile or \$0.33 fit the data equally well. Turning to the MPLN1 specification, a comparison of its log-likelihood value to the MPLN specification indicates it fits the data worse, but it also has four fewer parameters. Unfortunately, the likelihood ratio test is problematic in this instance, since the MPLN1 model represents a boundary restriction on the correlation parameters. However all of the trip variance and correlation coefficients have p -values of 0.00, indicating a rejection of this restriction. We also estimated two additional count data random effects models; the multivariate negative binomial 1 (MNB1) discussed by Winkelmann (2000), and the MPG. Both models were found to fit the data worse than any of the MPLN specifications reported here based on a likelihood dominance criteria, and contrary to Egan and Herriges (2006), the MNB1 did not fit this data set well.

Turning to the consumer surplus and WTP estimates (table 3), the average annual consumer surplus given improved water quality (CS_3) is always highest in all the models, as expected. The average per-person annual WTP for improved water quality is similar across the three models and ranges from \$160.77 to \$184.22. As expected, increasing the travel cost by 32% (from using \$0.25 to \$0.33 vehicle cost per mile), increases the mean annual WTP estimate by 11% (from \$166 to \$184) in the MPLN. Note that both of these vehicle cost per-mile estimates are conservative compared to official government reimbursement rates.¹⁴ However, Hagerty and Moeltner (2005) find a \$0.30 vehicle cost per mile is a “reasonable approximation” for their data, although their sample is dominated

¹³ We tested the restriction that the travel cost coefficients are equal across the three trip responses, and this restriction was rejected based on a likelihood ratio test at the 5% significance level.

¹⁴ For example, as of January 1, 2010, the official government reimbursement rate for a personal vehicle was \$0.50 per mile. See <www.gsa.gov/mileage>.

by SUV's towing jet skis; thus our sample of beach recreators can reasonably be expected to have lower perceived vehicle costs per mile. Therefore, we prefer the MPLN_\$.025 specification and use its results for estimating the aggregate WTP estimates.

Table 2
MPLN Regression Results^a

Variable	Coefficient	Coefficient Point Estimate (Std. Err.)		
		MPLN_\$.025	MPLN_\$.033	MPLN1
Constant (y_{i1})	α_1	0.226 (0.341)	0.283 (0.342)	0.337 (0.392)
Constant (y_{i2})	α_2	0.508 (0.333)	0.566 (0.335)	0.507 (0.391)
Constant (y_{i3})	α_3	0.612 (0.336)	0.671 (0.339)	0.784 (0.391)
Travel cost (y_{i1})	$\beta_{COST,1}$	-1.767** (0.202)	-1.561** (0.176)	-1.736** (0.244)
Travel cost (y_{i2})	$\beta_{COST,2}$	-1.457** (0.177)	-1.289** (0.155)	-1.417** (0.227)
Travel cost (y_{i3})	$\beta_{COST,3}$	-1.238** (0.170)	-1.103** (0.149)	-1.245** (0.216)
Income	γ_{Inc}	0.240 (0.129)	0.208 (0.127)	0.209 (0.227)
Male	γ_{Male}	-4.048** (0.854)	-4.028** (0.846)	-4.692** (1.353)
Age	γ_{Age}	0.367** (0.142)	0.357** (0.137)	0.423* (0.185)
Age ²	γ_{Age^2}	-0.028 (0.020)	-0.027 (0.019)	-0.044 (0.025)
Education	γ_{Edu}	-1.089 (0.839)	-1.012 (0.831)	-0.915 (1.415)
Household	γ_{HH}	-0.082 (0.243)	-0.094 (0.247)	0.035 (0.449)
y_{i1} trip variance	σ_1	0.906** (0.063)	0.901** (0.063)	
y_{i2} trip variance	σ_2	0.891** (0.057)	0.886** (0.056)	
y_{i3} trip variance	σ_3	0.989** (0.059)	0.984** (0.059)	
y_{i1} , y_{i2} , and y_{i3} trip variance	σ			0.894** (0.059)
σ_1 and σ_2 correlation or σ_1 and σ_3 correlation	ρ_1	0.935** (0.015)	0.934** (0.015)	
σ_2 and σ_3 correlation	ρ_{23}	0.999** (0.002)	0.999** (0.002)	
Sample size		178	178	178
Log-likelihood		-1,368.81	-1,368.20	-1,386.49

^a All of the coefficients are scaled by 100, except the constants (which are unscaled) and the income coefficient (which is scaled by 100,000). Standard errors are in parentheses. * and ** indicate statistical significance at 5% and 1% levels, respectively.

Table 3
Consumer Surplus Estimates for Current/Improved Water Quality Scenarios and the Mean Annual WTP per Visitor to Improve Water Quality Conditions^a

	Mean Annual Consumer Surplus		
	MVPLN_\$.025	MVPLN_\$.033	MVPLN1
CS ₁	174.88 (21.30)	197.89 (23.72)	179.82 (28.15)
CS ₂	265.39 (34.30)	299.68 (38.17)	277.56 (51.20)
CS ₃	431.39 (61.97)	483.90 (68.05)	438.34 (91.94)
	Mean Annual WTP for Water Quality Improvement		
WTP (CS ₃ - CS ₂)	\$166.00 (45.66)	\$184.22 (50.54)	\$160.77 (56.59)
	\$(91.72 - 264.80)	\$(102.04 - 294.13)	\$(83.99 - 293.11)

^a Standard errors are in parentheses.

