WESTERN REGIONAL RESEARCH PUBLICATION

W-133
BENEFITS AND COSTS OF RESOURCES POLICIES AFFECTING
PUBLIC AND PRIVATE LAND

12[TH] INTERIM REPORT
JUNE 1999

Compiled by
W. Douglass Shaw

Department of Applied Economics and Statistics
Mail Stop 204
University of Nevada
Reno, Nevada 89557-0105

INTRODUCTION

This volume contains the proceedings of the 1999 W-133 Western Regional Project Technical Meeting on "Benefits and Costs of Resource Policies Affecting Public and Private Land." Some papers from W-133 members and friends who could not attend the meeting are also included. The meeting took place February 24th - 26th at the Starr Pass Lodge in Tucson, Arizona. Approximately 50 participants attended the 1999 meeting, are listed on the following page, and came from as far away as Oslo, Norway.

The W-133 regional research project was rechartered in October, 1997. The current project objectives encourage members to address problems associated with: 1.) Benefits and Costs of Agro-environmental Policies; 2.) Benefits Transfer for Groundwater Quality Programs; 3.) Valuing Ecosystem Managment of Forests and Watersheds; and 4.) Valuing Changes in Recreational Access.

Experiment station members at most national land-grant academic institutions constitute the official W-133 project participants. North Dakota State, North Carolina State, and the University of Kentucky proposed joining the group at this year's meeting. W-133's list of academic and other "Friends" has grown, and the Universities of New Mexico and Colorado were particularly well represented at the 1999 W-133 Technical Meeting. The meeting also benefitted from the expertise and participation of scientists from many state and federal agencies including California Fish and Game, the U.S. Department of Agriculture's Economic Research and Forest Services, the U.S. Department of Interior's Fish and Wildlife Service, and the Bureau of Reclamation. In addition, a number of representatives from the nation's top environmental and resource consulting firms attended, some presenting papers at this year's meeting.

This volume is organized around the goals and objectives of the project, but organizing the papers is difficult because of overlapping themes. The last section includes papers that are very important to the methodological work done by W-133 participants, but do not exactly fit one of the objectives. -- I apologize for the lack of consistent pagination in this volume.

On A Personal Note... Any meeting or conference is successful (and fun!) only because of its participants, so I would first like to thank all the people who came and participated in 1999 - listed below. I also want to thank Jerry Fletcher for all his help at this meeting and prior to it, and John Loomis who passed on his knowledge of how to get a meeting like this to work, and who continues to have the funniest little comments to lighten the meetings up. I especially thank Paul Jakus, who helped me to organize this conference and have a lot of fun during it and afterward. Finally, I want to thank Nicki Wieseke for all her help in preparing this volume, and Billye French for administrative support on conference matters.

W. Douglass Shaw, Dept. of Applied Economics & Statistics, University of Nevada, Reno.
June, 1999

P.S. P.F. and J.C. - As far as I can tell, that darn scorpion is still dead!

1999 W133
Tucson, AZ
Feb. 24-26
DRAFT
3/4/99

META-ANALYSIS OF OUTDOOR RECREATIONAL USE VALUE ESTIMATES: CONVERGENT VALIDITY TESTS

Randy Rosenberger
John Loomis
Ram Shrestha

Dept. of Agricultural and Resource Economics
Colorado State University
Fort Collins, CO 80523

Funding for this project is provided by USDA Forest Service-Washington Office, Research Joint Venture #28-JV7-962.

Acknowledgements: We would like to acknowledge the help of Dennis Black, formerly of Colorado State University, in the literature search process. Shauna Page, formerly of Colorado State University, participated in the coding of studies and reconciling Douglas MacNair's database into ours. We would like to thank Linda Langner and Ross Arnold, USDA Forest Service-Washington Office, for sharing Douglas MacNair's database with us and providing direction and valuable feedback on this study. Dan McCollum, USDA Forest Service-Rocky Mountain Research Station, provided several useful suggestions for the analysis.

ABSTRACT

We update the Walsh et al. (1988) literature review of outdoor recreation economic studies to the present and merge our database with MacNair's (1993) coding of the Walsh et al. (1988) review. The database we use for analysis has 163 studies providing 741 outdoor recreation use value estimates. We then perform meta-analysis on the data to develop models for use in benefit transfer. Unbalanced panel models were tested on the data, finding no significant panel effects. Several OLS models are developed coinciding with different geographic divisions of the US studies, including a national model and four census region models. Convergent validity testing was performed on each model, assessing their precision in predicting the raw average values for each recreation activity in each defined geographic zone. While the census region models have the best statistical fit to the data, they are less robust to changes in the magnitude of explanatory variables under benefit transfer scenarios than the national model. We also compare the national model's precision to a simple national average value transfer and find that for point estimates alone, the simple transfer is as accurate as using the national meta model. However, meta provides the ability to adapt the values to recreation activities and recreation settings outside the bounds of the data set.

I. Purposes of Meta-Analysis

A. Traditional Uses

Meta-analysis was originally developed to understand the influence of different methodological and study specific factors on the outcomes of the studies and provide a statistical summary and synthesis of past research. The first two meta-analyses by Walsh et al. (1989, 1992) and Smith and Karou (1990) sought to explain the variation in consumer surplus per day estimated from contingent valuation and travel cost methods. More recent applications of meta-analysis for this purpose include groundwater (Boyle, et al., 1994), air quality via the hedonic property method (Smith and Huang, 1995), endangered species (Loomis and White, 1996), visibility (Smith and Osborne, 1996), price elasticities of water (Epsey et al., 1997), health effects (Desvousges et al., 1998), and recreational fishing (Sturtevant et al., 1998). Desvousges et al. (1998) and Sturtevant et al. (1998) also investigate panel data estimators.

B. Benefit-Transfer

A more recent use of meta-analysis is to more systematically utilize the existing literature for the purpose of benefit transfer. Essentially, the meta regression equation coefficients estimated using available study sites could be used to "forecast" benefits at unstudied policy sites. Thus, rather than use an average of a few point estimates from past studies, the meta equation has at least three advantages. First, it utilizes information from a greater number of studies providing more rigorous measures of central tendency sensitive to the underlying distribution of the study values. Second, methodological differences can be controlled for when calculating a value from the meta-analysis equation. Third, by setting the independent variables in the levels specific to the policy site, the analyst is potentially accounting for differences between the original studies and the policy studies. These advantages may sum up to better measures of central tendency than averaging approaches. Thus benefit transfer using a meta-analysis equation shares some of the potential advantages of benefit function transfer espoused by Loomis (1992).

In 1998, an entire workshop on meta-analysis for the purpose of benefit transfer was held at the Tinbergen Institute in Amsterdam. Krichhoff's paper (1998) illustrates the basic approach of using an estimated meta equation to predict consumer surplus values. She then evaluated the relative accuracy of the meta-analysis derived benefit transfer as compared to the original study and a benefit function transfer. She found that multi-site benefit functions outperformed meta-analysis, but that meta-analysis outperformed single-site benefit function transfer. However, in light of the bias of her evaluation criteria toward benefit function transfer, she concludes that the use of meta-analysis for benefit transfer is still encouraging. Sturtevant et al. (1998) support this conclusion by showing that, in general, estimates from the meta-analysis are more precise than point estimate transfers.

The purpose of our paper is to contribute to the refinement and testing of meta-analysis as a benefit transfer tool. To do this, we first update the meta-analysis of Walsh et al. (1988. 1989, 1992) with additional studies and investigate the empirical importance of the panel nature of the reported study values. Second, we perform an evaluation of the relative accuracy of the meta-analysis derived estimated benefits.

II. Econometric Issues in Meta-Analysis Estimation

A. Panel Nature of Data with Multiple Estimates from Same Study

Many of the recreation studies reported multiple estimates for targeted outcomes, such as benefit estimates for a sample population, subset of the sample population, different activities, or different sites. Multiple observations from the same source may be correlated and the error processes across several of these studies may be heteroskedastic. In the presence of panel effects, the classical OLS and maximum likelihood estimators may be inefficient and their estimated parameters biased.

The classical OLS model is:

$$y_i = \mu + \beta' x_i + \varepsilon_i, \qquad (1)$$

where *i* indexes each observation, y is the dependent variable (in this case, consumer surplus per person day adjusted to 1996 dollars), x is a vector of explanatory variables including methodology, site, and user characteristics, and ε is the classical error term with mean zero and variance σ^2_ε.

A generic panel model is:

$$y_{ij} = \mu_j + \beta' x_{ij} + \varepsilon_i \qquad (2)$$

where *j* indexes the individual study. Accounting for the panel nature of the data when estimating a statistical model is important because of the potential unobserved correlation of a unit's multiple observations. Classical regression models are inefficient if they cannot account for this correlation of the observation unit's multiple responses, if said correlation is present. An additional twist on the panel nature of the data is that it is unbalanced, that is, there are not a uniform number of observations from each unit. Each study has at least one, but can have several value estimates.

B. Candidate Panel Models: Fixed Effect and Random Effect

The panel data effects can be modeled as either having a unit-specific constant effect or a unit-specific disturbance effect.[1] The fixed effect model treats the panel effect as a unit-specific constant effect. The group effect parameter, μ_j, in the case of the fixed effect model, takes on the form:

$$y_{ij} = \alpha_j d_{ik} + \beta' x_{ij} + \varepsilon_i, \qquad (3)$$

[1] Desvousges et al. (1998) identify candidate models for meta-analysis as being an equal effect model (the classical OLS), a fixed effect model, a random effect model, and a Bayesian approach. Sturtevant et al. (1998) test a fixed effect, random effect, and a separate variances model (no common error term). We test the equal effect, fixed effect and random effect models.

where d_{ik} is a dummy variable taking on a value of one for all observations where i = k. The first term can be reduced to α_j, signifying a group effect constant for each study in our meta-analysis. The fixed effect model is simply the classical regression model with unit-specific constants.

