Estimating the Recreational Consumer Surplus at Maryland's State-Owned Forests

Prepared for
Harry R. Hughes Center for Agro-Ecology

By
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Independent Economic Analysis

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1. Introduction to the Travel Cost Model

The money and time that individuals spend to travel to a park or forest can be used to measure the value of their outdoor recreation experience. An extensive economic and statistical literature has been developed to analyze these time-and-money costs, known as "travel costs." The underlying concept and the set of analytical tools used to advance it have been applied to fishermen, beachgoers, hikers, birdwatchers, wildlife-viewers, picnickers, mountain bikers, and many others. This research generates measures of the value of a fishing spot, beach access, a hiking opportunity, and so on. Travel cost analysis thus presents a useful framework in which to examine the recreational values of Maryland's State-owned forests[1]. Note that this approach estimates the value of recreation to the users, that is, the recreationists. It is important to recognize that the approach does not measure the value of the forest to the local economy, which is a separate concept.

Travel cost estimates of the value derived from outdoor recreation assume a *revealed preference* in the relationship between participants' costs of traveling to a site and the number of trips that they take. Individuals who live farther from a site incur greater time and money costs to visit the site and therefore typically make fewer trips over any given time period. In simple terms: if people are willing to spend $\$X$ per trip to visit and use a site y times, they must get satisfaction worth at least $y \times \$X$ from doing so. This idea can be used, as described below, to estimate recreational value on a per-trip basis. Value in this context is what economists label "consumer surplus". Consumer surplus is a quantitative, dollar-denominated measure of the net benefit that a consumer derives from being able to obtain a good or service at a given price. It is the difference between what an individual is willing to pay for the items he purchases and what he actually has to pay. For regular market goods, we can define (and hope to measure) the consumer surplus that the individual receives for each unit that he purchases. For non-marketed goods such as recreation, which have only implicit prices, we typically can measure only the average consumer surplus per unit; that is, per trip.

Travel cost analysis requires us to measure the time and money costs of visiting a site. To gather the requisite information for this analysis, we conducted visitor surveys at Patapsco Valley State Park, Shad Landing State Park (Pocomoke), and Green Ridge State Forest from September 2005 to August 2006. A total of 461 surveys were conducted. Visitors were asked their trip distance, transit time, number of trips per year, and personal characteristics, including income, age, and education. These data are the essence of travel cost analysis. The surveying took place at high traffic areas at each site; for example near the ranger's office or near the camp store. On the chosen survey days the enumerator started mid-morning and continued until late afternoon. Such surveys must be quick and uncomplicated – individuals are eager to get on with their recreational

[1] The term "State-owned forests" is used throughout this paper as the frame of reference for the recreational values that are being estimated. These forests include State Parks and State Forests, among other state-owned forestland. While these different categories of forests have different management objectives, they all provide a similar basis for forest-based recreation, which was the parameter of interest in this study.

experience. Only rarely, however, is the surveyor turned down. Survey protocol is described further throughout Section 3.

Due to the quick and spur-of-the-moment nature of the surveying, travel cost data are rough but still quite useful and informative. Researchers, including this study, almost invariably find that a higher per-trip cost is associated with a lower number of trips, which is the basic relationship that motivates travel cost analysis. Other data problems arise not from the nature of the survey but from the limited variety of recreational experiences available. Ideally, researchers would like to compare visits between forests managed in one way versus otherwise-identical forests managed in some other way; such comparisons are rarely possible.

Along with data problems, many conceptual issues in travel cost remain unresolved even sixty years after the method was first proposed. For example, a conceptually sound treatment of overnight visits when some parties stay more nights than others has not been developed. Other conceptual issues, such as the role of site congestion and the treatment of multiple destination trips have been addressed to some degree but remain areas meriting further research. Even a principal focus of travel cost analysis, measurement of the value of the time cost of travel, is not fully settled (Smith, 1997).

Travel cost analysis is vital, however, even with these rough data and uncertain conceptual issues, because outdoor recreation is a highly valued experience and a key motivation for environmental protection and management. Travel cost analysis remains our best tool for valuing the recreational experience (Haab and McConnell, 2002).

Our analysis shows that visitors to the three study sites derive considerable utility from recreation there. Using the model described below, we estimate a per trip consumer surplus of $96 for day users and roughly $400 for overnighters. This "per trip" value can be combined with DNR data on the number of visitors to yield a measure of annual consumer surplus generated by access to these parks and forests.

Travel cost analysis is largely an exercise in survey methodology and statistical analysis. Readers who are interested in our bottom line results and general discussion should skip to Section 5, which is presented for readers unfamiliar with the technical issues of travel cost analysis.

2. Model for On-site Sampled Visits

The essence of a travel cost model is the relationship between (i) the number of trips a household makes per year to a given site and (ii) the cost per trip. Many functional forms can be used to capture the relationship between these two items. We model the natural log of the number of visits to the site per year reported by each survey respondent as a linear function of the per-trip costs he must incur and various personal characteristics. Under this format the coefficient on the cost variable is the inverse of the consumer surplus per visit. The basic model is given by:

$$\ln y = \alpha C + X\beta + \varepsilon \qquad (1)$$

where *y* is the trips per year by the survey respondent, *C* is his per-trip cost, *X* represents other individual characteristics, and *ε* is a normally distributed individual-specific element. Note that we expect, and uniformly find, $\alpha < 0$. That is, the greater the cost-per-trip, the fewer the number of trips. This model with a logged dependent variable and linear variable of interest, *C*, is also referred to as the semi-log.

The main alternatives to the semi-log include the Poisson and negative binomial. Both of these are discrete distributions: the number of trips can take on only integer values; for example, the respondent can only have taken 1, 2, 3 …etc. trips. In travel cost analysis these are also called count models.

The lognormal model in (1) has key advantages over the Poisson and negative binomial. It accommodates not only the typical individual (one with, say, 1, 2, or 3 trips per year) but also individuals who report: (i) less than one trip per year (e.g., "once every five years"), (ii) a range of number of trips per year, or (iii) a great many trips. These three types of visitors are common in our data but do not appear to have been considered or modeled in most of the travel cost literature. These individuals are either excluded from or "converted" for other common econometric models.

The log-normal's advantages actually consist of two distinct properties. As a continuous rather than discrete function it can include the first two types of individuals. Among continuous function specifications, the log format then provides a good fit for trip distributions that include many small numbers of trips and a few very large ones, which characterize our data (see histograms). This latter property can be accommodated by the negative binomial, but that model is difficult to work with and only allows an integer number of trips. Preliminary analysis showed a better fit for the lognormal than the negative binomial with all *y* converted to integers; we did not pursue the negative binomial further.

