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Panel Stratification in Meta-Analysis of Economic Studies: An Investigation of Its Effects in the Recreation Valuation Literature

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ABSTRACT

Statistical summarizations of literature review databases using meta-regression analysis provide insight into the differences in past estimates of economic variables such as benefits and price elasticities. The panel nature of the data is an issue that has not received adequate attention in past meta-analyses. This paper conceptually and empirically explores the complexity of stratifying data into panels that model the potential correlation and heterogeneity of past outdoor recreation benefit research. Although our tests of three stratifications of the data did not discern panel effects, the inherent complexity of the data maintains a strong presumption of heterogeneous strata.

Key Words: *meta-analysis, outdoor recreation economic benefits, panel data, stratification.*

As the body of empirical estimates of economic variables, such as benefits and price elasticities, accumulates over time, we can expect an increase in meta-analyses of literature reviews. Meta-analysis, using multivariate regression techniques, can increase our understanding of the systematic influence of different methodological and study-specific factors on the outcomes of empirical research (Stanley and Jarrell). The results of meta-analysis can provide additional insights into the systematic nature of the differences between research methodologies (e.g., revealed preference and stated preference valuation techniques), confirm previous evidence while promoting consensus on these differences (Carson *et al.*; Brown *et al.*), and provide direction for future research.

The first two meta-analyses in environmental economics were of accumulated studies on recreation benefits (Smith and Kaoru; Walsh, Johnson and McKean 1989, 1992). Meta-analysis has since been applied to the literature on economic studies of groundwater (Boyle, Poe and Bergstrom), of air quality (Smith and

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Huang; Smith and Osborne; Desvousges, Johnson and Banzhaf), of endangered species (Loomis and White), of price elasticities of water (Espey, Espey and Shaw), and of outdoor recreation (Sturtevant, Johnson and Desvousges; Rosenberger and Loomis 2000).

An important issue with applying meta-analyses is panel data effects. Databases composed of information from literature reviews often have properties of panel data. That is, a single observation (empirical study) can provide multiple estimates for a single issue (e.g., recreation benefits, price elasticities). Multiple observations in a database from the same source may be cross-sectionally correlated and or result in heteroskedastic regressors. For example, some empirical research uses the same sample of respondents or recreation participants to provide multiple estimates. These estimates are then the result of comparisons of valuation methodologies, tests of functional form, and model specification. In other cases, multiple estimates are provided from split-sample tests of methodology or for estimate comparisons. In the presence of panel data effects, econometric models of the data may lead to inefficient and inconsistent parameter estimates, leading to invalid inferences from seemingly significant factor effects.

The issue of panel data effects has been acknowledged since the first two meta-analyses were conducted on recreation research, although no formal tests for these effects were reported (Smith and Kaoru; Walsh, Johnson and McKean 1989, 1992). Nearly all subsequent meta-analyses identified above have acknowledged the potential for panel effects, but have not reported the results of any tests for these effects. Instead, meta-analysis models have been 'corrected' for these potential effects using various other econometric techniques. Smith and Kaoru used a Newey-West version of the White consistent covariance estimator that corrects regressors for heteroskedasticity and serial correlation. This procedure does not affect the parameter estimates of the model, but does provide robust standard errors of the parameters in the presence of heteroskedasticity and serial correlation (Driscoll and Kraay). Boyle, Poe and Bergstrom, Smith and Huang, and Smith and Osborne use a Huber-White technique to correct for heteroskedasticity and serial correlation. These 'corrective' procedures, however, assume at the micro-level that the underlying functional form is the same across studies (homoskedastic parameters) (Segerson). In addition, these procedures at the macro-level ignore the possibility of heteroskedasticity and correlation effects emanating from various strata of the data. Sturtevant, Johnson and Desvousges, and Desvousges, Johnson and Banzhaf use conventional panel data models in their analyses, but do not report test results on the presence of panel effects.