The random effect model treats the panel effect as a unit-specific disturbance effect. The group effect parameter, μ_j, in the case of the random effect model, can be written as:

$$y_{ij} = \alpha + \beta' x_{ij} + \varepsilon_{ij} + \mu_j, \tag{4}$$

where μ_j is the unit-specific disturbance effect and has a mean zero and variance σ^2_μ. Each study has an overall variance:

$$\mathrm{var}[\varepsilon_{ij} + \mu_j] = \sigma^2 = \sigma^2_\varepsilon + \sigma^2_\mu. \tag{5}$$

The random effect model is a generalized regression model with generalized least squares being the efficient estimator.

Two test statistics aid in choosing between classical OLS, fixed effect, and random effect models: Lagrange multiplier statistic and chi-squared statistic. Breusch and Pagan's Lagrange multiplier statistic tests whether a group effect specification is significant (H_0: $\mu_j = 0$). Hausman's chi-squared statistic tests the random effect model against the fixed effect model (H_0: μ_j as a random effect; H_1: μ_j as a fixed effect).

C. Pooled vs. Disaggregated Models: Hypothesis Tests

An additional issue with this data is whether all the studies can be pooled to estimate a single national model, or whether separate geographic regional models should be estimated. Separate regional models are preferred if the regions are structurally different in either the intercept parameter(s) or slope parameters. A Chow test (F-test) can be performed on the data to determine if the data can be pooled to estimate a national model, or whether regional models should be estimated. The hypotheses are:

$$\begin{aligned} &H_0\text{: National model, } \alpha_n\text{'s} = \alpha_m\text{'s, and } \beta_n\text{'s} = \beta_m\text{'s,} \\ &H_1\text{: Regional models, at least one } \alpha_n \neq \alpha_m\text{, or at least one } \beta_n \neq \beta_m, \end{aligned} \tag{6}$$

where *n* subscripts the estimated regional model coefficients and *m* subscripts the estimated national model coefficients. That is, if at least one region-specific constant or region-specific slope parameter is different from the others, then pooling the data to estimate a national model imposes a restriction on the coefficients.

III. Testing the Performance of Meta Equations for Benefit Transfer

A. In-Sample Comparisons Involving Individual Study Values

One means to evaluate the relative accuracy of the predictions from the meta-analysis equation is to compare the predictions to the actual individual study values. While the model R^2 provides some indication of goodness of fit, our real interest is in whether the dollar magnitude of the errors would be acceptable for a benefit transfer exercise. Further, we are interested in whether the meta-analysis estimated values might be less subject to small sample errors likely to arise from simply averaging the few available studies for that recreation activity in that region.

B. In-Sample Comparisons Involving Regional Average Values

Some government agencies perform benefit transfer by relying upon a set of standardized "unit day values". The USDA Forest Service has done this since 1980 using their Resources Planning Act (RPA) values. In the last decade, these values are specific to groups of similar activities and region of the country. The U.S. Bureau of Reclamation and U.S. Army Corps of Engineers have relied upon the U.S. Water Resources Council Unit Day Values (U.S. Water Resources Council 1979, 1983) for decades.

Recently, the USDA Forest Service has investigated the possibility of using consumer surplus estimates from a meta-analysis equation to fill in the missing values in their recreation activity by region table. Thus another evaluation is to compare original study values averaged by recreation activity and region to the meta-analysis equation's estimate of these same values for cells in the table which have original study values. This may provide some indication of the relative accuracy of using the meta-analysis equation to fill in the missing values in the table.

C. Evaluation of Out of Sample Accuracy: Within Time Period and Out of Time Period

Another way to evaluate the performance of a statistical model is to compare its estimates to those from original studies that were not used to estimate the model. These observations can be from the same time period or literally out of the sample time period. In this reporting of results, we only test the performance of the meta-analysis models by means of the in-sample comparisons, providing a form of convergent validity testing.

IV. Data Sources

Since we are updating the previous literature review effort of Walsh et al. (1988), new valuation studies performed since they completed their effort were collected. Thus, we limited our search to studies from 1988 to the present. Study values for years prior to this are obtained from MacNair's (1993) database previously assembled for the USDA Forest Service. We also added studies from Walsh et al. (1988), not used by MacNair (1993).

A. Data Search and Limitations

We searched a wide range of electronic databases including the American Economic Association's Econ Lit, First Search Databases, the University of Michigan-Dissertation and Master's Abstracts, NTIS and Water Resources Abstract Index. Unpublished or "gray literature papers" were also searched using W133 Proceedings from 1987 to 1996, Carson et al.'s (1994) CVM bibliography as well as our own collections of working papers, conference papers and reprints.

We focused primarily on studies in the U.S. but included Canadian studies as well (with appropriate currency conversion). Studies in Europe or the rest of the world were not included as the recreation settings are quite different than North America.

We did not look for or emphasize fishing studies as these are subject of two previous significant literature reviews: (a) Sturtevant et al. (1996); and (b) a joint effort directed by Kevin Boyle and Industrial Economic Incorporated (Markowski et al, 1997). Our initial study coding sheet was patterned after Markowski et al.'s (1997) to maintain comparability. Thus we concentrated our effort on activities that had not been previously studied such as rock climbing, snowmobiling, mountain biking as well as activities commonly valued by agencies such as the USDA Forest Service or U.S. Bureau of Reclamation. Therefore, saltwater boating or ocean activities were not given great emphasis either.

B. Coding Procedures

A master coding sheet was developed and used to code the studies we collected, and to guide the recoding of the MacNair (1993) database. The main database of values that underlies the averages contains 126 fields, with the last field being a comment section. There are six main coding categories:

1) complete citation to the study;
2) the benefit measure (original value, deflated to 1996$, adjusted to common units);
3) the nature of the benefit measure (e.g., WTP vs WTA, mean vs median);
4) details of CVM application if CVM used;
5) details of TCM application if TCM used; and
6) study location details (e.g., whether National Forest, Park, State Park, etc.), environment type (e.g., forest, wetland), recreation activity, etc.

We also recorded the geographic region of the country for the study and whether it provided an estimate of a site-specific, state, regional or national average recreation use value. Census Regions represent the four Assessment Regions (Northeast, Southeast, Intermountain and Pacific, as well as a separate region for Alaska) for USDA Forest Service, RPA purposes. We also recorded the USFS Regions (e.g., R1=Montana and No. Idaho; R2=WY and Colorado; R3=Arizona and New Mexico; R4=Nevada, Utah and So. Idaho; R5=California; R6=Oregon and Washington; R8= Southeastern U.S.; R9=Northeastern U.S.; R10=Alaska; note R7 does not exist).

In the past, the RPA average recreation values were reported per USFS Region. However, this results in two problems: (a) very small sample sizes per activity/region cell; and (b) numerous activity/region cells with no average value (due to the lack of any original studies). To address both of these problems, the USFS Regions were aggregated into the Census Regions. In the database, individual study values are identified by both Census Region and USFS Region, so users can sort the data to compute their own values for a USFS Region if desired.

All study values were updated from their original study year (not publication year) values to

1996 using the Implicit Price Deflator. Originally there were slightly more than 170 individual studies that produced slightly more than 750 individual values. A couple of Random Utility Model estimates were on a choice occasion basis and we were unable to determine a way to convert them to a per day value using the information provided in the publication, thus dropping them from the database. Additional studies were removed from the database because they did not report enough information to convert their reported units to a per day basis. Therefore, we ended up with 163 studies providing 741 individual values. We examined these remaining studies for outliers, or per day values for an activity which were more than two standard deviations from the activity mean value. These outliers were removed from the calculations of regional average values (table 1), which are based on 701 individual estimates. Due to recoding of MacNair's (1993) values into our categories, we have studies ranging back to as early as 1967, although the bulk of the values are from the 1980's and 1990's.

Table 1 provides the average consumer surplus per day estimates for the 22 primary recreation activities defined by the USDA FS RPA. These estimates are a simple averaging of the individual study reported values with region and activity segregating them.

V. Statistical Results

All of the subsequent models were estimated using LIMDEP software. Table 2 lists and defines the variables tested across the models. Out of the 741 observations recorded, 672 had reported enough information to fully code for each of the variables listed in table 2. These 672 observations were provided from 131 separate studies. The number of estimates per study ranged from 1 to 134. If there is correlation among these multiple observations for each study, then OLS assumptions are violated. While these studies may provide estimates that relate to tests of methodology, different sites, or different activities, there may still be unobservable, yet systematic effects of the study on their estimates. Panel models can account for these unobservable systematic effects.

Table 1. Mean Recreation Values Per Person/Day for Different Activities by Census Region (Review: 1967 - 1998).

