WESTERN REGIONAL RESEARCH PUBLICATION

W-133

Benefits and Costs of Resource Policies Affecting Public and Private Land

Thirteenth Interim Report

June 2000

Compiled by

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Introduction

This volume contains the proceedings of the 2000 W-133 Western Regional Project Technical Meeting on "Benefits and Costs of Resources Policies Affecting Public and Private Land." The meeting was held in conjunction with the 2000 Western Regional Science Association Meeting at the Sheraton Kauai Resort, Kauai, Hawaii, February 28 – March 1, 2000. The meeting included a joint WRSA-W-133 session that was attended by many WRSA participants.

The Kauai meeting was attended by academic faculty from many W-133 member universities in addition to researchers from non-land grant universities, federal agencies and private consulting firms. A list of those who attended the meeting follows.

The papers included in this volume represent a wide-range of current research addressing the W-133 project objectives, which are: 1) benefits and costs of agro-economic policies, 2) benefits transfer for groundwater quality programs, 3) valuing ecosystem management of forests and watersheds, and 4) valuing changes in recreational access. The complete program for the meeting follows the list of participants.

The trip to Kauai was a long one for most and made the meetings this year smaller than those in recent years. The overwhelming opinion of those who made the trip was that it was well worth it. The sessions were stimulating and the scenery and weather were superb. I'd like to thank Jerry Fletcher, John Loomis, Frank Lupi, Douglass Shaw for their help with this year's meeting and special thanks to David Plane of WRSA for taking care of so many of the logistics of the meeting.

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June 2000

List of Participants at the 2000 Meeting

Chris Azevedo	Iowa State University
Enoch Bell	USDA Forest Service
John Bergstrom	University of Georgia
Nancy Bockstael	University of Maryland
William Breffle	Stratus Consulting
Patricia Champ	USDA Forest Service
Earl Ekstrand	U.S. Bureau of Reclamation
Donald Epp	Penn State University
Michael Farmer	Georgia Tech. University
Ronald Fleming	University of Kentucky
Jerald Fletcher	University of West Virginia
Kelly Giraud	University of Alaska, Fairbanks
Joseph Herriges	Iowa State University
John Hoehn	Michigan State University
Paul Jakus	University of Tennessee
David Layton	University of California, Davis
Daniel Lew	University of California, Davis
John Loomis	Colorado State University
Frank Lupi	Michigan State University
Douglas MacNair	Triangle Economic Research
Ted McConnell	University of Maryland
Donald McLeod	University of Wyoming
Jim Opalauch	University of Rhode Island
Daniel Phaneuf	North Carolina State University
Steve Polasky	University of Minnesota
Joan Poor	University of Maine
Richard Ready	Penn State University
Sabina Shaikh	University of British Columbia
Scott Shonkwiler	University of Nevada, Reno
Brent Sohngen	Ohio State University
Tom Stevens	University of Massachusetts
Phil Wandschneider	Washington State University
Michael Ward	University of California, Berkeley

Program of the W-133 Research Meeting
Sheraton Kauai Resort, Hawaii
February 28 – March 1, 2000

MONDAY FEBRUARY 28

Session I: Benefits Transfer for Groundwater Quality Programs
8 – 9:30 am
Chair: Frank Lupi

Donald J. Epp and Willard Delavan "The Quest for a Benefits Transfer Protocol: Nitrate Contamination of Groundwater

John Bergstrom, Greg Poe, Kevin Boyle, "A Preliminary Meta Analysis of Contingent Values for Groundwater Revisited"

Jerald J. Fletcher, Tim T. Phipps, and Md. Kamar Ali, "Environmental Federalism through the TMDL Process"

Coffee Break
9:30 –10 am

Session II: Valuing Spatial Amenities and Hedonic Modeling
10 – 12
Chair: Paul Jakus

Donald M. McLeod, Chris T. Bastian, Matthew J. Germino, William A, Reiners Benedict J. Blasko, "Amenity Impacts on Rural Land Values: Geographic Information Systems Data Incorporated into a Hedonic Property Model"

Michael Farmer, "Re-Investing in the Built City"