One of the difficulties in modeling panel data effects in literature review databases is identifying the probable source of these effects. The above-mentioned 'corrective' procedures make implicit assumptions regarding the source of panel effects. Another approach would be to use insight regarding the structure of the data to identify different potential sources of panel effects. Once these probable sources are hypothesized, then they may be statistically accounted for through stratifying the data. Each strata or panel then becomes a separate factor in the panel regression model. In certain panel data cases, this stratification seems obvious. For example, when each respondent in a survey provides multiple-choice or judgment responses, the panel is the individual (Englin and Cameron; Loomis; Rosenberger and Loomis 1999). Or in the classic textbook example, when import/export data is collected from a sample of countries over time, the panel is the country.

We investigate this issue of how to stratify data by testing several intuitively plausible stratifications of the data. We conduct this investigation using panel data regression models and tests that are readily available in statistical analysis packages. The data we use is composed of outdoor recreation use value studies collected through a literature review spanning 1967 to 1998. The structure of this paper is as follows. First, we will describe the data used in this analysis. This will provide the base from which we explore different plausible stratifications of the data. Candidate panel models will be discussed and the different stratification approaches described. We will then report the results of hypothesis tests conducted on the applicability of the stratification approaches. While the results of these tests are not definitive of all meta-analyses, past or future, we hope that this information will provide a rudimentary foundation for future meta-analyses and begin a dialogue on this issue.

Data

The data used for this analysis is based on two extensive literature reviews of outdoor recreation use value studies. Walsh, Johnson and McKean conducted a literature review that spanned published studies from 1967 to 1988. MacNair extensively coded this review, enabling it to be integrated into the second review. The second literature review coded outdoor recreation use value studies spanning the period from 1989 to 1998 (Loomis, Rosenberger and Shrestha). One of the main objectives of the second literature review was to target recreation activities that were either unrepresented or underrepresented in the first literature review. Thus, heavily studied activities such as fishing and big game hunting were not emphasized in the second review, these activities being well represented by the previous literature review.

All study values (e.g., consumer surplus or compensating variation) were adjusted to per-person activity-day units and updated from their original study year (not publication year) values to 1996 dollars using the Implicit Price Deflator. Originally there were about 170 individual studies that produced slightly more than 750 individual values. Some of these studies were removed from the database because they did not report enough information to adjust their reported values to a per-day basis. Other studies were not included in the meta-analysis due to the lack of reporting of essential information that would enable the full coding of a study. Therefore, the database consists of 682 estimates from 135 separate studies. Table 1 presents a summary of the use-value estimates (a complete bibliography of individual studies and reported values is available from the authors upon request). The structure of the data seems to suggest that panel effects are a possibility when performing a meta-analysis; several studies supply multiple estimates since there are more estimates than studies.

A master coding sheet was developed that contains 126 fields. The main coding categories include reference, benefit measure(s), methodology used, recreation activity investigated, recreation site characteristics, and user or sample population characteristics. Appendix Table A1 lists and defines the variables used in the meta-analysis. The majority of these variables are qualitative dummy variables coded as 0 or 1, where 0 means the study does not have a characteristic, and 1 means that it does. For example, if an open-ended technique was used to elicit value information from respondents, then both METHOD (for stated preference model type) and OE would be coded as 1, while other mutually exclusive variables would be coded 0.

Appendix Table A1 groups the variables according to whether they are methodological [including revealed preference (RP) and stated preference (SP) valuation types and subtypes, survey mode, functional form specification], site (including geographic location based on USDA Forest Service regions and site characteristics), or activity-specific variables. The user population characteristics were rarely reported with the results of a study. Other means for obtaining data on user population characteristics, such as contacting the researchers of a study, were not feasible given the financial and time constraints of the project.

