Panel Stratification in Meta-Analysis of

Environmental and Natural Resource Economic Studies

By

Randall S. Rosenberger
John B. Loomis
Ram Shrestha

Presented at Western Agricultural Economics Association Annual Meeting
July 11-14, 1999
Fargo, ND

All authors are affiliated with the Department of Agricultural and Resource Economics at Colorado State University, Fort Collins, CO. They are, respectively, post doctoral research fellow, professor, and graduate research assistant.

Panel Stratification in Meta-Analysis of

Environmental and Natural Resource Economic Studies

ABSTRACT

Meta-analyses of past research outcomes are becoming more popular, however, the issue of the panel nature of data has not been empirically investigated. We test various forms of data stratifications into panels for outdoor recreation economic studies but do not find any significant effects, possibly because of inherent data complexity.

INTRODUCTION

Meta-analyses of past environmental and natural resource economic studies are becoming more applicable and popular as these studies accumulate. The first two meta-analyses on environmental and natural resource economic studies were by Smith and Kaoru (1990) on travel cost studies of recreation benefits and Walsh, Johnson and McKean (1989) on outdoor recreation benefit studies. These original meta-analyses were designed for the purpose of understanding and modeling the influence of different methodological and study specific factors on the outcomes of the studies. More recently, applications of meta-analysis for similar purposes include groundwater (Boyle, Poe and Bergstrom 1994), air quality via the hedonic property method (Smith and Huang 1995), endangered species (Loomis and White 1996), visibility (Smith and Osborne 1996), demand elasticities for gasoline (Epsey 1996), price elasticities of water (Epsey, Epsey and Shaw 1997), health effects (Desvousges, Johnson and Banzhaf 1998), recreational fishing (Sturtevant, Johnson and Desvousges 1998), and an update on outdoor recreation benefit estimates (Rosenberger, Loomis and Shrestha 1999).

Meta-analysis is the statistical summarizing or synthesizing of past research on specific topics, as evidenced by the list above. Although meta-analysis is fairly recent to environmental and natural resource economics, it enjoys a long history in the fields of psychology, education, and health sciences. However, meta-analyses of environmental and natural resource economic studies differ from these other fields in that they are not conducted under controlled conditions, involve modeling judgments on the part of the researchers (both then and now), and the panel nature of the research results reported (Smith and Kaoru 1990).

This paper is expressly concerned with the panel nature of the data and empirically explores different panel data estimators using a database of outdoor recreation benefit studies. Although nearly all of the referenced meta-analyses refer to the panel structure of their data, none of them explicitly test for panel effects in their models. The rest of the paper presents some of the econometric issues with panel data, a brief description of the data, and econometric models tested. Hypothesis tests and results are presented and conclusions are drawn concerning the issue of panel data in meta-analysis.

PANEL DATA ISSUES IN META-ANALYSIS

Many environmental and natural resource economic studies provide multiple estimates of targeted outcomes, such as benefit estimates for a sample population or subset of the population. Multiple observations from the same source may be correlated and the error process across several of these studies may be heteroskedastic. In the presence of panel effects, the classical ordinary least squares (OLS) and maximum likelihood estimators may be inefficient and their estimated parameters biased.

Panel effects from multiple observations may be observable or unobservable. In the case of observable differences, multiple observations can arise because the original studies test different functional forms, use different estimators, vary site definitions, use different modeling assumptions for the same site, and/or provide multiple estimates for multi-use sites. These observable factors can be accounted for through the coding of the characteristics of the studies and fully specifying the model. Unobservable or latent factors must be discovered statistically.

While nearly all of the meta-analyses referred to above recognize the panel nature of their data, none of them explicitly test for panel effects. Smith and Kaoru (1990) used OLS with a Newey-West version of the White consistent covariance estimator in the presence of heteroskedasticity and generalized autocorrelation. This procedure does not affect the parameter estimates of the model, but does correct for heteroskedasticity in the standard errors of these parameters. However, Smith and Kaoru (1990) show that hypotheses concerning their parameter estimates are largely unaffected by the corrected standard errors of the parameters.