ACT[a]	Activity / Region	N[b]	NOREAST	N	SOUEAST	N	INTERMT	N	PACIFIC	N	ALASKA	N	National Only[c]	N	US Aver.
1	Camping	6	27.70	7	17.91	20	25.06	2	77.27			1	28.61	36	35.31
2	Picnicking	1	55.22	1	37.24	4	22.95	3	53.52			1	15.69	10	36.92
3	Swimming	5	22.79	1	16.75	1	24.62	3	28.74			1	20.67	11	22.72
4	Sightseeing	13	26.94	16	27.36	20	24.60	4	39.56	1	13.09	1	18.83	55	25.06
5	Off-road driving					1	11.76	1	33.64			1	19.94	3	21.78
6	Float boating	1	66.75	2	8.40	6	37.86	4	21.69			1	21.61	14	31.26
7	Motor boating	3	40.54	1	15.04	8	50.48			1	15.13	1	38.70	14	31.98
8	Hiking/Backpacking	3	53.52	2	9.47	5	31.85	8	32.37	1	12.93	1	20.87	20	26.84
9	Biking	1	34.11	1	56.27	2	58.89					1	17.61	5	41.72
10	Downhill Ski					2	23.23	1	20.90			1	19.61	4	21.25
11	Cross Country Ski	3	28.83			7	24.90	1	40.32			1	13.20	12	26.81
12	Snow mobiling					2	69.97							2	69.97
14a	Big game hunting	54	42.18	26	35.99	65	41.46	11	43.77	5	52.40	1	15.98	162	38.63
14b	Small game hunting	3	36.73			13	25.75	1	27.37			1	15.87	18	26.43
14c	Waterfowl hunting	22	27.06	11	17.70	16	23.17	4	23.79	1	60.08			54	30.36
15	Fishing	40	23.33	13	27.74	36	32.45	15	36.97	1	39.22	4	37.26	109	32.83
16	Wildlife Viewing	42	25.79	25	30.38	26	34.03	11	28.97	4	50.63	1	17.06	109	31.14
17	Horseback Riding											1	15.10	1	15.10
19	Rock Climbing	2	85.74			3	42.04							5	63.89
22	Wilderness Recreation	4	19.64	1	17.39	6	26.83	5	39.16					16	25.76
20	General Recreation (mean of all types)	8	15.21	6	14.65	21	24.98	12	16.93	3	11.84			50	16.72
21	Others			2	26.21	5	28.56							7	27.38
	Total # of estimates[d]	207		114		263		81		17		19		701	

[a] Activity code; ACT 13 (snow playing) and ACT 18 (resorts) are not considered as there are no studies.
[b] N = number of estimates.
[c] This category includes only studies reporting national values.
[d] There are 701 estimates (excluding Canada) out of 741 estimates in the database. Outliers have been removed based on the rule of 2 standard deviations from the activity mean value.

Table 2. Variables Tested in the Meta- Regression Models.

VARIABLE	DESCRIPTION
Dependent variable	
CS	Consumer surplus per person day (1996 dollars). [36.14][a]
Method variables	
METHOD	Qualitative variable: 1 if stated preference valuation approach used; 0 if revealed preference approach used. [0.64]
DCCVM	Qualitative variable: 1 if dichotomous choice elicitation technique in a stated preference approach was used; 0 if otherwise. [0.18]
ZONAL	Qualitative variable: 1 if revealed preference approach was a zonal model; 0 if otherwise (random utility model is omitted category). [0.20]
INDIVID	Qualitative variable: 1 if revealed preference approach was an individual model; 0 if otherwise (random utility model is omitted category). [0.14]
TTIME	Qualitative variable: 1 if revealed preference demand model incorporated travel time; 0 if otherwise. [0.31]
SUBS	Qualitative variable: 1 if demand model incorporated substitute sites; 0 if otherwise. [0.26]
ONSITE	Qualitative variable: 1 if sample frame was on-site; 0 if otherwise. [0.29]
MAIL	Qualitative variable: 1 if survey type was mail; 0 if otherwise (in person is omitted category). [0.25]
PHONE	Qualitative variable: 1 if survey type was phone; 0 if otherwise (in person is omitted category). [0.50]
LINLIN	Qualitative variable: 1 if regression function was estimated as linear on both dependent (d.v.) and independent variables (i.v.); 0 if otherwise (linear d.v. and log i.v. is omitted category). [0.10]
LOGLIN	Qualitative variable: 1 if regression function was estimated as log d.v. and linear i.v.; 0 if otherwise (linear d.v. and log i.v. is omitted category). [0.16]
LOGLOG	Qualitative variable: 1 if regression function was estimated as log on both d.v. and i.v.; 0 if otherwise (linear d.v. and log i.v. is omitted category). [0.06]
VALUNIT	Qualitative variable: 1 if consumer surplus was originally estimated as per day; 0 if otherwise (e.g., trip, season, or year). [0.39]
TREND	Qualitative variable: year when CS estimate was recorded, coded as 1967=1, 1968=2, . . ., 1996=30. [19.04]
Site variables	
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]
SPECACT	Qualitative variable: 1 if recreation activity requires specialized skill or equipment, including off-road driving, float and motor boating, biking, skiing, snowmobiling, hunting, fishing, wildlife viewing, horseback riding, or rock climbing; 0 if otherwise. [0.74]
FSADMIN	Qualitative variable: 1 if the study sites were National Forests (i.e., administered by the U.S. Forest Service); 0 if otherwise. [0.14]
R1 . . . R9	Qualitative variables: 1 if study sites were in the respective USFS Region; 0 if otherwise (R10 is the omitted category; there is no USFS Region 7).

Table 2. Continued.

VARIABLE	DESCRIPTION
LAKE	Qualitative variable: 1 if the recreation site was a lake; 0 if otherwise (ocean or bay is the omitted category). [0.05]
RIVER	Qualitative variable: 1 if the recreation site was a river; 0 if otherwise (ocean or bay is the omitted category). [0.04]
FOREST	Qualitative variable: 1 if the recreation site was a forest; 0 if otherwise (non-forested is the omitted category). [0.30]
PUBLIC	Qualitative variable; 1 if ownership of the recreation site was public; 0 if otherwise. [0.96]
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]
NUMACT	Quantitative variable: the number of different recreation activities the site offers. [4.64]
Recreation activity variables	
CAMP . . . GENREC	Qualitative variables: 1 if the relevant recreation activity was studied,; 0 if otherwise (Other Recreation is the omitted category). Where CAMP is camping, PICNIC is picnicking, SWIM is swimming, SISEE is sightseeing, OFFRD is off-road driving, NOMTRBT is float boating, MTRBOAT is motor boating, HIKE is hiking/backpacking, BIKE is biking, DHSKI is downhill skiing, XSKI is cross county skiing, SNOWMOB is snowmobiling, BGHUNT is big game hunting, SMHUNT is small game hunting, WATFOWL is waterfowl hunting, FISH is fishing, WLVIEW is wildlife viewing, HORSE is horseback riding, ROCKCL is rock climbing, and GENREC is general recreation.
Demographic proxy variables	
INCOME	Quantitative variable: average state per capita income in $1,000's. [22.94]
AGE	Quantitative variable: percent of state older than 65. [0.12]
EDUC	Quantitative variable: percent of state with at least a bachelor's degree in education. [0.20]
POPUL	Quantitative variable: state population in 100,000s. [56.16]
BLACK	Quantitative variable: percent of state population that is of African American descent. [0.08]
HISPAN	Quantitative variable: percent of state population that is of Hispanic descent. [0.08]

[a] Sample average values reported in square brackets.

A. OLS vs. Fixed Effect vs. Random Effect

We investigate the use of panel data estimators – fixed effect and random effect – in estimating a meta-equation for the data. While Walsh et al. (1989, 1992) and Smith and Kaoru (1990) recognized the panel nature of their data, neither estimated a panel model.

The models were fit using all of the variables listed in table 2.[2] The regression results are reported in appendix table A-1. The baseline OLS model had an adjusted-R^2 value of 0.25. This specification of the model may not be the most efficient if it is overspecified, however, our interest here is in testing for panel effects. Therefore, we wanted to capture as much of the observable potential sources of panel effects by fully coding all characteristics of the data if reported. The residuals from the baseline OLS model are used to estimate the variance components for computing the random effect model. The Lagrange multiplier test rejects the null hypothesis at the 0.05 significance level that an OLS specification is preferred to a group effects specification (table 3). The Hausman's chi-squared test rejects the null hypothesis at the 0.10 significance level of a random effect specification in favor of the alternative fixed effect specification (table 3). Therefore, overall the fixed effect specification is the preferred model, although it is not highly suggested.

Table 3. Panel model test results.

Test	Hypothesis	Statistic	Result
Lagrange multiplier	H_0: no group effects H_1: group effects	3.93	P-value=0.05, reject OLS
Chi-square	H_0: random effects H_1: fixed effects	64.05	P-value=0.09, reject random effects

One of the goals of this research is to provide 'accessible' benefit transfer technology to field personnel of federal public land agencies. A fixed effect specification with 131 unit-specific constants increases the costs of the transfer function through increased complexity. Past treatments of fixed effect constants, while conceptually reasonable, are *ad hoc* (Englin and Cameron, 1996; Sturtevant et al., 1998; Desvousges et al., 1998). What is unknown is whether the increase in benefits from using a panel estimator is worth this increased cost of complexity. Therefore, because of this complexity along with the somewhat weak statistical evidence favoring a fixed effect specification, we decided to investigate the issue of the fixed effect model further.

Since the fixed effect model is the classical OLS with group effect dummies, we may be able to reduce the complexity of the model by accounting for significant group effects by explicitly identifying them in an OLS model through dummy variables. As Smith and Osborne note, "…a summary model using the data across studies can include either attributes that are unique to studies or a fixed effect factor, but not both" (1996, pg. 293). Of the 131 group effect constants, only six of them are significant at the 0.05 level based on t-statistics. We expected that these six group effects would be studies providing several observations each. The exact opposite was true.

[2] Several variables had to be dropped from the model due to a lack of variation across the studies or high correlation with fixed effect parameters. These variables include *ONSITE*, *PHONE*, *RECQUAL*, *OFFRD*, *SNOWMOB*, *WLVIEW*, *HORSE*, and *ROCKCL*.