Modeling Panel Data

Candidate Panel Models

Several models are available for modeling panel data effects in various statistical packages. The models we will be using include the fixed effect (a panel-specific constant component) and the random effect (a panel-specific error component) models. Other candidate panel models not tested include a separate-variances model (no common error component)

Table 1. Average Consumer Surplus Values per Activity Day per Person from Recreation Demand Studies—1967 to 1998 (Fourth Quarter, 1996 Dollars)

Activity	Number of Studies	Number of Estimates	Mean of Estimates	Median of Estimates	Std. Error of Mean	Range of Estimates
Camping	23	37	\$31.43	\$24.62	5.79	\$1.69–187.11
Picnicking	6	10	36.05	26.78	10.09	11.34–118.95
Swimming	9	12	31.34	23.40	8.49	1.83–113.84
Sightseeing	10	16	41.27	19.68	12.02	1.05–161.59
Off-Road Driving	3	3	21.78	19.94	6.38	11.76–33.64
Motorized Boating	10	15	39.25	21.61	11.97	4.40–169.68
Float Boating	10	15	57.20	36.42	16.32	15.04–263.68
Hiking	16	21	40.47	23.21	10.62	1.56–218.37
Biking	3	5	45.15	54.90	8.40	17.61–62.88
Downhill Skiing	5	5	27.91	20.90	7.07	12.54–52.59
Cross-Country Ski	7	12	26.19	26.73	2.82	11.70–40.32
Snowmobiling	2	2	69.97	69.97	33.74	36.23–103.70
Hunting[a]	43	247	40.53	30.82	1.98	2.16–209.08
Fishing[b]	38	118	36.52	20.65	3.51	1.73–210.94
Wildlife Viewing	13	155	31.07	39.00	1.32	2.36–134.89
Horseback Riding	1	1	15.10	15.10	0	15.10–15.10
Rock Climbing	2	5	59.52	50.95	11.25	29.82–85.74
General Rec.	10	48	22.05	15.38	4.42	1.18–214.59
Other Recreation	8	14	36.20	30.99	11.54	1.64–172.34

[a] Hunting includes all types of hunting such as big game, small game, and waterfowl hunting.
[b] Fishing includes all types of fishing such as cold water, warm water, and salt water fishing. The number of estimates for fishing is under-representative of the entire body of knowledge since fishing studies were not a primary focus of the literature review.

and a mixed-effect model (both panel-specific constant components and panel-specific error components) (Desvousges, Johnson and Banzhaf; Sturtevant, Johnson and Desvousges). We use LIMDEP for all subsequent analysis and hypothesis testing. Therefore, we will follow the developer's conventions in presenting the panel models (Greene).

Begin with the classical OLS (or equal effect) model:

$$(1) \qquad y_i = \alpha + \beta' x_i + \epsilon_i,$$

where i indexes each observation, α is a constant (intercept) term common across all observations, y is the dependent variable, x is a vector of explanatory variables which account for differences across and within the studies, and ϵ is the classical error term with mean zero and variance σ_ϵ^2.

A generic panel model may be defined as:

$$(2) \qquad y_{ij} = \mu_{ij} + \beta' x_{ij} + \epsilon_i$$

where j is the stratification index and μ_{ij} is the panel effect. In the fixed-effect model, the panel effect parameter, μ_{ij}, takes on the form:

$$(3) \qquad y_{ij} = \alpha_{ij} + \beta' x_{ij} + \epsilon_i,$$

where α_{ij} is the panel-specific constant component for each panel identified through the stratification indexing, and has a common error component (ϵ_i). In the random-effect model, the panel effect parameter, $\mu_{ij,}$ takes on the form:

$$(4) \qquad y_{ij} = \alpha + \beta' x_{ij} + \epsilon_i + \mu_{ij},$$

where μ_{ij} is the panel-specific disturbance component with a mean zero and variance σ_μ^2, and has a common constant component (α) and a common error component (ϵ_i). In an unbalanced panel (unequal panel sizes), all disturbances in the random-effect model have variance:

$$\text{(5)} \qquad \text{var}\left[\epsilon_i + \sum_j \mu_{ij}/T_j\right] = \sigma_{ij}^2 = \sigma_\epsilon^2 + \sigma_\mu^2/T_j,$$

where T is the number of observations in study *j*. Therefore, the random-effect model with unbalanced panels is necessarily heteroskedastic. This model is a generalized regression model with generalized least squares being the efficient estimator.