Boyle, Poe and Bergstrom (1994), Smith and Huang (1995), and Smith and Osborne (1996) use a Huber-White correction for heteroskedasticity and intra-study correlation while fitting OLS models. Only in the Smith and Osborne (1996) study are we told that the corrective measure used for the panel nature of the data had little impact on the overall results of the analysis. Additionally, Smith and Osborne (1996) estimate a model by Box-Cox and feasible generalized least squares, finding no significant difference from the OLS with Huber-White correction. Sturtevant, Johnson and Desvousges (1998) and Desvousges, Johnson and Banzhaf (1998) explicitly use panel data estimators in part of their analyses, however, the significance of the presence of panel effects is not reported.

MODELING PANEL DATA

Stratification

Ex ante information in the estimation of panel data models requires the stratification of the data into groups, with each group being assigned an index. In some panel data cases, this stratification seems obvious. For example, when each respondent in a survey provides multiple value responses, the group is the individual (Englin and Cameron 1996; Loomis 1997; Rosenberger and Loomis 1999). Or when import/export information is collected from a sample of countries over time, the group is the country. However, in meta-analysis, there may be several similarities among different studies and multiple ways of grouping the data based on these similarities. In the studies that use panel data estimators, stratification is by study (Desvousges, Johnson and Banzhaf 1998; Sturtevant, Johnson and Desvousges 1998), and in the latter case, by study by body of water. We expand on this issue and test three different stratifications of the data – by *Study*, by *Researcher*, and by *Data Structure*.

Candidate Panel Models

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

$$y_i = m + b' x_i + e_i, \qquad (1)$$

where *i* indexes each observation, y is the dependent variable, x is a vector of explanatory variables which account for differences across and within the studies, and e is the classical error term with mean zero and variance σ^2_ε.

A generic panel model may be defined as:

$$y_{ij} = m_j + b' x_{ij} + e_i \qquad (2)$$

where j is the stratification index and μ_j is the panel effect. This panel effect can be modeled as either having a unit-specific constant (fixed) effect or a unit-specific disturbance (random) effect.[1] In the fixed effect model, the group effect parameter, μ_j, takes on the form:

$$y_{ij} = a_j + b' x_{ij} + e_i, \qquad (3)$$

where a_j is the unit specific constant for each group identified through the stratification indexing.

In the random effect model, the group effect parameter, m_j, takes on the form:

$$y_{ij} = a + b' x_{ij} + e_{ij} + m_j, \qquad (4)$$

where m_j is the unit-specific disturbance effect and has a mean zero and variance s^2_m.

Each study has an overall variance:

$$\text{var}[e_{ij} + m_j] = \sigma^2 = \sigma^2_\varepsilon + \sigma^2_m. \qquad (5)$$

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

Hypothesis Test Statistics

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 ($H_0: m_j = 0$). Hausman's chi-squared statistic tests the random effect model

[1] Other candidate panel models include a separate variances model (no common error term) and a mixed effect model (both separate constants and separate variances) (Desvousges, Johnson and Banzhaf 1998,

against the fixed effect model ($H_0: m_j$ as a random effect; $H_1: m_j$ as a fixed effect). In the event that we fail to reject the null hypothesis of no group effect, the chi-square test is not applicable.