The cost per trip enters linearly in (1). In this case, the annual surplus over all trips for individual *i* has a closed-form solution given by:

$$S_i = -\frac{y_i}{\alpha} \qquad (2)$$

To get (2), transform (1) to $y = e^{\alpha C + X\beta}$ and integrate from C_i to ∞.

The surplus per trip is $-1/\alpha$. Surplus-per-trip is the commonly reported result in the travel cost literature. We also calculate the surplus accrued by all users (total surplus) in a given year by multiplying the total number of visits (as reported by the Maryland Park Service and individual State Forests) by $-1/\alpha$.

The observations of *y* and *C* that will be used to estimate equation (1) come from a sample of visitors, not the entire set of visitors. Sampling gives rise to two potential concerns: endogenous stratification and truncation. Both effects were first rigorously examined in Shaw (1988).

Endogenous stratification means that individuals who make a lot of trips are disproportionately represented in the sample, relative to their proportion of the population. Consider the following example based on Haab and McConnell (2002): Suppose there are 100 individuals, 75 of whom make 2 trips per year and 25 of whom make 1 trip per year, for a total of 175 trips. If we sample 25 trips (one-seventh of the number of trips) and if no individual is sampled twice, then our 25 trips will likely consist of ≈21 individuals who take 2 trips per year and ≈4 individuals who make 1 trip per year. The reason is that 2-trip individuals account for 6/7 of the total number of trips (150/175 = 21.4/25) and 1-trip individuals account for 1/7 of the total number of trips (25/175 = 3.6/25). Endogenous stratification arises because researchers are taking a sample of trips not a sample of visitors, even though visitors are the basis for the underlying consumer surplus calculations.

The estimates below do not account for stratification, for three reasons. First, the appropriate correction for (endogenous) stratification has not been derived for the semi-log model. Second, stratification does not bias our estimates. Stratification means that the observed costs are lower-than-average (for the population of visitors), but this affects only the distribution of covariates and does not bias estimates of α. Third, stratification would be important if we were using (1) to predict the aggregate number of visitors to a Forest. We instead use Park Service numbers for the aggregate number of visitors.

Truncation arises because only individuals who make a trip are surveyed; that is, $y > 0$. Truncation is a problem primarily when the estimates are used to predict the consumer surplus of any new visitors; that is, new visitors who might come to the Park as a consequence of a change in environmental quality (see Section 5.1). When equation (1) is estimated without a correction for sample selection ($y > 0$), no-trip individuals are not a random sample of the population and therefore their demand curve is not captured by (1). In other words, their consumer surplus may be systematically different from existing visitors. Statistical correction for this problem is difficult, since it requires predicting who visits or does not visit a park, based on observable characteristics, primarily the population of each zipcode.[2] Since the gains from such correction are likely to be small, we do not correct for truncation.

3. Data

3.1 Data Collection and Protocol

Data for the model were gathered through visitor surveys enumerated at Patapsco Valley State Park, Shad Landing State Park (Pocomoke), and Green Ridge State Forest. Key

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[2]For example, individuals from zipcode *Z* may have fewer visitors than predicted by (1), based on our estimates of zipcode-average costs (see section below). This fact could be used in the estimation of (1).

information gathered from survey respondents included zipcode at their starting-place, number of visits per year, time and distance traveled, income, money costs of travel, and age and other socio-economic characteristics.
Patapsco Valley State Park is a forested band tracking a considerable length of the Patapsco River through Central Maryland to near its outfall to the Chesapeake Bay. Within the park there are a number of different facilities (e.g., camping, picnic pavilions, hiking and biking trails, playgrounds, etc.) which are geographically convenient to Baltimore residents. Shad Landing State Park is within Pocomoke State Forest, on the Lower Eastern Shore of Maryland. It is about 120 miles from the large population centers around Baltimore and Washington and it also has a number of different park facilities, including a dock and boat landing providing access to the navigable Pocomoke River. Green Ridge State Forest is located about 120 miles west of Baltimore in Western Maryland. It has primitive camping, target ranges, and bike, hiking and ATV trails. It bounds the Potomac River on its southern edge and approaches the Pennsylvania border on its northern edge.

The forests at these three survey sites have different characteristics but each is part of a large forested area which provides a basis for natural amenities and outdoor recreation. All of them are opened to the public under similar time limitations. Patapsco collects a $2 per person fee for day visitors but neither Green Ridge nor Pocomoke have a day use fee. Descriptive statistics of the sites and samples from each are reported in **Table 1**.

Table 1: Descriptive Statistics for Sample Sites and Samples

		Patapsco	**Green Ridge**	**Pocomoke**
Annual visits	O/night	15,326	10,633	27,124
	Day	825,669	16,294^	69,057
Day-use fee		$2	0	0
Camping fee*		20/25/50	10	25/30/50
#Completed surveys		211	135	115
Travel distance, miles (mean)		24	118	132
Overnight stay, # of nights (mean)		2.3	2.2	3.5
Day use, hours (mean)		2.9	3.8	2.5

* Dollar costs for each of three options: Basic/electrified/cabin
^ People who register at HQ, an unknown fraction of total day visitors.

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In enumerating the questionnaire for the study, responses were elicited from only one person per party. Visitors younger than 18 years of age were excluded from the sample by research guidelines. Therefore, families were generally enumerated through one of the parents. Among couples, an effort was made to keep male and female response frequencies similar by so instructing enumerators.

3.2 Sampling Strategy

We first chose the number of survey visits to make for each site based on our survey budget and the number of visitors to that site in the preceding year. Our survey budget allowed us to conduct 34 days of surveys. We apportioned these 34 survey-days across the three sites roughly according to their total annual visitors. Because Patapsco so dominates visit rates, however, we adjusted the shares such that Patapsco was targeted at one half the intensity of the other two sites. This set of decisions generated a sample set of 8, 15, and 11 days for Green Ridge, Patapsco, and Pocomoke respectively.

Each of the sites was then surveyed on a schedule determined through a random draw procedure. For each site we used data on visits-per-day from the previous year to calculate the proportion of yearly visits expected for each day and from this we constructed the cumulative distribution of visits over the year, for each site. We then randomly drew 8, 15, and 11 numbers from a uniform [0,1] distribution. The chosen survey date was the date for which the cumulative proportion of visits was equal to the random number, with an adjustment for the yearly shift in dates and days. Some substitutions were made in the implementation of this schedule due to surveyor availability. Actual survey dates are listed in **Table 2**.

Table 2: Survey Sampling Dates for 3 Maryland Forests*

Green Ridge	Pocomoke	Patapsco
9/10/05	8/24/05	8/20/05
10/8/05	9/30/05	10/29/05
11/4/05	10/10/05	4/23/06
11/5/05	11/11/05	5/6/06
11/26/05	5/26/06	5/7/06
5/1/06	5/27/06	5/13/06
8/11/06	7/2/06	5/25/06
8/12/06	7/6/06	5/26/06
	7/7/06	5/27/06
	7/26/06	6/17/06
	7/27/06	6/10/06
	8/4/06	6/11/06
		7/7/06
		7/8/06

* Weekdays (Monday through Thursday) are highlighted in green.