Stratification Indexing Approaches

Panel data models require stratification indexing of the data. Stratification indexing is the explicit identification of different panels or strata that can be sources of correlation among the subsets of data composing a stratum. The panels are identified through indexing that assigns an index unique to each panel. A difficulty in applying panel models is in the *ex ante* identification of these panels. In the studies that reported estimated panel data models, the stratification is by study (Desvousges, Johnson and Banzhaf; Sturtevant, Johnson and Desvousges). In the other meta-analysis studies that did not report any panel data testing, the by-study strata were identified as potential sources of panel effects. Sturtevant, Johnson and Desvousges, in their meta-analysis of recreational fishing studies, also estimated a panel model that stratified the data across two dimensions—by study and by body of water. This bi-dimensional stratification allows for the assumption that heterogeneity across the sources of data can be more than unidimensional. That is, not only may activity estimates be heterogeneous based on research source, but also based on physical differences between the types of recreation sites. We expand on these previous data stratification approaches by testing three stratifications of the data—*by study, by researcher,* and *by data structure.* In all approaches, the panel nature of the data is unbalanced. That is, the number of observations (estimates) is not constant across all panels.

The first stratification approach is the *by study* indexing. The number of panels (j) is 135, with each study being indexed as a panel. The number of estimates per panel (i) ranges from 1 to 134, with a mean of five estimates and a median of one estimate. Not all studies provide more than one benefit estimate. Therefore, intra-panel correlations are not possible with many of the panels. An *ad hoc* convention that could be used to side-step panel data issues is to code a single estimate per study based on author recommendation, average of the study's estimates, or expert judgment. This would potentially reduce the plausibility of panel effects since each study would be supplying at most a single benefit estimate per activity or region. However, this convention could reduce insights gained from meta-analyses and would not necessarily eliminate commonalties for many of the estimates provided, which leads to our second stratification approach.

Our second stratification approach rests on the assumption that a researcher may be the source of latent panel effects. That is, a researcher may influence estimates in such a way that these estimates may be correlated across activities, regions, or time. We developed a stratification index based on lead author of the study report. Although the order of authors listed for a report does not necessarily perfectly reflect his/her influence on the research, we use this as a proxy for the *by researcher* index. There are 94 panels (j) based on this approach. This approach results in the number of estimates per panel (i) ranging from 1 to 135, with a mean of seven estimates and a median of one estimate.

The third approach we investigate is stratifying the data based upon an observable structure within the data. Three broad categories of the studies in the database were identified: (1) A single study provides a single benefit estimate for a recreation activity in a region (56 percent of the studies are of this type). (2) A study provides multiple estimates, but no more than one benefit estimate per target using the same user population sample (14 percent of the studies are of this type). For example, a study may provide an estimate for camping for different regions using different user population samples. And (3), a study provides multiple estimates for an activity or region using the same user population sample (30 percent of the studies are of this type). For example, a study may provide an estimate for different activities based on data from a single user population sample, or provide multiple estimates for the same activity using data from a single user population sample. This third category indexes individual study panel effects based on multiple observations for each respondent or agent in that study's data.

The *by data structure* indexing of the data results in 43 panels (j). The number of estimates per panel (i) ranges from 2 to 354. One of the panels reflects the first data category (j = 1)—single sample, single estimate—accounting for 354 estimates (i = 354). An estimated panel effect for this panel (j = 1) can be interpreted as a common factor for these types of studies. Another panel reflects the second data category (j = 2)—multiple estimates, separate samples—which accounts for 76 estimates (i = 76). An estimated panel effect for this panel (j = 2) can be interpreted as a common factor for these types of studies. The rest of the studies are individually indexed as composing the third data category, each study being assigned its own index (j = 3, . . . , 43). For this subset of panels, the estimates per panel (i) range from 2 to 50, with a mean of six estimates per panel and a median of three estimates. Our intention with this stratification approach is to isolate those studies that could result in intra-panel (study) correlated benefit estimates due to multiple estimates from a single user population sample.