Of these six studies, five reported a single observation each, and the other provided two observations. All seven of the values provided from the six studies were greater than two standard deviations from the mean value for the activity and each study did not have any other unique characteristic unaccounted for in the model specification. We believe these 'group effects' were accounting for an outlier effect, not a panel effect.

These seven studies can be dealt with in two ways: (1) they can be treated as outliers and removed from the data set, or (2) they can be explicitly specified in the model by creating a dummy variable for each of these studies. In either case, the resulting Lagrange multiplier test suggests an OLS specification over some group effects specification.[3] This result implies that even though the data fits a cursory definition of panel data, there are no significant panel effects evident, so that the classical OLS specification is efficient and preferred.

Another plausible explanation for our result is that the data as coded is really not of the panel type. A common definition of panel data is multiple observations from the same observation unit. In our case, multiple value estimates from the same study or group of researchers. If panel effects are present based on this grouping, then there is a systematic effect of the researchers on the values reported in each study. Our results suggest that there is no researcher x study effect, or at least that this effect is not discernible. Sturtevant et al. (1998) created a stratification index of their sample of recreational fishing studies by the intersection of study and body of water. This illustrates that other factors, or interactions across the studies, may result in panel effects.[4]

A common textbook example of panel data is cross-section/time-series data collected on imports and exports for several countries. The group would be defined as the country, and the panel effect would be some unobservable, yet systematic component of a country that helps explain its within-group variance. Another example of classic panel data is eliciting multiple choice responses from the same person in a survey. Here, the commonality of the group is the unobservable, yet systematic effects of the individual on his/her responses (for example unmeasured attitudes).

In our case, many of the studies are providing multiple estimates, but not of the same activity, at the same point in time, for the exact same good. In the majority of the cases, each study is providing one recreation value for a variety of activities over a variety of recreation sites, areas, states, or regions.[5] For example, the study that supplies the largest number of estimates (134), does so for different states and different hunting activities (Brown and Hay, 1987). In another study, 96 estimates are provided, but again for different states and different activities (Waddington et al., 1991). In other cases, different methods are being tested, such as comparing

---

[3] Because of correlation problems, removing these observations from the data set resulted in three more single observation units to have significant 'group effect' constants in a fixed effect model. Again, these observations are lower level outliers and not true group effects. Upon this second iteration, all outlier-like observations are purged from the data set and a classical OLS is suggested.

[4] We did not test different interaction dummies between the studies and different factors, such as activity, site attributes, geographic region, etc. Pooling a diverse and large number of studies make the number of interaction possibilities virtually intractable. We believe that identifying each of these factors with individual dummy variables provides a good indication of the overall effect of the factor on the values reported.

[5] For the 131 studies, the mean number of estimates provided is 5, with a median of 1, and a range of 1 to 134 estimates.

TCM with CVM derived values, functional form, or model specification. Only in those cases where the exact same data is generating the estimates may there be a pure panel effect. Otherwise, the specification of the meta-model may be already accounting for differences based on dummy variable coding for these factors. Therefore, we suggest that future meta-analyses give more thought to the issue of whether their data is of the panel type, and not assume so because they have multiple observations from the same source. While panel effects are unobservable, this may be due to latent tendencies in the data or unmeasured factors that may become apparent when the source of the panel effect is discernible.

To further investigate this issue, we stratified the data by two additional ways. We stratified by researcher as determined by lead author of the study. This results in 91 panels. We also stratified by data structure. We identified four broad structures: 1) single estimate, single sample (56% of the studies); 2) multiple estimates, single sample (e.g., tests of functional form, revealed vs. stated preference tests using the same sample of respondents) (15% of the studies); 3) multiple estimates, separate samples (e.g., same activity, different sites, or different activities same sites) (14% of the studies); and 4) multiple estimates, multiple samples (e.g., split sample testing) (14% of the studies). In each of these cases, we fail to reject the OLS without group effects up to the 0.50 significance level. These further results illustrate the difficulty of stratifying the data when the source of panel effects is uncertain. The inherent complexity and diversity of studies and study reporting may make panel effect undetectable, if they are present.

C. Benefit Transfer Models

We estimate five meta-models, one for each of the geographic regions and one national model. We based our model specifications in part on the Walsh et al. (1989, 1992) and Smith and Kaoru (1990) studies. To this list of variables we added specific ones we believed might be useful such as state level demographics derived from U.S. Bureau of Census data. All models were estimated using the classical OLS regression technique. Each model was optimized individually by retaining only those variables that were significant at the 0.20 level based on t-statistics.

The five models estimated include a pooled national model and four regional models. The regions are defined based on USDA FS Resources Planning Act Assessment Regions, which closely coincide with the Census Regions. We label each of the regional models as CR1 (northeastern states), CR2 (southeastern states), CR3 (intermountain west), and CR45 (pacific states plus Alaska). While there are five Census Regions, due to lack of degrees of freedom for CR5, Alaska, we tested and found that we could combine CR5 with CR4, the pacific states, thus preserving degrees of freedom.

Table 4 presents the final estimated models. The explanatory power of our national model is 0.27, slightly below that of Walsh et al. (1989, 1992) for their combined TCM/CVM Model. The regional models all had greater explanatory power, ranging from 0.38 for CR1 and CR45, 0.42 for CR3, to 0.88 for CR2. While the explanatory power of the CR2 model is significantly greater than the other models, it is also the most sensitive to perturbations of the variables as evidenced by the magnitude of the estimated coefficients for the model. Caution is suggested when trying to interpret coefficients from models with mostly qualitative variables beyond their sign and significance, such as interpreting them as marginal values (Boyle et al., 1994).

Table 4. Optimized OLS Regression Models.

	NATIONAL	CR1	CR2	CR3	CR45
VARIABLE	COEF	COEF	COEF	COEF	COEF
CONSTANT	31.195*** (10.31)	-36.812 (37.59)	702.55*** (75.69)	129.66*** (16.92)	34.17 (21.85)
METHOD	-28.735*** (4.59)	-106.79*** (26.37)	-396.54*** (50.47)	-47.848*** (7.787)	-55.086*** (20.54)
DCCVM	14.325*** (5.328)		204.54*** (24.22)	29.621*** (6.194)	24.052* (13.28)
ZONAL	-11.914*** (4.221)	-131.31*** (29.24)	-194.8*** (25.59)		-44.827** (20.42)
INDIVID		-79.117*** (26.45)	-307.14*** (48.56)		-25.32 (18.3)
TTIME			159.29*** (26.34)		
SUBS	-22.977*** (4.392)	-29.877*** (10.16)	-146.66*** (31.13)	-35.674*** (6.913)	-36.554** (15.18)
ONSITE	-9.7203* (5.434)		-95.022*** (18.12)		
MAIL	-7.59** (3.836)	42.914*** (6.382)		-10.007* (5.996)	-12.845 (9.309)
PHONE	-17.892*** (4.219)		87.062*** (13.06)	-15.199** (6.666)	
LINLIN	7.5394 (5.055)	36.963*** (11.61)			
LOGLIN				-25.887*** (6.91)	25.655** (12.76)
LOGLOG		67.611*** (15.65)			
VALUNIT	-12.265*** (3.197)			-11.852** (4.619)	
TREND	0.92447*** (0.311)		-7.1124*** (0.8778)		1.2467 (0.7598)
RECQUAL	9.4282** (4.572)	-16.973 (10.6)	56.861*** (13.34)		
SPECACT		103.29*** (31.51)	-245.63*** (23.88)		
FSADMIN	-14.678*** (3.929)			-23.122*** (7.019)	
R1	14.701*** (5.077)				
R2				-10.493** (4.141)	
R3				-11.279** (5.279)	
R4	5.2792 (3.657)				
R6	-8.7275* (4.667)				-9.6429 (6.034)
LAKE	-13.442** (5.917)	-27.868** (12.48)	-192.83*** (23.31)		
RIVER	16.997*** (5.659)	-41.638** (16.76)	-210.49*** (26.15)	25.589*** (8.289)	

Table 4. Continued.

	NATIONAL	CR1	CR2	CR3	CR45
VARIABLE	COEF	COEF	COEF	COEF	COEF
FOREST		13.035*** (4.361)	-55.861*** (9.114)	-23.545*** (5.339)	-14.496 (10.96)
PUBLIC	21.068*** (7.288)	54.01*** (12.55)		-32.116** (14.74)	
DEVELOP	-7.464* (4.135)		-155.64*** (17.53)	-26.093*** (7.926)	
NUMACT	0.69364*** (0.2593)	2.4785*** (0.722)	5.1295*** (1.038)	2.3661*** (0.4928)	
CAMP		80.378** (35.29)	-122.8*** (12.44)		99.043*** (16.2)
PICNIC		94.59** (41.09)	-135.7*** (15.15)		48.408** (19.19)
SWIM		111.00*** (33.76)			
SISEE		117.93*** (32.44)	-235.3*** (23.27)		31.764** (14.09)
MTRBOAT				25.388* (14.6)	
HIKE		84.382** (37.16)	170.32*** (22.87)		
BIKE			-131.95*** (25.91)	33.339 (21.35)	
BGHUNT	15.085*** (3.329)	12.759*** (4.389)	7.9353*** (2.267)	18.725*** (5.292)	32.466*** (10.4)
SMHUNT	10.276 (7.298)				
WATFOWL	11.807** (4.684)				28.181** (13.01)
FISH	11.186*** (3.88)				33.249*** (10.86)
WLVIEW					31.809*** (10.62)
ROCKCL	31.255** (13.41)	-56.911** (25.37)			
GENREC		79.524** (36.2)	-120.22*** (14.61)	14.718 (10.00)	56.954** (24.65)
Adjusted R^2	0.27	0.38	0.88	0.42	0.38
F-STAT	11.25*** [25, 656]	6.66*** [22, 183]	36.59*** [23, 88]	10.03*** [19, 218]	4.28*** [18, 76]
N	682	206	112	238	95

*p<0.10; **p<0.05; ***p<0.01 (all variables are p<=0.20).
Standard errors in parentheses, except for F-stat where degrees of freedom are given in brackets.
Dependent variable is CS per person day.