An alternative to this random-date approach is to choose survey dates to maximize the number of surveys per day; namely, to survey on pleasant weekend days in May and June, which have the most visitors and would yield the most completed surveys per enumerator-day. The random date-selection approach provides potentially superior information by allowing us to observe visitors who might be missed by high-visit-day sampling. Sampling on high-visit days could miss high- or low-value visitors or those with other unusual characteristics who come on less-visited days. Sampling strategies for travel cost models have often been overlooked in previous studies and their effects on estimated values remains unknown.

Our random-date selection plan is useful but possibly not optimal. A better approach would be to include the weather and relationships to holidays when deriving the sampling weights based on previous visitor data. Note that the value of this sampling strategy remains to be determined. If the population of visitors were constant throughout the year and if the number of sampling dates was fixed then it would be optimal to sample the highest-visits days. Furthermore, some last minute adjustment due to weather seems optimal since visitors will also be reacting to the daily weather, but it is difficult to know how to incorporate this information in choosing sampling dates.

3.3 Number of Visits and Sample Selection for Analysis

We asked individuals the number of visits they make to this forest in a typical year. In the analysis, an individual who claims to make one trip every three years is recorded as $y = 0.33$. An individual who claims to make a range of trips per year such as "2 to 3" is recorded as $y = 2.5$. Integer numbers of trips are treated as-is.

Histograms below (Figures 1-3) show the proportion of sampled visitors at each of the three forests who reported making x trips to that forest per year.[3] There are numerous people who visit the State Forests weekly or even more frequently; roughly 10 percent of visitors to all three sites make more than 25 visits per year. These people tend to live close to the forest and are calculated to experience high amounts of consumer surplus. Our data bear out this simple observation: Forests close to people are highly valuable.

We made two further adjustments from the raw data to the data that we analyzed. First, for $y < 0.2$ we set $y = 0.2$. When we work with log y, small values of y become particularly wide outliers. We limit this influence with a reasonable but admittedly arbitrary truncation. This truncation affects 7.4, 2.6 and 4.7 percent of visitors to Green Ridge, Pocomoke, and Patapsco, respectively.

Second, we drop all day use respondents who have traveled a very long distance; greater than 140 miles as measured by either reported or zip-code based distance, most of whom had multiple destinations. This removed 17 observations from the day-use sample set. The value these individuals place on their visit to the Forest should not be ignored, but such a value is difficult to estimate; furthermore, these individuals' trips do not belong in the same model of behavior as local visitors. We did not drop long trips for overnight

[3]Figures 1-3 are based on the set of visitors for whom we have valid responses on "number of visits," but not necessarily other valid data such as travel costs or distances. Therefore the samples used to generate these Figures are close but not identical to the samples used for estimation.

visitors, as these were quite common and the incidence of “multiple destinations” was much lower for that set of observations.

The other assumption we make is that all of an individual’s reported trips are identical in terms of costs, distance, and format (day-trip versus overnight). That is, when a survey subject reports making 3 trips per year, we assume each trip was made from the same starting zip code and that the trips were either all day trips or all overnight trips. This assumption is common in the literature and indeed unavoidable using the current survey questions, but clearly deserves deeper scrutiny.

Using the restrictions described above, we generated a measure of visits made in a year by each respondent to serve as our independent variable for estimating cost effects on visits.

Figure 1: Portion of Sample by Number of Annual Visits (Patapsco)

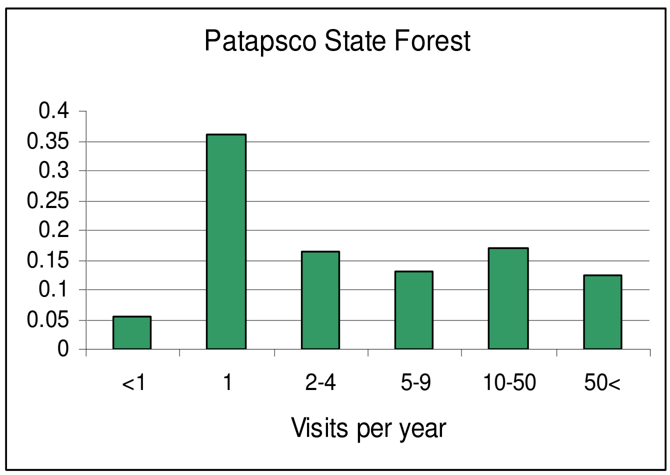


Figure 2: Portion of Sample by Number of Annual Visits (Pocomoke)

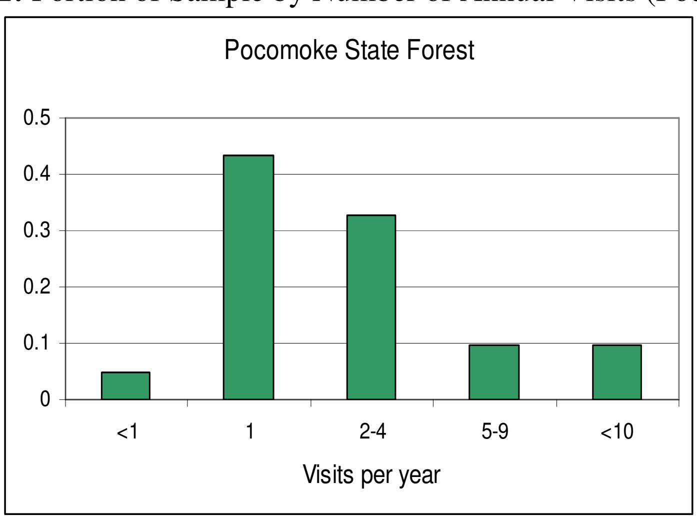
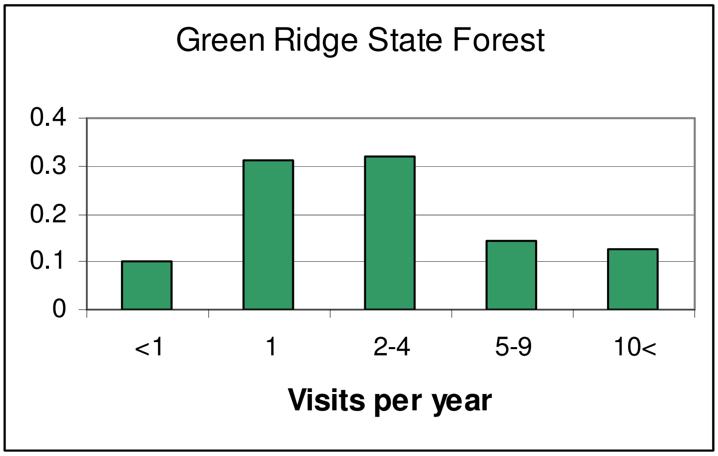