Hypothesis Testing

Two test statistics aid in choosing between equal-effect, fixed-effect, and random-effect models—Lagrange multiplier statistic and Chi-squared statistic. Breusch and Pagan's Lagrange multiplier statistic tests whether panel effects are significant (H_0: $\mu_{ij} = 0$ versus H_1: $\mu_{ij} \neq 0$). That is, this statistic tests for cross-sectional correlation and heteroskedasticity among the panels. The null hypothesis is that an equal-effect model is correct, whereas the alternative hypothesis is that a panel-effect model is correct. Hausman's Chi-squared statistic tests the random-effect model against the fixed-effect model (H_0: μ_{ij} as a random effect; H_1: μ_{ij} as a fixed effect). That is, this statistic tests whether the panel effects are uncorrelated with other regressors, where the random-effect model assumes orthogonality of the panel effects and regressors. If we fail to reject the null hypothesis of no panel effect, the Chi-square test is not applicable.

Results

An equal-effect, fixed-effect and random-effect model was estimated with each of the stratification approaches. All models were specified according to the variables listed in Appendix Table A1. Although overspecification leading to inefficient and inconsistent parameter estimates may result from modeling all of the defined variables, it also reduces the possibility of making Type I errors when testing for panel effects. By coding for identifiable and measurable sources of heterogeneity in benefit estimates, we focus the statistical tests on latent sources of panel effects. Observable effects, when unaccounted for in an underspecified model, may manifest themselves as panel effects. Therefore, by trading off potential inconsistencies and inefficiencies from overspecification, we increase the power of the Lagrange multiplier test for the presence of latent panel effects via the stratification approaches.

In certain cases a variable that is essentially coding for a unique characteristic of a potential panel may be almost perfectly correlated with that panel. This is evident from differences in the regression results for each model (estimated models are available upon request from the authors). At least one variable in each model had to be omitted because it was perfectly correlated with a panel in a respective stratification indexing approach. For example, benefit estimates provided on the national level (NATL) were nearly perfectly correlated with a panel either identified by study or by researcher. This is because a single study or

Table 2. Hypothesis Test Results

Test	Hypothesis	Statistic	Result
	Panel Stratification BY STUDY (N = 682; j = 135)		
Lagrange multiplier	H_0: no panel effect	5.80	Reject equal effect
	H_1: panel effect		(p-value = 0.02)
Chi-square	H_0: random effect	75.78	Reject random effect
	H_1: fixed effect		(p-value = 0.01)
	Panel Stratification BY RESEARCHER (N = 682; j = 94)		
Lagrange multiplier	H_0: no panel effect	0.34	Fail to reject equal effect
	H_1: panel effect		(p-value = 0.56)
Chi-square	H_0: random effect	—	Not applicable
	H_1: fixed effect		
	Panel Stratification BY DATA STRUCTURE (N = 682; j = 43)		
Lagrange multiplier	H_0: no panel effect	1.37	Fail to reject equal effect
	H_1: panel effect		(p-value = 0.24)
Chi-square	H_0: random effect	—	Not applicable
	H_1: fixed effect		

Note: N = number of observations in the dataset; j = number of panels in stratification approach.

lead author provides all or the majority of national benefit estimates for an activity.

Our interest in this investigation is to begin a discussion about stratifying meta-analysis literature review databases. Therefore, we will not place any emphasis on interpreting the parameter estimates from each model. We will, instead, focus on the results of the hypothesis tests.

Table 2 provides the results of the hypothesis tests for the different stratification approaches. For the first panel stratification, *by study,* the Lagrange multiplier statistic of 5.80 rejects the equal-effect model in favor of a panel-effect model at the 0.02-confidence level. The Chi-square statistic of 75.78 rejects a random-effect specification in favor of the fixed-effect specification at the 0.01-confidence level. Therefore, we may conclude that a fixed-effect specification is the correct one. A disadvantage of the fixed-effect model when based on a wide, longitudinal dataset is that it may exacerbate the problem of overspecification, in addition to being costly in terms of degrees of freedom lost (Greene). Also, interpreting the relative incremental and decremental effects of estimated parameters for the variables in a fixed-effect model can be cumbersome when the panel specific constants are numerous (Greene; Englin and Cameron; Desvousges, Johnson and Banzhaf). Therefore, the specification of the fixed-effect model requires more effort to reduce the inefficiency of these regressor parameter estimates. This could be accomplished through reducing overspecification of the model due to correlation between regressors and panel-specific constants (in this model there are 135 panel-specific constants).