However, the CR2 model's coefficients are several magnitudes larger than the other models' estimated coefficients, which are of the same order of magnitude. There is also a concern with degrees of freedom for the CR2 and CR45 models, having about half the number of observations as the other regional models.

For the most part, the signs of the methodology variables are consistent with past scientific results. *METHOD* is negative, meaning that CVM yields lower values than TCM, which is consistent with the previous meta-analysis (Walsh et al., 1989, 1992) and the bulk of TCM-CVM comparison studies (Carson et al., 1996). *DCCVM* is positive, meaning that dichotomous choice CVM studies yield higher benefit estimates than other forms of CVM (Walsh et al., 1989, 1992; Brown et al., 1996).

ZONAL and *INDIVID* travel cost models both yield lower values than random utility models, although this result should be treated with caution since there are very few random utility models present in the data. In the CR2 model, where *TTIME* is significant, it has a positive effect on benefit estimates. That is, when travel time is included in a model higher benefit estimates are yielded. *SUBS* is negative as expected, as the better job a model does of reflecting substitutes, the lower the benefit estimate will be (Rosenthal, 1987).

In terms of survey methodology used, *ONSITE* sample frames yield lower value estimates than sample frames developed from user lists or the general population. This seems to indicate that economists are becoming more successful in accounting for endogenous stratification in their demand estimating models. The effect of *MAIL* and *PHONE* surveys is not as clear. For the most part, mail and phone surveys yield lower benefit estimates than in-person surveys, which is consistent with at least some prior recreation studies (Mannesto and Loomis, 1991). However, the effect of *MAIL* is positive for CR1 and the effect of *PHONE* is positive for CR2. This may be due to their being the only significant effect in each regional model, so that the impact may be in comparison to phone and in-person surveys for the former and in comparison to mail and in-person surveys for the latter.

The effect of functional form presents a mixed bag. In the two models where a *LINLIN* functional form is significant suggests this form yields higher benefit estimates than other forms. The one model where a *LOGLOG* form is significant suggests that this form yields higher benefit estimates than the other forms. However, in the two models where a *LOGLIN* form is significant it has opposite signs. *VALUNIT* is negative and significant in two models, suggesting that if the original study reported the value in units such as per trip or per season, then this tended to yield higher per day benefit estimates than those already reported on a per day basis. Therefore, either there may be a recall bias introduced when requesting values per trip, season, or year as compared to per day estimates, per day estimates understate the total trip or season value when aggregated, or our estimate of number of days per trip or season are understated. Our *TREND* variable also shows that the effects over time may be in either direction.

The site characteristic variables significant in the different models do not, generally speaking, provide consistent results with each other. One explanation is that the results are specific to the region as intended, and therefore, direct comparisons across regions are not valid. For example, *RECQUAL* is positive for the national model and CR2, but is negative for CR1 where there are fewer designated National Parks, National Recreation Areas or Wilderness, than across the nation as a whole. Other explanations could be that studies in the northeast were not primarily from high quality sites, or that the quality of recreation sites that are not designated as such are still of higher quality than designated ones.

SPECACT has a positive effect in CR1, meaning specialized activities provide larger values to their practitioners than non-specialized activities, which is as expected. However, in CR2, *SPECACT* yields lower benefit estimates. Overall for the national model and for CR3, *FSADMIN* yields lower values. These USFS administered sites, however, are juxtaposed to sites designated to be of higher quality (e.g., National Parks, State Parks, and National Wildlife Refuges). Therefore, it is plausible that USFS sites would have somewhat lower recreation value than these other sites.

We also found, in the national model, that *R1* and *R4* (comprising Idaho, Montana, and Utah) have higher values relative to other regions in the US. Besides having outstanding natural areas, these are also areas that tend to be less crowded than many other regions of the country. Surprisingly though, *R6* (Oregon and Washington) has lower values for recreation than other regions, a finding similar to Walsh et al. (1989, 1992). Why this is the case is not clear. In the regional models, we find that *R2* and *R3* (comprising the central to southern Rocky Mountain range) have lower values relative to the northern Rockies in the CR3 model. And again, *R6* in the CR45 model shows lower values than for areas in the southern pacific coastal area and Alaska.

LAKE has a negative sign in the national and CR1 and CR2 models, showing that lake recreation has lower values than recreation activities in bays (the omitted category). This makes more sense when we consider that reservoirs were coded as lakes in this analysis. River recreation (*RIVER*) yields higher values than bay recreation for the national model and CR3, but lower values for CR1 and CR2. Recreation in forested areas (*FOREST*) yields higher values in CR1 than non-forested areas, which seems plausible given the quality of the northern woods. However, in CR2, CR3 and CR45, forest recreation yields lower values than non-forested recreation. *PUBLIC* lands provide higher valued recreation than private areas for the national model and CR1. One possibility is that private areas charge substantially more for access and onsite facilities and services than public areas, therefore extracting much of the consumer surplus from visitors, while visitors to public areas are charged much lower prices and therefore retain much of their consumer surplus. However, curiously, public lands in CR3 (intermountian range) yield lower values for recreation on public lands as compared to private areas.

Areas with *DEVELOP* facilities have lower values in the national, CR2 and CR3 models. Again, this may be due to such areas charging fees, whereas dispersed recreation areas often do not charge fees. It also may be that developed areas tend to be more crowded, such that congestion is being reflected in this variable as well (no variable for crowding was included as few studies reported such information). The number of recreation activities (*NUMACT*) available at a recreation site has a small, but positive influence on the estimated value.

The rest of the variables found to be significant in the various models are all recreation activity dummy variables. An interesting point to note is that the consumptive use of wildlife or fish activities (*BGHUNT, SMHUNT, WATFOWL,* and *FISH*) all yield higher values than 'other' recreation and by default omitted recreation activity categories (removed from the models' specifications because of insignificance). Thus, besides providing a recreation experience, these activities also provide a tangible product that may be a symbolic trophy of the trip and/or consumed. This finding is also consistent with the Walsh et al. (1989, 1992) study. It is also interesting to note that big game hunting is the only recreation activity variable that is significant in all five models. While big game hunting consistently has the most observations in the data set, fishing and wildlife viewing have nearly as many.

Our demographic proxy variables were consistently not significant in the models. We hoped that because the majority of users of recreation sites come from the local region, our proxy variables would serve well as demographic indicators of participants. We attempted this proxy approach because few of the coded studies provided demographic statistics on the user population of their studies (Rosenberger, 1998). However, our state level aggregate measures for the local population may not contain enough variability for our intended purposes. It is also interesting to note that while income and education are positively correlated, as expected, racial composition of the state population is positively correlated with certain FS regions, such as *HISPAN* with region 6 and *BLACK* with region 8. These FS regions were used in the Walsh et al. (1989, 1992) study as proxies for socio-demographic characteristics.

D. Pooled Model vs. Regional Models

We are also interested in whether we can pool all of the studies conducted in various regions of the United States and estimate a single model, or if the studies based on geographic location are structurally different in methodology and/or site characteristics. In the latter case, separate models for each region would have to be estimated. We conducted a Chow test of equality of coefficients. The F statistic of 3.66 suggests at the 0.01 level that at least one of the regional intercept terms or slope coefficients differs from one of the others (table 5). This means that there is not equality of coefficients and that separate models can be estimated for each census region.

Table 5. Chow test for pooling data.

Hypothesis	F-stat	Result
H_0: α_n's = α_m's, and β_n's = β_m's H_1: at least one $\alpha_n \neq \alpha_m$, or at least one $\beta_n \neq \beta_m$	3.66	Reject H_0 at 0.01 level, do not pool data Critical F-stat = 2.04

VI. Convergent Validity Tests of Meta Benefit Transfer Models

There are essentially four ways in which field personnel could use the information provided to them from this project for benefit transfer. First, they could use the raw average consumer surplus values supplied by activity by census region. This is similar to prior RPA outdoor recreation tables and the Water Resources Research Council's unit-day value tables. Second, they could use the accompanying database to do single or multiple point estimate benefit transfer, selecting which values they transfer by some criteria (e.g., similarity of study site to policy site, specific activity for subregions, etc.). Third, they could use the predicted values based on the meta-models provided. And fourth, they could adapt the meta-models by adjusting the level of the explanatory variables to better reflect the policy site (e.g., quality of the recreation site, number of activities at the site, type of site, etc.).