Turning to the WTP estimate from the MPLN1 specification, we see that the estimate is only \$5.23 lower (3.2% change) than the corresponding MPLN_0.25 specification WTP estimate, and the 95% confidence intervals for the WTP estimates overlap.¹⁵ Thus, while there is likely a statistically significant difference between the restricted MPLN1 specification and the MPLN specification in regards to fitting the data, there is no statistically significant difference for the WTP estimates. Our overall conclusion is that there is no economically significant difference, as we observe similar fitted coefficients and WTP point estimates. Moreover, assuming perfect correlation for the unobserved heterogeneity for the three trip responses from each individual ($\sigma = \sigma_1 = \sigma_2 = \sigma_3$ and $\rho_1 = \rho_{23} = 1$) is a reasonable assumption for our pseudo-panel data, where the estimated correlation coefficients in the MPLN specification are close to one anyway (0.93 to 0.999), and the three trip response variance terms are similar (0.89 to 0.99). However, if the MPLN count data model was being used to estimate a small system of demands, such as a group of five or six nearby beaches (*e.g.*, Shonkwiler [1995] or Moeltner and Shonkwiler [2010]), then the MPLN1 specification may be a more serious economic restriction on preferences, as it would restrict all of the sites to having nonnegative covariances, whereas the MPLN specification allows for an unrestricted correlation structure (Winkelmann 2000).

Considering that 37,300 visitors visit the site annually, on average, and using the mean annual WTP of \$166 per person based on the MPLN_0.25 model, we calculated the aggregate benefit from the improved water quality at the MBSP beach to be \$6.19 million annually. Note that this value has been underestimated because we only surveyed existing beach visitors, and there could be new visitors due to the improvement in water quality. Also, we have only estimated the WTP of the beach visitors from the restored wetlands, and no WTP has been included from visiting the wetlands directly.

Conclusion

This article estimates the recreational swimming benefits of restoring nearby wetlands to value wetland potential for bacterial contamination reduction and the elimination of swimming advisories at Maumee Bay State Park beach. Data for the study was collected on-site, and respondents were asked to report their actual number of visits made to the beach during the past season and the anticipated number of trips in the upcoming season under current water quality and given improved water quality due to restored wetlands. We jointly model observed and contingent trip responses using three versions of the multivariate Poisson lognormal models while correcting for on-site sampling. In the first two, we allow all three trips to exhibit different variances and different correlation coefficients. However, travel cost in model one is evaluated using \$0.25 vehicle cost per mile, while travel cost in model two is evaluated using \$0.33 vehicle cost per mile. In the third model, we restrict the variances of all three trip responses from each individual to be equal and set the correlation coefficients equal to one, imposing perfect correlation between the trip responses.

We found that the WTP estimates from the three models used were not very different from each other, indicating the MPLN1 specification is an economically reasonable restriction with pseudo-panel data. Also, we found that increasing the vehicle cost per mile by 32% results in about an 11% increase in WTP. Finally, using an average per-person consumer surplus of \$166 estimated from model two (MVPLN evaluated at \$0.25 vehicle cost per mile) and an estimated 37,300 current annual visitors to the beach, we estimated the aggregate WTP of the wetland restoration to be \$6.19 million annually. Note this WTP estimate only includes the increased trips from current visitors and excludes potential new

¹⁵ For all the WTP estimates we constructed standard errors and confidence intervals using the Krinsky and Robb (1986) technique.

visitors. Based on a benefit-cost analysis and our partial estimate of the benefits from restoring additional wetlands at MBSP, it is efficient for policy-makers to incur costs up to approximately \$6.2 million annually to ensure the elimination of high bacteria levels at MBSP beach and thus eliminate swimming advisories.¹⁶

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¹⁶ A very preliminary estimate of the cost to build the proposed restored wetlands is a \$1.8 million one-time cost with small maintenance costs, indicating a potentially large net benefit from the project (Hull & Associates, Inc. 2007).

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Appendix

Portions of the Maumee Bay State Park Beach Survey:

II. SWIMMING ADVISORIES

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From 1999–2004, the following swimming advisory was posted at the Maumee Bay State Park Beaches a total of 148 days:

Water Quality Advisory – Bacterial levels here currently exceed state standards. Children, the elderly and those in ill health are advised not to swim.

For the 2006 season, swimming advisories are posted based on the past days E. coli bacteria measurements. The high (i.e., exceeding state standards) bacterial levels in the water increase the risk of illness to people who swim in it.

Possible Symptoms from Exposure to High Bacterial Levels

- Nausea
- Stomach cramps
- Sore throat
- Diarrhea
- Eye, ear, skin, & respiratory infections

III. EXPECTED TRIPS

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1. How many trips do you expect to take to this beach **next year (2007)**? _____

IV. POSSIBLE RESTORATION OF WETLANDS

Experts predict that restoring natural wetlands, which used to exist extensively in this area, will improve the water quality at Maumee Bay State Park Beach.

Benefits of Restored Wetlands

- **Elimination of high bacterial levels (i.e., 0 swimming advisories)**
- Bird watching or other wildlife observation
- Improved spawning habitat for sport fish
- Increased numbers of endangered wildlife species and rare plants native to Ohio

1. How many **additional trips** would you take to this beach next year (2007) if conditions were improved as described above?

_____ I expect to take the same number of trips.
 _____ I expect to take additional trips. How many more? _____