One approach to reducing the number of panel-specific constants is based on the fact that the fixed-effect model is also known as the *least-squares dummy-variable model* (where each panel is essentially coded as a dummy variable in the model) (Greene). Only retaining those individual panel constants that are significant in the model may reduce the complexity of a fixed-effect model. We found that only six of the panel-specific constants were significant in the model at the 0.10 level or better, based on t-statistics. However, contrary to our expectations, these individual panel constants were not associated with studies that provided multiple benefit estimates, but were for studies that provided a single benefit estimate each. Since there can be no intra-panel correlation when the panel is composed of a single benefit estimate, the implied dummy variable for these significant effects must be accounting for inter-panel heterogeneity. Upon further investigation we found that these six studies provided uniquely large benefit estimates for their respective recreation activities. Therefore, what was at first assumed to be a panel effect was in reality a large value (and possibly outlier) effect. We can explicitly model these large value effects by creating a dummy variable for each of the six studies. The dummy variable model strongly resembles the equal-effect model, but without the further complexity of the 135 panel-specific constants in the latter model.

In the *by researcher* and *by data structure* stratification approaches, we failed to reject the equal-effect specification based on the Lagrange multiplier statistics [0.34 ($p = 0.56$) and 1.37 ($p = 0.24$), respectively]. This means that either panel effects are not present based on the stratification approach, or that these effects were not discernible by the tests used.

Conclusions

This paper explored the issue of identifying panel stratifications of a literature review database being used for meta-analysis. The issue of panel effects is important for meta-analyses as panel effects can lead to inconsistent and inefficient parameter estimates. This could lead to incorrect conclusions from meta-analyses regarding the effect of measured factors on research outcomes. Therefore, it is important to test for the presence of panel effects when conducting meta-analyses on databases exhibiting panel structures.

We tested three approaches to stratifying our data on outdoor recreation use value studies obtained from a literature review spanning 1967 to 1998. We stratified the data based on a by-study stratification, by-researcher (lead author) stratification, and by-data-structure stratification. Each approach was tested according to whether an equal-effect (no panel effects), fixed-effect, or random-effect model was correct. In all three cases we could reject the presence of panel effects, favoring an equal-effect specification. However, these results are neither definitive nor conclusive regarding past and future meta-analyses.

What is illustrated is the complexity in identifying plausible stratifications of literature review data. The exact structure of panels in wide, longitudinal data may be unknowable. This is because of the potential multi-dimensionality of panel structures. That is, sources of heterogeneity and correlation (cross-sectional and serial) in the data may not be based on a single dimension such as study, researcher, or region. In the data used for this analysis, the potential complexity of literature review datasets is exacerbated. In addition to the traditional temporal and spatial dimensions, there are also issues of improvements of state-of-the-art in valuation methodologies over time, inter- and intra-methodological differences, inter-activity differences, and potential interactions between these various dimensions.

Future meta-analyses should be more sensitive to the panel nature of literature review data. Although many statistical packages provide relatively straightforward programs for estimating panel data models, the stratification of the data is still dependent upon the judgment of the analyst. Reducing the overall complexity of the data may reduce the complexity of identifying and modeling panel stratifications. That is, meta-analyses may be most capable of providing definitive conclusions regarding variation in research results when these results are from fairly homogeneous sources. However, this may come at the cost of being able to account for variation in research results from seemingly heterogeneous sources, especially when the differences between these sources are multi-dimensional.

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APPENDIX: Variable Descriptions

Table A1. Description of Variables in the Meta-Analysis Panel Models.