Michael Ward, Michael Hanemann, John Winkler, Linwood Pendelton and David Layton, "The Impact of Quality Variation on Southern California Beach Recreation"

Sabina Shaikh and Douglas Larson, "An Inverse Demand Count Data Model of Oregon Marine Fishing"

Lunch Break
12 – 1:30 pm

Joint WRSA W-133 Session: Spatial Dimensions of Natural Resource Valuation and Conservation
1:30 – 3; 3:30 – 5 pm
Chair, John Loomis, Dept. of Ag and Resource Economics, Colorado State University

Steve Polasky, Dept. of Applied Economics, University of Minnesota
Title: Strategies for Choosing Sites to Conserve Biodiversity
Discussant: John Hoehn, Dept. of Agricultural Economics, Michigan State University

John Loomis, Dept. of Agricultural and Resource Economics, Colorado State University
Title: How Large is the Geographic Market for Public Goods: Results from Five National Contingent Valuation Surveys
Discussant: John Bergstrom, Dept. of Agricultural Economics, University of Georgia

Thomas Stevens, Dept. of Resource Economics, University of Massachusetts.
Title: Valuing Visibility Improvements in the White Mountains: A Comparison of Visitor and Household Responses using Different Survey Modes
Discussant: Earl Ekstrand, U.S. Bureau of Reclamation

Nancy Bockstael, Dept. of Ag and Resource Economics, University of Maryland.
Title: Interacting Agents, Spatial Externalities and the Evolution of Land Use Pattern
Discussant: Jim Opaluch, Dept of Environmental Economics, University of Rhode Island.

TUESDAY FEBRUARY 29

W- 133 Business Meeting
9 - 9:45 am
Chair: Steve Polasky

Coffee Break
9:45 – 10 am

Session III: Stated Preference Methodology
10 –12
Chair: Patty Champ

John K. Horowitz and K.E. McConnell, "Willingness to Pay versus Compensation Demanded: The Implications of Meta-Analysis"

John Hoehn, "Does Information Matter?: A Utility-Theoretic Model of Injury Perception and Natural Resource Valuation"

David Layton, "The Analysis of "First and Worst" Survey Data"

Karin Steffens, Frank Lupi, Barbara Kaninnen, John P. Hoehn, "Optimal Experimental Designs for Binary Choice Experiments: An Application to Bird Watching in Michigan"

Lunch Break
12 – 1:30 pm

Session IV: Valuing Ecosystem Management: Carbon Sequestration and Fire
1:30 – 3 pm
Chair: Joan Poor

Brent Sohngen and Robert Mendelsohn, "The Effect of Alternative Policies on Carbon Sequestration Costs in Forests"

Jeff Englin, John Loomis and Armando Gonzalez-Caban (USDA Forest Service), "How Similar is the Demand and Values for Forest Recreation in the Intermountain West: A Comparison of Fire Effects in Colorado, Idaho and Wyoming Forests"

Coffee Break
3 – 3:30 pm

Session V: Roundtable Discussion on Valuing Ecosystem Services
3:30 – 5 pm
Chair: John Loomis

WEDNESDAY MARCH 1

Session VI: Combining Stated and Revealed Preferences
8 – 9:30 am; Chair: Rich Ready

Doug MacNair, "Alternative Methods for Combining RP and SP Data"

William Breffle, Edward Morey and Donald Waldman, "Combining Stated Preference Choice Data with Stated Preference and Revealed Preference Frequency Data"

Christopher Azevedo, Joseph Herriges and Catherine Kling, "Combining Revealed and Stated Preference Data: The Role of The Opportunity Cost of Time"

Coffee Break
9:30 – 10 am

Session VII: Time to Go? The Value of Time and Other Issues in Travel Cost Models
10 – 12; Chair: Joe Herriges

J.S. Shonkwiler and Nick Hanley, "Rock Climbers' Valuation of Approach Time"

Daniel Lew and Douglas Larson, "Joint Weak Complementarity and the Value of Travel in Recreation Demand Models"

Dan Phaneuf, "Options for Including the Opportunity Cost of Time in Kuhn-Tucker Models of Recreation Demand"