Figure 3: Portion of Sample by Number of Annual Visits (Green Ridge)



3.4 *Distance, Time, and Travel Cost*

The basic premise of the travel cost model is that the cost of a recreational trip provides a bound on the value of the destination to the person taking it. Making empirical use of this insight requires that the per-trip cost be accurately specified. We calculate this cost by multiplying how far the visitor lives from the forest (in distance and in travel time) by the cost-per-mile (for budgetary travel costs) and cost-per-hour (for the opportunity cost of time), respectively. This cost is shown in (3):

$$C = (\text{Roundtrip distance} \times \text{Cost-per-mile}) + (\text{Roundtrip travel time} \times \text{Per-hour time cost}) + \text{Entrance fees} \tag{3}$$

where C is the cost variable in equation (1).

We use a standard rate of $0.33 per mile for the cost per mile. Although some studies attempt to account for the specific vehicle used for the trip, since some vehicles have higher per-mile costs than others, we applied the same per-mile cost to all households.

Thus, we must measure 3 remaining variables: distance, travel time, and per unit time cost. These are different for each respondent. Of the three variables, per unit time costs have garnered by far the most attention in the travel cost literature.

Our analysis does not examine the time spent enjoying recreation at the site. McConnell (1992) suggests that when the on-site time is valued at a constant rate, one can ignore the time costs of time spent at a site. The reason is that the on-site time is endogenous, and therefore the area under the demand curve for trips (without conditioning on the time spent at the site) is the correct measure of the value of site access.

Such a result does not, however, allow us to treat day and overnight trips in a single undifferentiated model. The reason is that individuals who take day trips are at a corner solution with respect to staying overnight; therefore, the McConnell argument does not directly apply to overnight visitors. Day-trip individuals who decide to spend more time on-site incur no further costs except for the opportunity cost of time. Individuals who decide to overnight must incur an extra cost (*i.e.*, lodging). In addition, it is reasonable to assume that the opportunity cost of time is different for a day trip than an overnight visit. In our analysis we therefore distinguish two different sets of visitors: day visitors and overnight visitors and calculate separate measures of per-visit consumer surplus.

A further complication remains in accounting for overnight lodging costs, even when visitors are estimated in a separate model. The McConnell argument that researchers can ignore time spent on-site (albeit with some qualification) relies on the fact that additional time spent onsite is valued in exactly the same way as travel time, that is, as the opportunity cost of time. This is obviously not true with overnight visits, since an overnight visit incurs a discrete cost (e.g., the cost of lodging) that varies with the on-site time. In a sense, the individual is at one of several corner solutions with respect to whether to stay n nights. This problem would disappear if all overnight visitors stayed the same number of nights; in this case, the total lodging cost would be added to (3). Of course, overnight visitors do not all spend the same number of nights, so this solution is of little practical value. (A unified treatment of overnight and day visitors would remain elusive even if all overnight visitors stayed the same number of nights, although presumably some conceptual resolution would eventually be derived for such a situation.)

Larson (1993) presents a joint model of number of trips and time spent on-site, although for a different purpose. He argues that travel time may have a different opportunity cost (which may be positive or negative, depending on whether traveling is a source of pleasure) from on-site time. Although such a model might be extended to treat overnight visits, such an extension has not yet been published.

An alternative approach, and the approach we adopt in this analysis, is to (implicitly) treat overnight visits as a continuous variable with a continuous cost. The approximately correct treatment under this approach is to add the unit cost (per-night lodging) to the travel cost in (3), in the spirit of McConnell and then to treat number of nights as endogenous and therefore subsumed in the consumer surplus calculation, (2). Treating discrete variables as continuous has a long tradition in economic analysis, both empirical and conceptual.

3.4.1 Travel Distance

Survey respondents were asked both the distance and time for their trip. Because individuals are often uninformed about the distance they traveled, we also calculated a separate measure of travel distance using the imputed distance between the reported home zip code and the survey sites based on Google. The Google distance can also be computed for individuals who did not report their travel distance.

When we examined the differences between Google distance estimates and reported travel distances we found that Google distances were on average 10 percent longer than reported distances. Some discrepancies are due to trips having originated at the home of friends or family rather than the subject's home. In order to examine the effect of the measure of travel distance on estimates of consumer surplus, we ran separate regressions using reported and Google distances as described below. Among Google distances we dropped six observations for which those distances were five or more multiples of reported travel distance, since these responses either have an error in the reported distance or else represent a different sort of demand.[4]

3.4.2 Travel Time

The measurement of travel time (i.e., travel duration) raises similar issues to those described for distance. Although the travel time question had fewer missing answers than travel distance, we used Google to estimate travel times to provide consistent measures of reported versus zip-code-based travel estimates. Google travel times were on average 8.8 percent longer than reported travel times. The data used in our final sample are summarized in **Table 3**.

Table 3: Summary Statistics of Recreational Visit Data

		Entire Sample			
Variable	Obs	Mean	Std. Dev.	Min	Max
Truncated Visits	439	12.50	34.39	0.2	365
Income (Reported)	398	71420	34637	7500	127500
Median Inc. (Census)	428	53791	19384	13750	140222
Reported Distance	439	70.94	79.84	0.1	500
Zip-Code Distance	436	76.89	107.11	0	1583
Reported Travel Time	439	1.49	1.60	0.017	9
Google Travel Time	438	1.64	1.87	0	19.267
Age	439	41.19	13.13	18	81
		Day Use Visitors			
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Truncated Visits	232	20.98	45.57	0.2	365
Income (Reported)	207	69457	35186	7500	127500
Median Inc. (Census)	228	52967	19537	13750	140222
Reported Distance	226	26.29	30.47	0.1	137
Zip-Code Distance	229	28.10	33.37	0	137
Reported Travel Time	232	0.62	0.68	0.017	5
Google Travel Time	231	0.77	1.44	0	19.267
Age	232	41.11	13.95	19	81

[4] It is likely that a Google distance of 948 miles compared to a reported travel distance of 20 miles is an instance of the trip originating somewhere different from the person's home (such as a friend's home). The relevant travel cost for this particular trip is the local distance but the overall number of trips depends more on the longer home-based distance. Because of this discrepancy we must drop such observations, although the cut-off comparison is necessarily arbitrary.