A. Assessment Procedures

Benefit transfer methods three (meta predicted values) and four (adapting meta-equation to policy issue) above require an assessment of the performance of the meta-models for benefit transfer purposes. This performance assessment would provide evidence for a level of confidence in using the models for benefit transfer purposes. We assess these models by calculating the precision of the models in predicting the raw average values. The raw average values are used as the benchmark values for the assessment. The raw average values used for this assessment are included as appendix table A-2. The values in table 1 differ from appendix table A-2 in that not all observation units available for table 1 are fully coded for use in developing the meta-models.

i) In-sample Comparison Involving Individual Study Values

The 'in-sample comparisons involving individual study values', which is similar to a goodness of fit statistic, uses the individual predicted values from the regression. From the classical OLS regression model (equation 1), the individual predicted values are:

$$\hat{y}_{ir} = y_{ir} - \varepsilon_{ir} = \alpha + \beta' \mathrm{x}_{ir}, \tag{7}$$

where r subscripts the regression model used. We then calculate a predicted average value under the same guidelines as were used to calculate the raw average values; an averaging of individual predicted values according to activity and region segmentation.

ii) In-sample Comparison Involving Regional Average Values

The 'in-sample comparisons involving regional average values' is based on adapting the meta-models to regional and activity specific conditions by substituting different values for the explanatory variables. This approach provides a predicted average value based on the regression model. The predicted regional average values are:

$$\hat{\bar{y}}_r = \alpha + \beta' \bar{x}_r . \tag{8}$$

The $\bar{x}_r$ values are comprised of three different aggregation approaches (s). (1) Mean values for the explanatory variables can be calculated by geographic region (national mean values and census region mean values). (2) Mean values can be calculated by activity (camping, sightseeing, wildlife viewing, etc.). Or (3), mean values can be calculated by the intersection of (1) and (2), that is by activity by geographic region (e.g., camping in CR1 studies, hiking in CR45 studies, etc.).[6]

[6] Mean values used in each treatment are available upon request from the authors.

The different combinations we investigate for benefit transfer purposes results in eight different treatments. Each treatment is described in table 6. Treatments A and D are the 'in-sample involving individual study values' comparison, and treatments B, C, E, F, G, and H are the 'in-sample using regional average values' comparison. We use these approaches for assessing the transfers because they express a form of convergence validity and represent a simple approach to adapting the models.

Table 6. Description of Benefit Transfer Treatments of Meta-Models.

Benefit Transfer Treatment	Regression Model	Description of Benefit Transfer Treatment
Treatment A	National	Average of individual predicted CS from regression.
Treatment B	National	Average CS by holding independent variables at their national mean values, except for activity variables when appropriate.
Treatment C	National	Average CS by holding independent variables at their census region mean values, except for activity variables when appropriate.
Treatment D	Census Region	Average of individual predicted CS from regression.
Treatment E	Census Region	Average CS by holding independent variables at their census region mean values by activity.
Treatment F	Census Region	Average CS by holding independent variables at their national mean values by activity, except for activity variables when appropriate.
Treatment G	Census Region	Average CS by holding independent variables at their census region mean values, except for activity variables when appropriate.
Treatment H	Census Region	Average CS by holding methodology independent variables at their national mean value by activity and site characteristic independent variables at their census region mean values, except for activity variables when appropriate.

B. Assessment Results.

i) In-sample Comparison Involving Individual Study Values Results

Treatments A and D can be directly compared as the 'in-sample individual study values' assessment, where the overall performance of the model is similar to a goodness of fit statistic. Table 7 provides the overall results of the assessment. Treatment A of the national model had a grand average absolute difference of 41% for all activities and Treatment D of the CR models had a grand average absolute difference of 8%. For an activity in a region, the difference estimates ranged from –127% to 207% for Treatment A and from –44% to 66% for Treatment D. Thus, the 'fit' of the CR models is better than the national model, supporting the results of the Chow test that the data not be pooled. This is also consistent with the adjusted-R^2 statistics for each model, with each CR model having a larger adjusted-R^2 than the national model.

Table 7. Efficiency of Benefit Transfer Treatments.

		NATIONAL MODELS			CENSUS REGION MODELS				
		Treatment A	Treatment B	Treatment C	Treatment D	Treatment E	Treatment F	Treatment G	Treatment H
Act.#	Activity	% Diff	% Diff	% Diff	% Diff	% Diff	% Diff	% Diff	% Diff
1	Camping	37.29%	39.76%	54.46%	0.56%	9.26%	150.68%	166.16%	192.91%
2	Picnicking	35.99%	38.77%	47.71%	16.64%	16.65%	16.65%	59.09%	94.35%
3	Swimming	98.48%	26.92%	59.69%	19.32%	19.31%	47.26%	159.64%	49.70%
4	Sightseeing	29.20%	38.77%	64.19%	4.97%	5.39%	23.05%	112.03%	46.95%
5	Off-road driving	30.79%	42.58%	15.16%	38.39%	38.40%	38.40%	90.30%	36.01%
6	Float boating	95.91%	104.80%	88.23%	0.64%	0.67%	883.61%	305.06%	110.16%
7	Motor boating	34.92%	63.71%	82.18%	11.55%	11.55%	72.79%	67.17%	77.54%
8	Hiking/Backpacking	91.03%	51.69%	76.79%	3.19%	2.07%	87.38%	108.26%	76.97%
9	Biking	33.22%	37.13%	32.72%	0.00%	0.00%	87.03%	44.91%	89.88%
10	Downhill Ski	118.81%	14.14%	68.89%	11.09%	11.09%	88.23%	61.00%	53.57%
11	Cross Country Ski	12.70%	71.14%	153.56%	38.80%	38.78%	117.36%	108.99%	185.25%
12	Snow mobiling	4.49%	22.60%	29.05%	12.00%	12.00%	84.02%	39.96%	23.55%
14a	Big game hunting	13.28%	11.97%	12.43%	0.23%	2.19%	27.90%	49.04%	9.81%
14b	Small game hunting	23.80%	32.92%	60.95%	11.62%	11.03%	5.91%	40.42%	27.37%
14c	Waterfowl hunting	15.30%	49.68%	53.05%	10.11%	13.14%	14.12%	105.78%	74.60%
15	Fishing	15.17%	15.80%	24.92%	2.72%	2.69%	25.30%	62.74%	39.69%
16	Wildlife Viewing	8.09%	21.24%	22.50%	5.35%	7.62%	10.02%	52.89%	30.73%
17	Horseback riding	NA	NA	NA	NA	NA	NA	NA	NA
19	Rock Climbing	15.31%	35.95%	59.04%	19.79%	32.27%	60.18%	79.45%	52.56%
20	General Recreation	39.56%	72.45%	98.49%	3.08%	6.35%	128.82%	302.27%	337.18%
21	Others	5.32%	24.21%	11.95%	6.43%	12.61%	107.56%	118.10%	492.59%
Summ	Grand Difference								
	All activities	40.59%	40.81%	59.82%	7.66%	9.39%	117.55%	121.65%	118.12%
	Std Error	0.0866	0.0849	0.1463	0.0279	0.0327	0.8191	0.4832	0.6855

Abs-Avg calculated as: Average[Abs(percent differences)]
Act-Avg calculated as: Average[Abs-Avg]

ii) In-sample Comparison Involving Regional Average Values Results

The rest of the Treatments (B, C, E, F, G, and H) compare predicted regional values per activity to the raw average regional values per activity. Treatments B (national model) and F (CR model) are directly comparable since they both use national mean values of the explanatory variables to predict average regional values. Table 7 provides the overall results of the assessment. Treatment B of the national model had a grand average absolute difference of 41% for all activities and Treatment F of the CR models had a grand average absolute difference of 118%. For an activity in a region, the difference estimates ranged from –80% to 234% for Treatment B, and from –2567% to 513% for Treatment F. This result makes sense since the mean values used to adapt the regression models are based on national averages for each activity, which is the level of development for the national model. More variability is introduced to the CR model transfers because the national mean values are not sensitive to regional model differences.

Treatments C (national model) and G (CR models) are directly comparable since they both use census region mean values of the explanatory variables to predict average regional values. Table 7 provides the overall results of the assessment. Treatment C of the national model had a grand average absolute difference of 60% for all activities and Treatment G had a grand average absolute difference of 122%. For an activity in a region, the difference estimates ranged from –75% to 299% for Treatment C, and from –391% to 809% for Treatment G. This result does not support previous conclusions drawn and does not meet expectations. We expected that using CR specific mean values for adapting the regressions to predict average values would be more precise than using national averages, and that these CR specific mean values for the explanatory variables would better fit the CR models. The opposite is true. The national model is more robust to perturbations in adapting the model for benefit transfer than the CR models. Because of this and the Chow test results, we decided to assess the CR models further.

Treatment E arose because we wondered if the CR models, despite better statistical fit to the data, were as volatile in predicting benefits if even more specific values were used for the explanatory variables. Therefore, in Treatment E, the CR models are adapted to benefit transfer by using the most precise mean values available for the explanatory variables. Mean values in this treatment are for studies on an activity in a given region. For example, when predicting a value for camping in CR1, we used the mean value for the independent variables from just camping studies in CR1. One disadvantage of this approach is that where there is no data, the model cannot be adapted to that region. Table 7 provides the overall results of the assessment. Treatment E of the CR models had a grand average absolute difference of 9% for all activities. For an activity in a region, the difference estimates ranged from –64% to 67%, which is significantly different than the other treatments.

Treatment H arose because we thought that maybe the CR models would be more responsive to a mixture of mean values for adapting the models for benefit transfer. We speculated that methodology would be invariant to application across the models, but that site characteristics would be somewhat unique to each region. Therefore, we used the national mean values from an activity for methodology variables and census region mean values for site characteristic variables. Table 7 provides the overall results of the assessment. Treatment H of the CR models had a grand average absolute difference of 118% for all activities. For an activity in a region, the difference estimates ranged from –227% to 990%. This result supports the conclusion that even though the CR models have a better fit for the data, they are not robust to perturbations of the explanatory variables. All treatments of the national model are significantly more precise than comparable treatments of the CR models, and are not significantly different from each other for the national and CR models. Only when the adaptation of the CR models is specific to the within group characteristics of the models does it perform better than the national model.