Kelly L. Giraud and Mark L. Herrmann, "Travel Cost Survey Design: Personal vs. Whole Group Expenses"

Lunch Break: 12 – 1:30 pm

Session VIII: Valuing Ecosystem Management: Species (Good and Bad)
1:30 – 3, Chair: Jerry Fletcher

Patty Champ and Anna Alberini "Valuing a Noxious Weeds Program in National Forests: The Effects of Varying the Response Format"

Phil Wandschneider, "Values, Values, Values"

The Quest for a Benefits Transfer Protocol: Nitrate Contamination of Groundwater

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February 28, 2000

Financial support for this research was provided under Pennsylvania Agricultural Experiment Station Project Number 3647. The authors acknowledge the contributions of John C. Bergstrom and Kevin J. Boyle, who directed the studies in Georgia and Maine and who consulted on procedures used in the valuation studies as well as the benefits transfer study.

INTRODUCTION

Benefits transfer is the practice using benefits estimates from one or more existing studies to value changes in a similar good or service in a different time or place in lieu of directly estimating the benefits. This practice, if successful, reduces research costs (Kask and Shogren 1994) as well as potentially reducing the time it takes policy makers to make informed decisions (Bingham 1992).

There are several additional reasons why benefits transfer is important. Most benefits estimation methods involve some type of transfer. In fact, from a valuation standpoint benefits transfer is a natural extension of non-market valuation (Opaluch and Mazzotta 1992). Unfortunately, the present state of non-market valuation does not adequately serve benefits transfer (Brookshire 1992) because of the issues of aggregation and market scope. From a policy standpoint, however, information about benefits transfer is vital to non-market valuation in the current political and research climate (Feather and Hellerstein 1997).

THE STUDY

The current attempt to develop a benefits transfer protocol used data from three studies coordinated through Regional Research Project W-133. These studies, conducted in Georgia, Maine and Pennsylvania, examined people's willingness-to-pay (WTP) to protect groundwater in their area from contamination with nitrates. The questionnaires were administered in 1996 and were nearly identical in all three studies. The distribution of the bid amount in the dichotomous choice portion was derived from pretests conducted in the three states. The common format among all three studies was a dichotomous choice question asking for a yes/no response to a stated amount of a special tax to support a program designed to protect groundwater from nitrate contamination. The dichotomous choice question was followed by an open-ended question asking the respondent to state the maximum amount his or her household would be willing to pay in a special tax to support the groundwater protection program.

The Pennsylvania questionnaire also contained a group of questions testing respondents' knowledge about nitrate contamination of groundwater--both about physical characteristics of groundwater and about possible health effects from ingesting nitrates. The test contained questions taken directly from the information section common to all three surveys. The inclusion of this information check made the Pennsylvania questionnaire slightly longer than the Maine and Georgia questionnaires. Whether or not this extended version altered respondents' answers is unknowable.

The scenario description in the Pennsylvania questionnaire differed slightly from the others. It told respondents that adopting the proposed program would reduce the proportion of wells exceeding 10 ppm nitrate from the present 50% to 25% after ten years of the program. The Georgia and Maine scenario descriptions did not indicate the target proportion of wells with nitrate contaminated water. In all three questionnaires, respondents were asked to indicate the present level of safety of their water supply as well as estimating the probability that their water would be safe ten years later, both with and without the proposed program.

The response rate for the Pennsylvania study was 68%. The Pennsylvania respondents are statistically representative of the population in the study area with regards to income and education. The response rates for the Georgia and the Maine studies were each 53%.

DEVELOPMENT OF A TRANSFER PROTOCOL

The efforts to develop a benefits transfer protocol began with estimating the mean WTP for each site for both the dichotomous choice (DC) responses and the open-ended (OE) responses. The econometric approach was to find one model that theoretically suits *a priori* expectations of factors contributing to WTP for groundwater safety. An explicit decision was made to retain all theoretically relevant variables in our models. Although this may lead to the inclusion of statistically insignificant variables, it is preferable to excluding possibly relevant variables. Observations with missing data or where the respondent indicated that their response was for reasons that we coded as a protest against the hypothetical program or the scenario were deleted from the data set. The model was estimated using the data from each site individually and combined into a single data set.