DATA

The data used in empirically testing for panel effects consists of studies on outdoor recreation use value estimates collected from a literature review dating from 1967 through 1998. For a detailed reporting of the data and optimized regression models see Rosenberger, Loomis and Shrestha (1999). The database for present purposes consists of 131 studies providing 682 benefit estimates. The number of estimates per study ranged from 1 to 134, with a mean of 5 estimates and a median of 1 estimate per study. Therefore, any grouping of the data will consist of an unbalanced structure and will require an unbalanced panel estimation technique. Existing econometric methods are capable of dealing with unbalanced datasets. The database contains 126 fields coded across six main coding categories: 1) complete citation to the study; 2) the benefit measure (original value, adjusted to per person per day in 1996$, whether stated or revealed preference method was used); 3) the nature of the benefit measure (e.g., willingness-to-pay vs. willingness-to-accept, mean vs. median); 4) details of a stated preference application if used; 5) details of a revealed preference application if used; and 6) study location details (e.g., whether National Forest, Park, State Park, etc.), environment type (e.g., forest, wetland), recreation activity, etc. Table 1 provides descriptions of the variables used in the model estimation and their mean values.

Sturtevant, Johnson and Desvousges 1998).

We also provide for three distinct ways of grouping the data, or *ex ante* identification of similarities that may be a source of panel effects. The first is by *Study*, which results in 131 groups. Second, we can stratify based on *Researcher* as determined by lead author. This stratification results in 91 groups. And third, we can stratify the data based on four different *Data Structures* which may produce panel effects: 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, different sites using different samples of respondents) (14% of the studies); and 4) multiple estimates, multiple samples (e.g., split sample testing) (14% of the studies).

HYPOTHESIS TEST RESULTS

The model is fit by fully specifying the model using all of the variables identified in table 1.[2] By fully specifying the model, we can account for any observable similarities across some of the studies or unique characteristics of individual studies. As Smith and Osborne (1996) note, unique characteristics of specific studies can be explicitly modeled through variables in the model or by a fixed effect parameter, but not both. Therefore, any panel effects that may be discovered statistically will be the result of unobservable sources defined by the different forms of stratification and/or random error processes.

[2] Some of the variables had to be dropped from the model due to a lack of variation across the studies (e.g., no horseback riding studies) or high correlation with the fixed effect parameters, including *ONSITE*, *PHONE*, *RECQUAL*, *OFFRD*, *SNOWMOB*, *WLVIEW*, *HORSE*, and *ROCKCL*.

Table 1. Variables Tested in the Panel 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 1. 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.

The baseline OLS model had an adjusted-R^2 of 0.26, which is lower but consistent with the performance of the Walsh, Johnson and McKean (1989) and Smith and Kaoru (1990) meta-analyses. The model may not be the most efficient if it is overspecified, however, our interest here is in testing for panel effects. Optimized models are reported elsewhere as noted above. The residuals from the baseline OLS model are used to estimate the variance components for computing the random effect model.

Table 2 provides the results of the hypothesis tests. When stratified by *Study*, the Lagrange multiplier test rejects the OLS specification in favor of a group effect model. The Chi-square test rejects the random effect model in favor of the fixed effect model. However, a significant problem with the fixed effect model is the potentially inordinate number of study-specific constants; in this case, 131 constants. Large numbers of constants is a problem when applying the model, for example in calculating welfare estimates from a linear demand model (Englin and Cameron 1996) or predicting benefit estimates for benefit transfer purposes (Rosenberger, Loomis and Shrestha 1999). An *ad hoc* procedure to deal with this issue of multiple constants is by calculating a weighted average constant, where the weights may be based on the frequency of estimates per study (Desvousges, Johnson and Banzhaf 1998; Sturtevant, Johnson and Desvousges 1998).

Another way to deal with the fixed effect constants is to explicitly enter them in the model through dummy variable specification. This is possible because the fixed effect model is simply an OLS with group-specific constants. Some of these constants may not be statistically significant. In our analysis, we found six of the constants to be statistically significant at the 0.05 level based on t-statistics. However, contrary to our expectations, these constants were not associated with studies providing multiple estimates, but studies providing primarily single estimates (5 studies provided one estimate each, the other study provided 2 estimates). Upon further investigation, it was determined that these seven estimates were outliers; they were greater than 2 standard deviations from the activity mean estimate. If these outliers are culled from the dataset,

Table 2. Hypothesis test results.