Overnight Visitors					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Truncated Visits	207	3.00	3.73	0.2	23
Income (Reported)	191	73547	33996	7500	127500
Median Inc. (Census)	200	54730	19214	25095	140222
Reported Distance	207	121	88.03	2	500
Zip-Code Distance	207	129	132.52	2	1583
Reported Travel Time	207	2.47	1.76	0.083	9
Google Travel Time	207	2.61	1.82	0.05	10.383
Age	207	41.29	12.18	18	80

3.4.3 Time Cost

The time cost of travel is by far the most voluminously debated issue for travel cost analysis. Time and its associated cost have played such a large role because recreation is a time-intensive activity, as Larson and Shaikh (2004) and others have pointed out.

The original insight is that the time cost of a trip is the opportunity cost of the travel time; therefore the time cost of travel is the foregone wage. Most travel cost analysis uses some function of the visitor's wage rate as the per-unit time cost.[5]

This approach raises at least three issues. First, few workers can adjust their work hours freely, so the imputed hourly wage rate may not represent the opportunity cost of time. Second, transit time might not be as onerous as work; therefore, it might count less than the wage rate. Third, the wage rate or income-per-work-hour is extremely difficult to measure.

A common approach to the first two problems has been to value the time spent traveling at one-half or one-third of the imputed wage rate. McConnell (1990), in her study of the time-costs of vehicle inspection, asked subjects what alternative activity they gave up and then valued surrendered work time at full cost and surrendered recreational time at half the wage cost. A more typical approach is to use the same wage discount for all survey participants.

Palmquist, Phaneuf, and Smith (2004), noting that the value of time for short term decisions can be different than the shadow value of time implicit in long-term choices (i.e., the wage rate), test the hypothesis that different sized blocks of recreational time have different marginal opportunity costs for the same person. They base their analysis

[5]Larson and Shaik (2001, 2004) argue against this view and propose that time allocation be jointly modeled with the budget allocation. See also Feather and Shaw (2000). Although both articles will potentially change the modeling of recreational value, they apply only to specific recreational settings (with special data requirements), in the case of Larson and Shaikh, or involve further assumptions (with special data requirements), in the case of Feather and Shaw.

on the idea that, in addition to income earning time and leisure time, there is a "maintenance time" which consumes part of people's non-income earning time and which provides an appropriate measure of the opportunity cost of recreational time. Using stated preference data, they assess people's willingness to pay for maintenance functions and then use this to value time employed in recreation and changes in that value, depending on the length of the recreational experience. Interestingly, the estimated dollar valuations for such blocks of recreational time exceed their long term (income-based) value of time at an increasing rate, as the length of the time block increases.

The third problem arises in observing respondents' incomes or imputed wages. This problem further affects, even dwarfs, the first two, since the correction of one-half that is commonly applied to the wage rate is in turn no stronger than the underlying calculated wage rate itself. In general, economists and surveyors have greatly understated the problems in (a) defining the right measure of income (household vs. individual; endogeneity of income and number of workers; wage income vs. non-wage income), (b) determining the number of hours of work that this income entails, in order to derive the implied opportunity cost per hour, and (c) eliciting accurate measures.

Our survey used two approaches to measure household income: (i) a categorical survey question and (ii) an imputation based on zipcode-level median income.

The categorical income question asked respondents for their household income by category, by far the most common strategy for income measurement. This measure is highly imprecise, is subject to top-coding, and does not contain hours worked. Furthermore, even this straightforward and unobtrusive elicitation yields a number of missing observations (41). These missing data are not a representative sample of visitors.

Bhat (1994) showed how to estimate incomes for missing observations and also how to impute incomes from categorical data. We attempted this procedure for our travel cost data but could not get the likelihood function to converge. Therefore, we assigned each individual the mid-point of the relevant income category.

Our second measure of income is the median household income by zip code from the 2000 Census. This measure, though also imprecise, was available for most respondents. Over the sample there are only 12 missing observations for zip code.

We divided both estimates of household income by 3400, the median number of hours worked per married household per year in the 2000 Census. The hourly figure has varied dramatically across studies. Huang et al. (2007), for example, divided household income by 2080. Whitehead et al. (2007) divided household income by 2000. The reason for these widely different values is not clear. The variation in assumptions about hours-worked has not been remarked on in the literature. Note that a higher number of hours worked leads to a lower implicit wage, which then yields lower consumer surplus estimates.

Our estimates of time value-per-hour were then multiplied by the round-trip travel times to generate estimates of the time cost of travel.

3.4.4 Travel Costs: Summed

The variable *C* in equation (1) is the mileage cost plus the time cost of travel to the site. Our two measures of distance and time (reported and zip-code-based) and the two measures of income (categorical and census) allow us to calculate these costs in four different ways: Categorical income/reported distance and time; census income/reported distance and time; census income/zip-code distance and time; and, categorical income/zip-code distance and time. Although it is possible to use separate sources for distance and time (that is, zip-code distance and reported time and vice versa), our analysis always uses the same source for these two variables. Summary statistics for the factors and sums of estimated travel costs are reported in **Table 4**. These statistics are reported for both the pooled sample and the sub-samples of overnight respondents and

Table 4: Summary Statistics for Travel Costs and Components

		Entire Sample			
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Veh. Cost1 (reported miles*$0.33)	46.82	52.69	0.07	330.00	46.82
Veh. Cost2 (zip-code miles*$0.33)	51.58	70.97	1.32	1044.78	51.58
Time costs:					
TC1 - category inc/rep. time ($)	62.45	74.87	0.38	401.47	62.45
TC2 - census inc/rep. time ($)	45.56	49.57	0.33	306.72	45.56
TC3 - census inc/zip. time ($)	50.01	53.98	0.00	332.30	50.01
TC4 - category inc/zip. time ($)	69.10	86.18	0.00	765.01	69.10
Summed Travel Costs (eq. (3))					
TC1 + Veh. Cost1 ($)	109.88	120.84	1.04	669.71	109.88
TC2 + Veh. Cost1 ($)	91.47	97.58	1.10	604.24	91.47
TC3 + Veh. Cost2 ($)	100.87	112.09	2.60	1107.54	100.87
TC4+ Veh. Cost2 ($)	118.83	124.72	1.54	792.43	118.83
		Day Use Observations			
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Veh. Cost1 (reported miles*$0.33)	232	17.35	20.11	0.07	90.42
Veh. Cost2 (zip-code miles*$0.33)	222	18.54	22.02	0	92.42
Time costs:					
TC1 (category inc/rep. time)	207	26.66	32.70	0.38	154.41
TC2 (census inc/rep. time)	228	19.55	24.42	0.33	161.44
TC3 (census inc/zip. Time)	227	23.29	32.84	0.00	306.64
TC4 (category inc/zip. Time)	206	33.41	63.61	0.00	765.01
Summed Travel Costs					
TC1 + Veh. Cost1	207	45.90	49.99	3.03	233.16
TC2 + Veh. Cost1	228	37.64	40.74	3.10	187.66
TC3 + Veh. Cost2	223	40.66	45.42	2	215.93
TC4+ Veh. Cost2	201	49.40	57.29	2	314.76