Probit regression was used to estimate the model for the DC responses and tobit regression was used for the OE responses. The mean WTP estimates from these regressions were compared to determine if a benefits value approach would give reasonable results. This was done with both the probit and the tobit estimates of mean WTP. The benefit function approach used the parameter estimates from one site and the data from a second site to obtain a transferred WTP value that was compared with the WTP value estimated with the parameters and data from the second site.

RESULTS

Although we analyzed both DC and OE responses in our study, only the results from the DC analysis are presented in this paper. The results of the probit regressions are shown in Table 1. The dependent variable is the yes/no response to one of eight payment amounts: \$25, \$50, \$75, \$100, \$150, \$200, \$350 and \$500. The independent variables are BID, CHANGE IN H_2O SAFETY, CONCERN, INCOME, PROACTIVE, CHILDREN PRESENT and PRIVATE

WATER.

The independent variables are defined as follows: BID is the payment amount in the dichotomous choice portion of the question format. Perceived effectiveness of the program is the difference between the perceived level of safety with the program and the perceived level of safety without the program (CHANGE IN H_2O SAFETY). Concern for water is a dummy variable equal to one if the respondent both places a high priority on local government expenditures for groundwater protection and is concerned about groundwater safety (CONCERN). INCOME is a categorical income variable although it is treated as a continuous variable by using the midpoint values of each income category. PROACTIVE, another dummy variable, indicates that respondents reported having taken some type of averting action to avoid health risks due to groundwater contamination in the past five years. PRIVATE WATER is a dichotomous variable representing the type of water supply--private well or public supply.

In the combined model, all variables were significant at the 10 percent level or higher. The coefficient estimates for BID, CHANGE IN H_2O SAFETY, CONCERN, and INCOME were significant at better than the one percent level. The negative sign on BID was expected; as the program cost increases, the probability of a yes response decreases. The signs on the other variables are as expected, except for CHILDREN PRESENT and PRIVATE WATER. The negative sign on CHILDREN PRESENT is counter to expectations since young children are most susceptible to adverse health effects. The sign on PRIVATE WATER is also

Table 1. Marginal Effects Probit Results

Variable	Combined	Pennsylvania	Georgia	Maine
Constant	-0.657***	-0.799**	0.0288	-1.27***
	(0.0769)	(0.33)	(0.321)	(0.39)
BID	-0.003***	-0.002***	-0.003***	-0.0029***
	(0.0005)	(0.0008)	(0.0008)	(0.0009)
CHANGE IN H_2O	0.020***	0.020***	0.019***	0.018***
SAFETY	(0.003)	(0.005)	(0.006)	(0.007)
CONCERN	0.524***	0.573**	0.236	0.674**
	(0.14)	(0.239)	(0.266)	(0.271)
INCOME (000)	0.007***	0.011**	-0.0005	0.011*
	(0.003)	(0.0047)	(0.004)	(0.006)
PROACTIVE (0,1)	0.26*	0.177	0.146	0.418*
	(0.142)	(0.246)	(0.261)	(0.237)
CHILDREN	-0.279*	-0.088	-0.393	-0.551
PRESENT (0,1)	(0.170)	(0.254)	(0.328)	(0.372)
PRIVATE	-0.242*	-0.377	-0.052	0.073
WATER (0,1)	(0.140)	(0.246)	(0.300)	(0.282)
WTP(dollars)	65	70	205	-50
Percent yes	42	42	53	31
Percent Yes Predicted	37	38	61	24
Percentage error	12	10	15	23
Percentage correctly predicted by individual model	74	80	65	78

standard errors in parentheses,
***significant at the 1 percent level; **significant at the 5 percent level; *significant at the 10 percent level.

counterintuitive--since the program benefits private well owners more than public water users, who are already protected by regulations. Signs on BID, CHANGE IN H_2O SAFETY, INCOME, CONCERN, and PROACTIVE (averting action behavior) are all as was expected.