C. Efficiency of National Average Value Transfer

We use the same procedure to assess the simple benefit transfer of a national average value of a recreation activity to a region. That is, we calculate the percent difference between the national average value to the raw average value of an activity in a region. The grand absolute average difference for this transfer approach is 38%, which is not significantly different than the national model. For an activity in a region, the difference estimates ranged from –62% to 269%, which is also similar to differences for the national model. What is gained over the simple national average value transfer with the national model approach is that the national model approach provides the ability to adapt the model to the unique characteristics of the policy site. For example, a value for camping near a lake is needed but not all of the studies behind the regional average or national average are based on lake camping. One could then adapt the national model by turning the lake variable 'on' (setting equal to one), providing a value for camping near lakes.

VII. Conclusions

Several criteria have been suggested for selecting candidate studies for benefit transfer.[7] Desvousges et al. (1998) grouped these into three distinct categories: scientific soundness, germaneness, and richness of detail. Likewise, the quality of a meta-analysis will be dependent upon these criteria. We were strictly interested in the quantitative aspects of a meta-analysis and did not make any qualitative decisions concerning the studies we included in our analysis. However, studies which did not have sufficient richness of detail reported in them could not be included in the meta analysis since observations were missing on variables.

Meta-analysis as a benefit transfer tool provides several advantages over simple point estimate, average value, or benefit function transfers. First, it utilizes information from a greater number of studies providing more rigorous measures of central tendency sensitive to the underlying distribution of the study values. Second, methodological differences can be controlled for when calculating a value from the meta-analysis equation. Third, by setting the independent variables at the levels specific to the policy site, the analyst is potentially accounting for differences between the original studies and the policy studies.

While meta-analysis is a conceptually sound approach to benefit transfer, the quality of original research and full reporting of data and results is as necessary a component to critical meta-analysis as the statistical methods used. A meta-analysis can be no better than the data that it is

[7] See Brookshire and Neill (1992), Rosenberger (1998), and Desvousges et al. (1998) for a summary of these criteria and other issues related to benefit transfer. A special issue of *Water Resources Research* (1992) was devoted to the issue of benefit transfer.

built on. The ability of meta-analysis to capture nuances in the data – differences between sites, user populations, and/or affected activities – is dependent upon not only the quality of the original studies, but also on the sheer volume of studies conducted. One of the limitations of our meta-analysis is the lack of an adequate number of studies for certain recreation activities. Separate meta-analyses of different recreation activities, given enough observations, may provide models that are more robust to factors affecting them, and therefore an increased ability to function for benefit transfer.

Our database of outdoor recreation use value studies contains over 131 studies providing more than 700 use value estimates. We estimate several models from this data and test the convergent validity of the models' ability to accurately predict the raw value from the averaging of the available estimates. We found that while the regional models statistically fit the data better than the national model, they also have the greatest variability in predicting values than the more robust national model. This implies that in addition to sensitivity of these regional models to variability within the bounds of the data, they are probably more sensitive to 'noise' emanating from outside the bounds of the data set. We also found that the simple transferring of a national average recreation value is as precise as using the national model to predict values for transfer. However, the national model has the advantage of being controllable for factors outside of the existing database and specific to the policy site. However, we did not out-of-sample test these models or apply them under real transfer conditions.

There are different approaches to using existing information for benefit transfer when original data collection is not possible or not warranted. Our database and meta-analysis provides for each of these approaches. First, study specific values, or an average of a subset of the available estimates, can be accomplished by sorting the database on those studies deemed relevant to the issue at hand. Second, the simple average values per activity per region (table 1) can be transferred to a policy site. Third, the national average value of an activity can be transferred (table 1). Fourth, the meta-analysis predicted value for an activity in a region can be transferred to the policy site. And fifth, the meta regression equations (table 5) can be adapted to specifics of the policy site and issue to predict a recreation use value. As Desvousges et al. (1998) remind us, an important component in any benefit transfer is the involvement and judgment of the transfer analyst. While it would be nice to have a purely mechanistic approach to benefit transfer, this is not the case. Meta-analyses will probably never be a panacea for valuation needs. But it can be another important tool for analysts to add to their toolbox.

Several studies have performed convergent validity tests on benefit transfer trials (Loomis, 1992; Loomis et al., 1995; Downing and Ozuna, 1996; Kirchhoff, Colby and LaFrance, 1997; Kirchhoff, 1998). While the evidence provides some confidence in pursuing benefit transfers, with several cases producing values very similar to the 'true' values (as low as a few percentage points), in other cases the disparity between the 'true' value and the transfer value are quite large (in excess of 800%). On average, we found our national model to predict values within about 40% of the average value of the relevant studies. Individually, we found the difference between predicted values from the national model to the 'true' values to range from –80% to 299%. The regional models predicted, on average, values in excess of 100% of the 'true' values, and ranged from more than –2000% to 990%, depending on the treatment of the model.

We also tested the data for panel effects based on study and did not find any such effects. The only effect external to our model specification is an outlier effect. Therefore, a classical OLS regression was used to estimate the different models.

REFERENCES

Boyle, K., G. Poe, J. Bergstrom. 1994. What Do We Know about Groundwater Values?: Preliminary Implications from a Meta Analysis of Contingent-Valuation Studies. *American Journal of Agricultural Economics*, 76(5):1055-1061.

Brookshire, D. and H. Neill. 1982. Benefit Transfers: Conceptual and Empirical Issues. *Water Resources Research* 28(3):651-655.

Brown, G. and M. J. Hay. 1987. Net Economic Recreation Values for Deer and Waterfowl Hunting and Trout Fishing, 1980. Working Paper No. 23. Washington, DC: USDA Fish & Wildlife Service, Division of Policy and Directives Management.

Brown, T. C., P. A. Champ, R. C. Bishop and D. W. McCollum. 1996. Which Response Format Reveals the Truth about Donations to a Public Good? *Land Economics* 72(2):152-166.

Carson, R. T., J. Wright, A. Alberini, N. Carson and N. Flores. 1994. A Bibliography of Contingent Valuation Studies and Papers. CA: NRDA, Inc.

Carson, R. T., N. E. Flores; K. M. Martin and J. L. Wright. 1996. Contingent Valuation and Revealed Preference Methodologies: Comparing the Estimates for Quasi-Public Goods. *Land Economics* 72(1):80-99.

Desvousges, W. H., F. R. Johnson and H. S. Banzhaf. 1998. Environmental Policy Analysis With Limited Information: Principles and Applications of the Transfer Method. Northampton, MA: Edward Elgar.

Downing, M. and T. Ozuna, Jr. 1996. Testing the Reliability of the Benefit Function Transfer Approach. *Journal of Environmental Economics and Management* 30(3):316-322.

Englin, J. and T. A. Cameron. 1996. Augmenting Travel Cost Models With Contingent Behavior Data: Poisson Regression Analysis With Individual Panel Data. *Environmental and Resource Economics* 7(2):133-147

Epsey, M., J. Epsey and W. D. Shaw. 1997. Price Elasticity of Residential Demand for Water: A Meta-analysis. *Water Resources Research* 33(6):1369-1374.

Krichhoff, S. 1998. Benefit Function Transfer vs. Meta-Analysis as Policy Making Tools: A Comparison. Paper presented for the Workshop on META Analysis and Benefit Transfer. Tinbergen Institute, Amsterdam. April 6-7.

Kirchhoff, S., B. G. Colby and J. R. LaFrance. 1997. Evaluating the Performance of Benefit Transfer: An Empirical Inquiry. *Journal of Environmental Economics and Management* 33(1):75-93.

Loomis, J. B. 1992. The Evolution of a More Rigorous Approach to Benefit Transfer: Benefit

Function Transfer. *Water Resources Research* 28(3): 701-705.

Loomis, J., B. Roach, F. Ward and R. Ready. 1995. Testing the Transferability of Recreation Demand Models Across Regions: A Study of Corps of Engineers Reservoirs. *Water Resources Research* 31(3): 721-730.

Loomis, J. and D. White. 1996. Economic Benefits of Rare and Endangered Species: Summary and Meta-analysis. *Ecological Economics* 18(3):197-206.

MacNair, D. 1993. 1993 RPA Recreation Values Database. USDA Forest Service, RPA Program, Washington DC.

Mannesto, G. and J. Loomis. 1991. Evaluation of Mail and In-Person Contingent Value Surveys: Results of a Study of Recreational Boaters. *Journal of Environmental Management* 32():.

Markowski, M., R. Unsworth, R. Paterson and K. Boyle. 1997. A Database of Sport Fishing Values. Industrial Economics Inc. prepared for the Economics Division, U.S. Fish and Wildlife Service, Washington, DC.

Rosenberger, R. S. 1998. Benefits Transfer in RPA: Current Projects. Paper presented at USDA Regional Research Project W-133 Technical Meeting, March 18-20, 1998, Colorado Springs, CO.

Rosenthal, D H., D.M. Donnelly, M.B. Schiffhauer & G. E. Brink. 1986. User's Guide to RMTCM: Software for Travel Cost Analysis. USDA Forest Service, General Technical Report RM-132.

Rosenthal, D. 1987. The Necessity for Substitute Prices in Recreation Demand Analyses. *American Journal of Agricultural Economics* 69(4):828-837.

Smith, V. K. and J. Huang. 1995. Can Markets Value Air Quality? A Meta-Analysis of Hedonic Property Value Models. *Journal of Political Economy* 103(1):209-227.

Smith, V. K. 1984. Environmental Policy under Reagan's Executive Order. University of North Carolina Press, Chapel Hill.

Smith, V. K. and L. Osborne. 1996. Do Contingent Valuation Estimates Pass a Scope Test?: A Meta-analysis. *Journal of Environnmental Economics and Managment* 31:287-301.

Smith, V.K. and Y. Kaoru. 1990. Signals or Noise?: Explaining the Variation in Recreation Benefit Estimates. *American Journal of Agricultural Economics* 72(2):419-433.