Table 4, continued

Overnight Observations					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Veh. Cost1 (reported miles*$0.33)	207	79.86	58.10	1.32	330.00
Veh. Cost2 (zip-code miles*$0.33)	207	85.02	87.46	1.32	1044.78
Time costs:					
TC1 category inc/rep. time ($)	191	101.23	87.45	2.21	401.47
TC2 census inc/rep. time ($)	200	75.22	54.16	2.53	306.72
TC3 census inc/zip. time ($)	200	80.34	57.23	1.28	332.30
TC4 category inc/zip. time ($)	191	107.60	90.80	1.54	456.23
Summed Travel Costs					
TC1 + Veh. Cost1 ($)	191	180.73	134.35	5.86	669.71
TC2 + Veh. Cost1 ($)	200	154.42	104.98	6.49	604.24
TC3 + Veh. Cost2 ($)	200	164.81	125.65	2.60	1107.54
TC4+ Veh. Cost2 ($)	191	187.82	135.86	2.86	792.43

day-use respondents. Average hourly time costs ranged from $15.82 (census-based income) to $21 (category income). The categorical income estimate is very close to the baseline time costs derived by Palmquist and others (2004).

Across the two sub-samples, travel costs for day users are significantly lower than travel costs for overnight visitors. This is because respondents in the overnight sample have often traveled farther than day-use visitors. The census-based time estimate is available for a larger share of the total sample so estimates using that measure include 30 more observations than reported time costs.

3.5 Age

Age has been shown to be positively correlated with numbers of trips, as referenced in Zawacki *et al*. (2000). Older people may have more available time and take more frequent trips as a consequence. Alternatively, there could be a learning process that makes recreational visits to these sites easier with experience or perhaps people come to enjoy the types of recreation available at these sites more with time. In our analysis, the regressions consistently generated positive, significant estimators for the effect of age on the dependent variable. We did not estimate separate consumer surplus figures by age, because of our relatively small number of observations.

3.6 Other Variables

Our survey (see Appendix) also asked individuals about their education and about the reasons why they were visiting the parks (question 16). We did not include education in the results reported here since it had essentially zero effect on the estimates of α. The "reasons for visiting" had larger effects, but since we were interested in the average value of a recreation-day based on the "average" reason to visit, we did not include them in the final estimates. Unfortunately, the number of responses was too small for us to be able to estimate the value of a recreation day for any of the individual uses.

4. Results

This section shows estimates of model (1) with the estimates of travel costs described above. We do this separately for respondents who were day visitors and for those who stayed overnight. In the basic regression we pool responses across the three survey sites. In Section 4.3 we estimate separate demand functions for each site to test whether there are area effects and we report results of our sensitivity tests for changes in the imputed value of travel time.

4.1 Day-use Visitors

Using the sample of day-use visitors, we regressed the log of truncated visits on summed travel costs (mileage plus time) and age. While this is a very simple specification it provides robust estimators and, because we stay with this specification across sample sets, we are able to easily compare consumer surplus measures across models.

We focus our attention on the coefficient of the cost variable. As described in Section 2, the inverse of the cost coefficient is our estimate of per trip consumer surplus. We ran separate equations to examine the impact of using reported versus census-based data for our travel cost estimates. Regression results and estimated consumer surplus (CS) are summarized in **Table 5**.

Table 5: Day-Use Regression Results for Four Estimates of Travel Costs

Cost Measure	obs	alpha	t statistic	R^2	CS/Trip
Category Inc./Reported Time	207	-0.01042	-4.41	0.11	$96.00
Category Inc./Google Time	228	-0.01181	-4.28	0.10	$84.67
Census Inc./Reported Time	223	-0.01180	-4.71	0.11	$84.78
Census Inc./Google Time	201	-0.00943	-4. 47	0.11	$106.00

We chose category income and reported time as our estimate for total consumer surplus because these have heretofore been the standard way in which travel costs have been measured and because they do not yield outstandingly high or low estimates of per trip consumer surplus. We use this measure to estimate total annual consumer surplus at the three survey sites in **Table 6**. Total consumer surplus is based on the respective visit records of the three Forests.

Google time and distance and zipcode income are likely to be used more widely in travel cost estimation in future research. But they have not yet been widely adopted nor have their effects been studied, to our knowledge. In future research we hope to make more use of these measures.

Table 6: Annual Day-Use Consumer Surplus at the Three Forests		
Site	**Annual Day Use Visitors**	**CS from Day Use @ $96/visit ($millions)**
Patapsco	825,669	79.26
Green Ridge	16,294	1.56
Pocomoke	69,057	6.63

Few travel cost estimates of U.S. forest recreation have been published, for purposes of comparison with the estimates in Table 5 or Table 9 (below). Zandersen and Tol (2005) examined 25 studies of forest recreation in Europe. They found mean consumer surplus per trip of $19 (using 2000 dollars), but also a very wide range. Kaval (2007) examined an extremely large number of U.S. studies (1,200 observations) and determined that an average day of recreation at a park yielded surplus of $60.50 per person per day (2006 dollars). For state parks, the figure was $53 per person per day.

4.2 Overnight Visitors

An evaluation of the consumer surplus generated by overnight visits should follow the same rationale used for day visits. Unfortunately, no theoretically consistent treatment is available for the time and costs of staying over night. We argued above that the per-unit lodging cost is the most defensible of the possible options for treating lodging costs. For the sake of analysis we also considered two other treatments: No lodging costs included with travel costs, and total lodging costs (per-night costs multiplied by number of nights) added to travel costs. Sample averages for our measures of overnight costs are as follows:

- Travel costs only – $180.73
- Per night lodging plus travel costs – $208.33
- Total lodging costs plus travel costs – $256.95

Lodging costs are taken from the sample survey and generally match the fees for either campsites or cabins at the sites. A very small number of respondents reported costs associated with a stay outside the sample site.

Data from overnight visitors at the three survey sites were combined for the results shown in **Table 7**. Following the analysis above, we use reported travel times and distances and category-based income to calculate the basic travel costs.

Because it appears that consumer surplus from overnight visits differs substantially across sites, we focus on site-specific analysis of overnight visits (section 4.3) rather than on the results in Table 7.

Table 7: Overnight-Use Regression Results for Three Measures of Travel Costs

Cost Factors	obs	alpha	t statistic	R^2	CS/Trip
Travel Costs only	191	-0.00154	-3.10	0.09	$649
TC + Per night lodging	187	-0.00163	-3.42	0.10	$615
TC + Total lodging	187	-0.00139	-3.55	0.11	$722

4.3 Site-specific estimates

When separate recreational sites serve similar populations and offer similar recreational experiences, the value-per-trip should be roughly the same for each of the sites. This assumption applies to the Maryland Forests we surveyed and therefore the previous analysis has estimated a single value-per-trip applicable to each of the three surveyed Forests.