Variable	Description[a]
Dependent variable	
CS	Consumer surplus (CS) per person per activity day (1996 dollars) [36.10 (32.39)]
Method variables	
METHOD	Qualitative variable: 1 if stated preference (SP) valuation approach used; 0 if revealed preference (RP) approach used [0.64 (0.48)]
DCCVM	Qualitative variable: 1 if SP and dichotomous choice elicitation technique was used; 0 if otherwise [0.18 (0.38)]
OE	Qualitative variable: 1 if SP and open-ended elicitation technique was used; 0 if otherwise [0.36 (0.47)]
ITBID	Qualitative variable: 1 if SP and payment card elicitation technique was used; 0 if otherwise [0.01 (0.30)]
PAYCARD	Qualitative variable: 1 if SP and payment card elicitation technique was used; 0 if otherwise [0.01 (0.05)]
RPSP	Qualitative variable: 1 if SP and RP used in combination; 0 if otherwise [0.01 (0.08)]
ZONAL	Qualitative variable: 1 if RP and a zonal travel cost model was used; 0 if otherwise [0.20 (0.40)]
INDIVID	Qualitative variable: 1 if RP and an individual travel cost model was used; 0 if otherwise [0.14 (0.34)]
RUM	Qualitative variable: 1 if RP and a random utility model was used; 0 if otherwise [0.03 (0.16)]
HEDONIC	Qualitative variable: 1 if RP and a hedonic travel cost model was used; 0 if otherwise (omitted category for METHOD) [0.02 (0.15)]
TTIME	Qualitative variable: 1 if RP model included travel time; 0 if otherwise [0.31 (0.46)]
SUBS	Qualitative variable: 1 if RP model included substitute sites; 0 if otherwise [0.26 (0.44)]
ONSITE	Qualitative variable: 1 if sample frame was on-site; 0 if otherwise [0.29 (0.46)]
MAIL	Qualitative variable: 1 if primary data collection used mail survey type; 0 if otherwise [0.25 (0.43)]
PHONE	Qualitative variable: 1 if primary data collection used phone survey type; 0 if otherwise [0.51 (0.50)]
INPERSON	Qualitative variable: 1 if primary data collection used in-person survey type; 0 if otherwise [0.35 (0.48)]
SECOND	Qualitative variable: 1 if secondary data was used (omitted category for data collection) [0.06 (0.24)]
LINLIN	Qualitative variable: 1 if functional form was linear on both dependent (d.v.) and independent variables (i.v.); 0 if otherwise [0.10 (0.31)]
LOGLIN	Qualitative variable: 1 if functional form was log d.v. and linear i.v.; 0 if otherwise [0.16 (0.36)]
LOGLOG	Qualitative variable: 1 if functional form was log on both d.v. and i.v.; 0 if otherwise [0.06 (0.24)]
LINLOG	Qualitative variable: 1 if functional form was linear on d.v. and log on i.v.; 0 if otherwise (omitted category for functional form) [0.01 (0.05)]
VALUNIT	Qualitative variable: 1 if CS was originally estimated as per day; 0 if otherwise (e.g., trip, season, or year) [0.39 (0.49)]

Table A1. (Continued)