BY STUDY (all observations)			
Test	Hypothesis	Statistic	Result
Lagrange multiplier	H_0: no group effect H_1: group effect	3.93	Reject OLS (p-value=0.05)
Chi-square	H_0: random effect H_1: fixed effect	64.05	Reject random effect (p-value=0.09)
BY STUDY (outliers removed)			
Test	Hypothesis	Statistic	Result
Lagrange multiplier	H_0: no group effect H_1: group effect	0.49	Fail to reject OLS (p-value=0.48)
Chi-square	H_0: random effect H_1: fixed effect	0.00	Not applicable
BY RESEARCHER			
Test	Hypothesis	Statistic	Result
Lagrange multiplier	H_0: no group effect H_1: group effect	0.47	Fail to reject OLS (p-value=0.49)
Chi-square	H_0: random effect H_1: fixed effect	0.00	Not applicable
BY DATA STRUCURE			
Test	Hypothesis	Statistic	Result
Lagrange multiplier	H_0: no group effect H_1: group effect	0.53	Fail to reject OLS (p-value=0.47)
Chi-square	H_0: random effect H_1: fixed effect	0.00	Not applicable

the by *Study* with outliers removed Lagrange multiplier statistic in table 2 shows that we fail to reject the OLS specification.

The by *Researcher* and by *Data Structure* Lagrange multiplier statistics fail to reject the OLS specification as reported in table 2. In each of the latter three cases, an OLS specification is favored, suggesting that at least with these different stratifications of the data, no panel effects were discernible. There is still the possibility of heteroskedasticity that needs to be accounted for, but there are no discernible systematic unequal variances in the form of the random panel effect.

CONCLUSIONS

As environmental and natural resource economic empirical studies continue to accumulate, we can expect more meta-analyses of these studies for the purposes of investigating methodological and site factors across the studies and for benefit transfer purposes. An important issue that has been noted since the first meta-analysis of these types of studies is the panel nature of the data collected. However, the majority of these studies did not explicitly tested for panel effects nor investigate stratifying the data beyond the study level. If panel effects are not accounted for in meta-analysis databases then the estimated models may be biased and inefficient due to correlation of multiple values from the same source or through heteroskedastic error processes across the groups.

We tested for panel effects by stratifying the data by three different structures – by *Study* (the seemingly most obvious source of panel effects), by *Researcher*, and by *Data Structure*. In each case we fail to reject an OLS without group effects specification. What this implies is that either there are no panel effects in our dataset or there are many ways to stratify the data. Not all ways of stratifying the data are obvious. Panel effects in meta-analysis databases should always be considered. However, our results show that, possibly because of the inherent complexity of research conducted, the source of panel effects may not be easily discernible.

REFERENCES

Boyle, K., G. Poe, and 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.

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.

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. 1996. Explaining the Variation of Elasticity Estimates of Gasoline Demand in the United States: A Meta-Analysis. *Energy Journal* 17(3):49-60.

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.

Loomis, J. B. 1997. Panel Estimators to Combine Revealed and Stated Preference Dichotomous Choice Data. *Journal of Agricultural and Resource Economics* 22(2):233-245.

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

Rosenberger, R. S. and J. B. Loomis. 1999. The Value of Ranch Open Space to Tourists: Combining Observed and Contingent Behavior Data. *Growth and Change* (summer): forthcoming.

Rosenberger, R. S., J. B. Loomis and R. Shrestha. 1999. Meta-Analysis of Outdoor Recreational Use Value Estimates: Convergent Validity Tests. Paper presented at the Western Regional Research Group W133 annual meeting, 24-26 February, 1999, Tucson, AZ.

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. and L. Osborne. 1996. Do Contingent Valuation Estimates Pass a Scope Test?: A Meta-analysis. *Journal of Environmental Economics and Management* 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.

Walsh, R. G., D. M. Johnson and J. R. McKean. 1989. Issues in Nonmarket Valuation and Policy Application: A Retrospective Glance. *Western Journal of Agricultural Economics* 14(1):178-188.