In this section, we examine this assumption. We repeat the regressions of the previous sections on a forest-by-forest basis and generate separate estimates of consumer surplus per trip, again treating day and night visitors separately. **Table 8** shows the regression results for day users, using category income and reported time. Patapsco, with many more observations than either Green Ridge or Pocomoke, generates a consumer surplus per trip estimate that is $9 greater than the combined sample average. The Green Ridge sample gives a consumer surplus measure that is $35 greater than the combined average and Pocomoke's sample generates an estimate that is $24 less. These differences likely arise due to the different environmental characteristics and services of each of the sites. But it is not possible to know which specific characteristics are the source of higher or lower values.

Table 8: Site-specific Regression Results

	obs	alpha	t-stat	R^2	CS/Trip
Patapsco	145	-0.0095	-2.02	0.06	$105
Green Ridge	36	-0.0077	-2.04	0.13	$131
Pocomoke	22	-0.0139	-2.28	0.33	$ 72

With respect to overnight visitors, **Table 9** reports regression results and site-specific estimates for per trip consumer surplus. In this case, the nature of overnight visits differs substantially between Patapsco and the other two more distant forests. Consumer surplus per overnight trip as an average of the three cost measures is $468 for Green Ridge and about the same ($463) for Pocomoke. Overnight consumer surplus for Patapsco is clearly higher than either of these but is surely less than the number that the estimated coefficient implies. Something about Patapsco observations appears to be driving estimates of consumer surplus in our analysis of the combined sites higher, but what this is is not immediately apparent.

Table 9: Estimates by forest, overnight visitors only

	obs.	average cost	alpha	t-stat	R^2	CS/trip
Green Ridge						
Travel Cost only	71	177	-0.00243	-1.76	0.08	$411
TC+ Per night lodging	68	194	-0.00271	-2.11	0.10	$369
TC+ Total lodging	68	213	-0.00160	-1.52	0.07	$625
Patapsco						
Travel Cost only	41	70	-0.00041	-0.32	0.10	--
TC+ Per night lodging	40	96	-0.00018	-0.14	0.10	--
TC+ Total lodging	40	128	0.000126	-0.10	0.10	--
Pocomoke						
Travel Cost only	79	242	-0.00235	-4.09	0.22	$425
TC+ Per night lodging	79	276	-0.0023	-4.10	0.22	$434
TC+ Total lodging	82	333	-0.0019	-4.03	0.21	$526

Because of this uncertainty about the Patapsco overnight consumer surplus, in our estimate of total consumer surplus at each site we use the average of the per trip consumer surplus estimates for travel costs plus per night lodging at Green Ridge and Pocomoke as a lower bound for Patapsco's per trip consumer surplus. These per-trip estimates for overnight visitors cannot be used to calculate total surplus as readily as the day-use estimates, however. In the Park Service's accounting, overnight visits are counted as visitors per night so that a party of four staying two nights is counted as eight, rather than four (staying 2 nights). Since we are measuring consumer surplus on a per-trip basis, our measure does not map directly to this facility stay data.

To generate a common denominator for DNR's stay data and our average consumer surplus per visit, we deflated the "campers per night" data by the average length of stay at each facility. Patapsco and Pocomoke averages were taken from the Park Service's reservation system. Green Ridge is outside this system and the estimate used here is the survey sample average. We then multiplied this "annual overnight visits" times the site-specific consumer surplus estimates for Green Ridge and Pocomoke, and the average of those two ($400) as a lower-bound estimate for Patapsco.

Results are shown in **Table 10**. This treatment assumes that our estimate of average consumer surplus is for the respondent only and that each other member of a respondent's party derives the same amount of welfare.

Table 10: Annual Overnight Consumer Surplus at the Three Forests*

Site	Annual Person Overnights	Average Nights Per Visit	Annual Overnight Visits	Total CS (million)
Patapsco	15,326	1.2	12,772	$5.11
Green Ridge	10,633	2	5,317	$1.96
Pocomoke	27,124	2	13,562	$5.89

*Visits over the (one year) survey period from MD DNR Forest and Park Service data.

5. Conclusion

5.1 Value Estimates

The travel cost method yields estimates of the per-trip-value that recreationists experience at a given recreational site. Our best estimate of the average per-trip value for day visitors is $96. Our best estimate of the average per-trip value for overnight visitors is $369, $400 and $434 for Green Ridge, Patapsco and Pocomoke, respectively. Since each of the State Forests collects data on daily and overnight visitors, it is straightforward to use the travel cost estimates to calculate a total value for each site. Using the per-trip values, we calculate this total value as $3.52 million for Green Ridge, $84.37 million for Patapsco, and $12.52 million for Pocomoke.

These calculations represent the value of *access* to the site. They measure the recreational value that would be lost if the Forest were to disappear or, equivalently in the case of recreation, if no recreational visitors were allowed.

Government administrators may also like to know the value of changing the services at a forest or park. These changes may include simple changes, such as in the variety and quality of available facilities, or broader changes, such as in forest management approaches that would change the scenery, wildlife populations, or forest age mix. Ideally, travel cost analysis could measure the value of such changes. Such an analysis would require us to measure travel cost behavior across a range of forests and parks that had different levels of these attributes but that were otherwise similar. In practice, real-world forests rarely provide the kind of comparison that would be necessary for this kind of analysis.

One approach would be to use this study's per-day values in combination with a (separate) model of the number of visitors. Suppose that some change in available services or management option were proposed for the Forest. To the extent that such a change led to a change in the number of annual visitors, it would be appropriate (in a rough sense) to multiply our dollars-per-visit figures with the predicted change in the number of visitors to derive an estimate of the value of the proposed change to the Forest.

Of course, these estimates must be treated with caution. The per-trip value relies on assumptions about the opportunity cost of time and on correct accounting of visitors' time, distance, and number of visits. Time and distance can be measured rather precisely compared to the other data that are used in environmental valuation. The number of visits a household might make per year are measured less accurately since they rely on individual memory. Income and hours-worked, which are key variables for the time cost of recreation, remain poorly measured; much progress remains to be made on this front. Calculations that rely on the total number of visitors, such as the value of outcome, obviously depend on the accuracy of visit statistics. The underlying assumptions of the model also urge caution. We have used standard assumptions in dealing with multiple-person households, day versus overnight visitors, and labor supply (wage rates), but each of these assumptions reduces the accuracy of the final estimates.