Variable	Description[a]
TREND	Qualitative variable: year when data was collected, coded as 1967 = 1, 1968 = 2, . . . , 1996 = 30 [19.04 (5.33)]
Site variables	
SPECACT	Qualitative variable: specialized activity variable coded as 1 if recreation activity requires specialized equipment and/or experience (e.g., rock climbing, boating, hunting, fishing, etc.); 0 if otherwise [0.81 (0.39)]
RECQUAL	Qualitative variable: site quality variable coded as 1 if the author stated site was of high quality or the site was either a National Park, National Recreation Area, or Wilderness Area; 0 if otherwise [0.11 (0.31)]
FSADMIN	Qualitative variable: 1 if the study site(s) were National Forest (i.e., administered by the U.S. Forest Service (FS)); 0 if otherwise [0.14 (0.34)]
R1	Qualitative variable: 1 if study sites were in FS Region 1 (Montana, No. Idaho); 0 if otherwise [0.05 (0.22)]
R2	Qualitative variable: 1 if study sites were in FS Region 2 (Wyoming, Colorado); 0 if otherwise [0.12 (0.32)]
R3	Qualitative variable: 1 if study sites were in FS Region 3 (Arizona, New Mexico); 0 of otherwise [0.06 (0.24)]
R4	Qualitative variable: 1 if study sites were in FS Region 4 (Nevada, Utah, So. Idaho); 0 if otherwise [0.11 (0.32)]
R5	Qualitative variable: 1 if study sites were in FS Region 5 (California); 0 if otherwise [0.05 (0.22)]
R6	Qualitative variable: 1 if study sites were FS Region 6 (Oregon, Washington); 0 if otherwise [0.06 (0.24)]
R8	Qualitative variable; 1 if study sites were in FS Region 8 (Southern United States east of Rocky Mountains); 0 if otherwise [0.16 (0.37)]
R9	Qualitative variable: 1 if study sites were in FS Region 9 (Northern United States east of Rocky Mountains); 0 if otherwise [0.30 (0.46)]
R10	Qualitative variable: 1 if study sites were in FS Region 10 (Alaska); 0 if otherwise [0.03 (0.16)]
NATL	Qualitative variable: 1 if study sites were the entire United States; 0 if otherwise [0.03 (0.17)]
CANADA	Qualitative variable: 1 if study sites were in Canada; 0 if otherwise (omitted category for geographic location of study site) [0.02 (0.12)]
LAKE	Qualitative variable: 1 if the recreation site was a lake; 0 if otherwise [0.05 (0.22)]
RIVER	Qualitative variable: 1 if the recreation site was a river; 0 if otherwise [0.04 (0.20)]
FOREST	Qualitative variable: 1 if the recreation site was a forest; 0 if otherwise [0.30 (0.46)]
OCEAN	Qualitative variable: 1 if the recreation site was an estuary or bay of an ocean; 0 if otherwise (omitted category for site type) [0.17 (0.37)]
PUBLIC	Qualitative variable; 1 if ownership of the recreation site was public; 0 if otherwise [0.96 (0.20)]
DEVELOP	Qualitative variable: 1 if the recreation site had developed facilities, such as picnic tables, campgrounds, restrooms, boat ramps, ski lifts, etc.; 0 if otherwise [0.19 (0.39)]

Table A1. (Continued)

Variable	Description[a]
NUMACT	Quantitative variable: the number of different recreation activities the site offers ([4.64 (9.08)]
Recreation activity variables	
CAMP . . . OTHERREC	Qualitative variables: 1 if the relevant recreation activity was studied; 0 if otherwise. Where CAMP is camping [0.03 (0.18)], PICNIC is picnicking [0.01 (0.09)], SWIM is swimming [0.01 (0.10)], SISEE is sightseeing [0.02 (0.14)], OFFRD is off-road driving [0.01 (0.05)], NOMTRBT is float boating [0.01 (0.09)], MTRBOAT is motor boating [0.02 (0.13)], HIKE is hiking/backpacking [0.02 (0.14)], BIKE is biking [0.01 (0.08)], DHSKI is downhill skiing [0.01 (0.08)], XSKI is cross country skiing [0.01 (0.08)], SNOWMOB is snowmobiling [0.01 (0.04)], BGHUNT is big game hunting [0.25 (0.43)], SMHUNT is small game hunting [0.03 (0.16)], WATFOWL is waterfowl hunting [0.09 (0.28)], FISH is fishing [0.17 (0.38)], WLVIEW is wildlife viewing [0.23 (0.42)], HORSE is horseback riding [0.01 (0.04)], ROCKCL is rock climbing [0.01 (0.08)], GENREC is general recreation (defined as a composite of recreation activity opportunities at a site) [0.07 (0.25)], and OTHERREC is other recreation (for sites with recreation opportunities undefined or obscure—omitted category for recreation activity) [0.02 (0.12)]

[a] Mean (and standard deviation) values reported in square brackets; N = 682.