Sturtevant, L. A., F. R. Johnson and W. H. Desvousges. 1998. A Meta-analysis of Recreational Fishing. Unpublished Manuscript. Durham, NC: Triangle Economic Research.

U.S. Water Resources Council. 1979. Procedures for Evaluation of National Economic Development (NED) Benefits and Costs in Water Resources Planning (Level C). *Federal Register*, 44(243): 72892-72976.

-----. 1983. Economic and Environmental Principles and Guidelines for Water and Related Land Resources Implementation Studies. U.S. Government Printing Office, Washington DC. March 10, 1983.

Waddington, D. G., K. J. Boyle and J. Cooper. 1991. 1991 Net Economic Values for Bass and Trout Fishing, Deer Hunting, and Wildlife Watching. Washington, DC: US Fish and Wildlife Service, Division of Federal Aid.

Walsh, R. G., D. M. Johnson and J. R. McKean. 1988. Review of Outdoor Recreation Economic Demand Studies With Nonmarket Benefit Estimates, 1968-1988. Technical Report No. 54, Colorado State University, Fort Collins, CO.

-----. 1989. Issues in Nonmarket Valuation and Policy Application: A Retrospective Glance. *Western Journal of Agricultural Economics* 14(1):178-188.

-----. Benefit Transfer of Outdoor Recreation Demand Studies: 1968-1988. *Water Resources Research* 28(March 1992):707-713.

Water Resources Research, 1992, 28(3).

Appendix Table A-1. Unbalanced Panel Data Models.

VARIABLE	OLS	FIXED EFFECTS	RANDOM EFFECTS
CONSTANT	-3.9427 (24.65)[a]	α_i[b]	43.299 (28.18)
METHOD	-32.951*** (9.791)	-9.4462 (17.38)	-23.534* (13.34)
DCCVM	10.720** (4.910)	11.149 (15.49)	14.193 (9.726)
ZONAL	-13.256 (8.844)	-0.49514 (18.10)	-2.6643 (12.23)
INDIVID	2.4391 (8.790)	14.173 (13.13)	14.468 (11.10)
TTIME	1.1009 (6.185)	-9.5802 (9.769)	-8.5826 (7.954)
SUBS	-22.950*** (4.987)	4.4830 (11.60)	-11.211 (7.371)
MAIL	8.0480** (3.335)	-31.479 (36.77)	2.0925 (8.275)
LINLIN	12.782* (7.774)	26.022 (18.19)	21.847* (11.33)
LOGLIN	5.6491 (7.499)	-6.2556 (15.19)	-3.7053 (10.15)
LOGLOG	5.1274 (8.755)	-5.2087 (16.08)	-5.5307 (11.72)
VALUNIT	-10.364*** (3.492)	-10.847 (15.96)	-3.4213 (8.278)
TREND	1.0187*** (0.3311)	-24.437 (18.55)	0.30565 (0.6988)
SPECACT	8.3077 (11.50)	10.349 (15.89)	11.514 (13.51)
FSADMIN	-13.085*** (4.426)	1.9487 (4.953)	-3.0723 (4.547)
R1	18.582* (9.644	3.1767 (10.20)	0.2422 (9.668)
R2	4.5550 (7.754)	1.8732 (8.680)	-3.5341 (8.207)
R3	-7.9537 (11.10)	0.82868 (12.40)	-4.9432 (11.63)
R4	10.521 (7.805)	3.3670 (8.414)	-0.05561 (7.993)
R5	2.8964 (11.19)	2.5269 (11.21)	-2.3637 (10.64)
R6	-1.7217 (8.377)	-5.9663 (8.925)	-11.118 (8.486)
R8	1.5595 (8.963)	-0.5165 (9.739)	-6.1615 (9.222)
R9	8.0652 (7.818)	-2.6286 (8.865)	-7.0506 (8.388)
LAKE	-14.957** (7.255)	25.892** (11.22)	0.8703 (8.484)
RIVER	24.676*** (6.986)	40.798** (18.62)	23.562** (10.35)
FOREST	-5.2554 (3.947)	-4.4470 (5.710)	-1.811 (5.023)

Appendix Table A-1. Continued.

VARIABLE	OLS	FIXED EFFECTS	RANDOM EFFECTS
PUBLIC	21.858*** (8.246)	-1.7534 (18.80)	4.8764 (12.40)
DEVELOP	-3.8083 (6.171)	-2.4187 (9.433)	0.18788 (7.234)
NUMACT	0.60509** (0.2837)	-2.3539 (3.311)	-0.41916 (0.8073)
CAMP	16.720 (12.36)	9.9388 (13.83)	5.9536 (12.30)
PICNIC	9.8333 (16.00)	-7.526 (14.27)	-6.6941 (13.24)
SWIM	7.7678 (15.20)	-0.5456 (15.18)	-2.0466 (13.88)
SISEE	13.679 (11.75)	22.654 (16.79)	20.382 (14.31)
NOMTRBT	-0.21016 (13.64)	-9.7448 (14.18)	-8.679 (12.39)
MTRBOAT	5.4431 (11.44)	42.789** (17.86)	23.106 (14.39)
HIKE	4.7191 (13.23)	-21.774 (15.42)	-14.635 (13.39)
BIKE	0.5711 (17.29)	25.788 (19.69)	21.963 (17.69)
DHSKI	12.699 (16.72)	-27.130 (17.84)	-25.248 (15.73)
XSKI	0.05126 (15.29)	-19.791 (18.51)	-18.576 (16.41)
BGHUNT	14.916*** (3.961)	-20.574** (8.797)	-7.7539 (7.555)
SMHUNT	8.7073 (7.841)	-32.017*** (10.37)	-18.485** (9.124)
WATFOWL	10.701** (5.255)	-26.652*** (9.306)	-12.531 (7.997)
FISH	7.5243 (4.821)	-28.965*** (9.237)	-14.708* (7.885)
GENREC	5.9279 (12.42)	22.051 (28.95)	1.4363 (16.98)
INCOME	-0.72574 (0.7228)	0.5910 (0.5379)	0.447 (0.5283)
AGE	43.527 (86.24)	-84.099 (76.92)	-30.047 (73.98)
EDUC	70.395 (56.30)	-45.803 (42.09)	-23.054 (41.37)
POPUL	-0.05591 (0.04035)	-0.0082 (0.0324)	-0.0164 (0.0312)
BLACK	24.318 (24.66)	-7.0473 (18.50)	1.7083 (18.12)
HISPAN	72.294** (34.33)	41.579 (27.50)	43.789* (26.59)

Appendix Table A-1. Continued.

VARIABLE	OLS	FIXED EFFECTS	RANDOM EFFECTS
ADJ R2	0.25	0.68	0.03
F-STAT	5.40*** [50, 621]	8.81*** [180, 491]	na
N	672	672	672

[a] Standard errors in parentheses, except for F-stat where degrees of freedom are given in brackets.
[b] 131 individual group effects constants were estimated.
*p<0.10; **p<0.05; ***p<0.01 (all variables are p<=0.20).
Dependent variable is CS per person day.

Appendix Table A-2. Raw Average Recreation Values per Person/Day for Use in Model Assessments.

(Review: 1967 - 1998)

			CR=1		CR=2		CR=3		CR=4		CR=45		CR=5		
Act.#*	Activity	N	NO.EAST	N	SO.EAST	N	Intermtn	N	Pacific	N	Pac+AK	N	Alaska	N	National only
1	Camping	3	$30.07	6	$20.35	10	$22.42	3	$113.88	3	$113.88			1	$28.61
2	Picnicking	1	$55.22	1	$37.24	1	$32.30	2	$73.95	2	$73.95			1	$15.69
3	Swimming	5	$37.21					1	$14.95	1	$14.95			1	$20.67
4	Sightseeing	14	$34.23	17	$31.27	19	$32.42	4	$39.56	5	$39.56	1	$13.09	1	$18.83
5	Off-road driving							1	$33.64	1	$33.64			1	$19.94
6	Float boating			2	$8.40	4	$72.42	4	$21.69	4	$21.69			1	$21.61
7	Motor boating	2	$52.44			2	$68.76			1	$15.13	1	$15.13	1	$38.70
8	Hiking/Backpacking	2	$45.01	2	$109.96	3	$37.42	5	$21.88	6	$21.88	1	$12.93	1	$20.87
9	Biking	1	$34.11	1	$56.27	2	$58.89							1	$17.61
10	Downhill Ski					2	$23.23	1	$20.90	1	$20.90			1	$19.61
11	Cross Country Ski	2	$28.83			1	$11.71							1	$13.20
12	Snow mobiling					1	$36.23								
14a	Big game hunting	55	$45.22	26	$35.99	68	$45.05	11	$43.77	16	$43.77	5	$52.40	2	$104.90
14b	Small game hunting	3	$36.73			13	$25.75							2	$103.02
14c	Waterfowl hunting	23	$32.09	11	$17.70	19	$36.74	5	$24.51	6	$24.51	1	$60.08		
15	Fishing	42	$31.63	13	$27.74	39	$42.49	15	$36.97	16	$36.97	1	$39.22	4	$37.26
16	Wildlife Viewing	43	$27.06	25	$30.38	26	$34.03	13	$40.33	18	$40.33	5	$54.57		
17	Horseback riding													2	$16.08
19	Rock Climbing	2	$85.74			3	$42.04								
20	General Recreation	8	$15.21	6	$14.65	20	$33.51	12	$16.93	15	$16.93	3	$11.84		
21	Others			2	$26.21	5	$57.92								
	Total # of cases	206		112		238		77		95		18		21	

N = Number of cases
* = Act-13, Snow playing, and ACT-18, Resorts, were not considered as there was no study.