It is also important to recognize what our values, per-day and total, do not measure: they are not a measure of the value of the park to the local economy. In general, local economic effects “wash out” in the aggregate since any change in economic activity in one locale is typically offset by a change in economic activity elsewhere. This broad claim is based on services such as capital and labor being mobile and fully employed. This is the correct assumption for a state with a high-level of economic activity and efficiency, such as Maryland. The same assumption does not apply to parks and forests – there may indeed be value from changes in how they are managed – because they are not the same sort of market good. Travel cost analysis should help government administrators and the public at large understand and assess the value of changes in forest access, services, and management.

5.2 Contributions

Travel cost data are among the roughest data that economists might work with, yet they are still remarkably informative. This project has made five methodological innovations.

(i) Functional form. Our log-linear specification shown in equation (1) allows us to use data from individuals who report less than one trip per year or a range of trips per year. Previous studies have either had to drop these observations or adjust the observations. The log-linear form also exhibits the desirable ability to model small numbers of high-frequency visitors

(ii) Sampling strategy. By pre-selecting our sampling schedule through the random draw we have limited any bias that might result from focusing on high-use days.

(iii) Google-times and distances. Travel cost relies on measures of travel times and distances. Although individuals should in principle be able to report these numbers accurately, they may not always do so. Google time and distance measures provide an alternative that is potentially more accurate. Future surveys may be able to use the Google feature even better than we were able to; see Section 5.3.

(iv) Census-based incomes. As with the time and distance measures, census-based measures of income may be more accurate measures of income than individual reports, despite the fact that individuals should in principle be able to report their incomes with greater accuracy. Census-based measures have the advantage of specifying a clear and rigorous method for calculating income. Greater effort is expended, by statisticians and individuals, to make sure this method is applied correctly. No information will be lost by individuals reporting their incomes in categories, as is currently done. Like the time-distance measures, future surveys may be able to use census-based measures even more profitably than we were.

(v) Separate treatment of day visitors and overnight visitors. The literature remains unclear about the proper treatment of overnight visitors when visit lengths differ across parties. Our research has highlighted the problems involved in correctly accounting for overnight visitors.

5.3 Lessons for Future Travel Cost Analyses

Like many areas of analysis, travel cost modeling will benefit substantially from changes in computer technology. These changes have not yet shown up in the travel cost literature.

Perhaps the greatest advance would be in obtaining both income and time-distance measures, namely by using a computer to have individuals pinpoint their exact or approximate origination site. For example, we could ask individuals to type in their address (unwatched by us) and let the computer find and store the census tract. This would provide simple and accurate measurement of the relevant variables, with almost no missing observations. (For example, if individuals entered an incorrect zipcode or address, the computer could spot this immediately.)

Given the apparent consumer surplus differences between day-use and overnight camping and, given the difficulty in assigning an appropriate value for on-site time across these two activities, it may be useful to focus on visitors' alternative use of time (e.g., if they were not visiting the site) as a means of valuing both their travel time and their "time of use" for day-use recreation versus overnight camping. Following Palmquist and others (2004), a promising approach might be to target expenditures for services that free visitors to take trips of different time lengths. This would not only provide a theoretically defensible standard for establishing value, it might also advance our understanding of the value of day trips versus overnight trips.

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Maryland Parks and Forest Recreational Use Value Survey Questionnaire

Survey Location: ________________________ Respondent Number: ____________

Respondent's home zipcode: __________ (Mr / Ms) Date: __________

About your travel

1. How far did you travel (from the start of your current trip) to get here? _____(miles)
2. How long did it take you to get here? __________(hours)
3. How many people are with you on this visit? ____
   In one vehicle or multiple vehicles? _______
4. What is your best estimation of how much you will spend on your trip for the following: (Place multiple vehicle answers after the item)
   $__________ Lodging ____
   $__________ Fuel ______(gals)______________________________________
   $__________ Park fees____
   $__________ Other ____
5. **A hypothetical question**: Someone you know (but, not very well) has a last-minute problem getting to this site and asks you to drive him. For whatever reason, you agree and, at the end of the trip, he offers you a money gift. How large would this gift need to be to make driving him here perfectly painless to you. (Note: question applies to travel on the same day of the week as respondent's travel) $_______

About the respondent

6). How often do you come here per year? _________

7). How often to you visit similar, other places in a year? ________

8). What is your age? ________________

9). Education: ____ HS, ____ College/ Technical, _____ BA/BS, ______MS or Ph. D

10). Are you a student, currently? ______yes, _______no

11). If you are willing, please tell us the correct category for your annual household income. (Note: if multiple households record all salary or wage rates)

a) $0 – $15,000 per year
b) $15,001 – $30,000 per year
c) $30,001 – $45,000 per year
d) $45,001 – $60,000 per year
e) $60,001 – $75,000 per year
f) $75,001 – $90,000 per year
g) $90,001 – $105,000 per year
h) $105,001 – $120,000 per year
i) Over $120,000 per year

12). If you are an hourly employee, what is your current hourly wage? _________/hour

About your stay

13. What is your primary reason for this visit?

__________ Main Destination – to spend time in the park

__________ Part of a longer trip (vacation) with other destinations

14. How long will you stay? **Day visit** ___ (hours) or **Overnight** ____ (days)

15. If you are staying overnight, which are you staying in: 1) a cabin, 2) a paid campsite, 3) an unpaid campsite, 4) nearby hotel, 5) nearby campground, 6) other __________

16. Please rate each one of the following site characteristics with respect to how important each is to you for a pleasurable visit.

Characteristic/Rating	Very Important	Important	Not so Important	Didn't Notice
1. Forest				
2. Trails				
3. Water/fishing				
4. Water/swimming&boating				
5. Privacy/Absence of congestion				
6. Stay Facilities (sites, showers,etc)				
7. Programs				
8. Birds and wildlife				

Maryland Parks and Forest Recreational Use Value Survey Questionnaire

To the survey respondent: This survey is being undertaken to study the use of State-owned forestland in Maryland. Your participation in this survey is anonymous, and all answers will be strictly confidential. You may withdraw from the survey at any time. You may decline to answer any of the individual questions. However, your thoughtful and accurate answers will help us to provide reliable information about the use of Maryland's State Forests. Your participation is greatly appreciated.

By participating in this survey, you certify that you are at least 18 years old.

Please note that the research is not designed to help you (the survey respondent) personally but to help Maryland make decisions about its forests.

There are no known risks associated with participation in this research.

This research is being conducted by John Horowitz of the Department of Agricultural and Resource Economics at the University of Maryland, College Park. If you have any questions about the research study itself, please contact Prof. Horowitz at 301-405-1273 or horowitz@arec.umd.edu.

If you have questions about your rights as a research subject or wish to report a research-related injury, please contact: **Institutional Review Board Office, University of Maryland, College Park, Maryland, 20742; irb@deans.umd.edu; 301-405-0678**

This research has been reviewed according to the University of Maryland, College Park IRB procedures for research involving human subjects.

(Survey participant's copy)