In the Pennsylvania model, BID, CHANGE IN H_2O SAFETY, CONCERN, and INCOME are significant, while in Georgia only BID and CHANGE IN H_2O SAFETY remain significant. In Maine all variables are significant except CHILDREN PRESENT and PRIVATE WATER.

The combined model correctly predicts 74% of the outcomes. The Pennsylvania model predicts 80% correctly, while the Georgia model predicts approximately two-thirds correctly and the Maine model correctly predicts nearly 80% of the responses. Because the percent of yes responses differs greatly across the sites (Table 1), we calculated an error percentage to measure the effectiveness of the model at each site. We subtracted the percent of predicted Yes answers from the actual percentage of Yes answers in the sample from each site and divided that difference by the actual value. This provides a relative measure of the estimation error. The Pennsylvania sample had 42% yes responses and the model predicted there would be 38% yes answers. The evaluation yielded a 10% error. The Georgia sample, however, had 53% yes answers and the model predicted 61%, yielding a 15% error. For the Maine sample there were 31% yes answers and the model predicted 24% yielding a 23% error.

Willingness-to-pay estimates vary widely among the combined and individual site models. The combined model and the Pennsylvania model give similar WTP amounts, but the Georgia and Maine amounts are widely divergent. Such a wide difference makes it unlikely that a benefit value approach to benefits transfer will produce reasonable results.

BENEFITS TRANSFER

The probit and tobit estimates of mean WTP for the combined sample and each of the sites are presented in Table 2. The last row of the table shows the difference in the two estimates for each sample. The estimated WTP is about the same for the combined sample and Pennsylvania, but there are substantial differences between the two estimates for Georgia and Maine. If one were to perform a naive benefits transfer using the value of the mean WTP at one site as the estimate of the mean WTP at another site, there will be substantial errors of estimation in almost every case. For example, if the probit estimate for the Pennsylvania site ($70) were used to estimate the mean WTP of either the Georgia or Maine sites, it would underestimate the Georgia value by $135 and overestimate the Maine value by $120. If one chose the tobit estimates of the mean values to use in a benefits transfer, the errors are smaller, but still larger than most policy analysts are willing to accept. That is, the Pennsylvania estimate of mean WTP ($83) is not statistically significantly different from the mean WTP estimates of either Georgia or Maine. But, the Georgia mean is $22 more than the Pennsylvania mean and the Maine mean is $22 less.

Table 2. Directly Estimated WTP (dollars)

	Combined	Pennsylvania	Georgia	Maine
Probit	65	70	205	-50
	(62.63 to 67.37)	(60.44 to 79.56)	(199.12 to 210.88)	(-58.71 to -41.29)
Tobit	80	83	105	61
	(67.96 to 92.04)	(62.34 to 103.66)	(78.90 to 131.10)	(45.91 to 76.09)
Difference	-15	-13	100	-111

95% confidence interval in parentheses

If one chose to use a functional transfer instead of the naive transfer, the results are not encouraging either. In Table 3 the columns show the results of using the parameter estimates of the model for the indicated site with the data from the site indicated by the row heading. Thus, the three estimates of the mean WTP for the Pennsylvania site are shown in the top row: $70 using the Pennsylvania model, $139 using the Georgia model and $25 using the Maine model. Similarly the three estimates for the Georgia site are in the second row and for the Maine site in the third row. The WTP amounts on the diagonal from upper left to lower right are the computed WTP amounts also found in Tables 1 and 2. The estimates shown in Table 3 are statistically significantly different except for one case--Georgia data using Pennsylvania or Georgia parameters. In all other comparisons, the means are significantly different from each other in a statistical sense and there are cases which exhibit large numerical differences.

Table 3. Probit Estimates of Mean WTP Using Functional Transfers (dollars)

	Pennsylvania Parameters	Georgia Parameters	Maine Parameters
Pennsylvania Data	70 (60.44 to 79.56)	139 (128.54 to 149.46)	25 (14.51 to 35.49)
Georgia Data	212 (203.3 to 220.7)	205 (199.12 to 210.88)	60 (50.88 to 70.12)
Maine Data	-23 (-33.09 to -12.91)	135 (125.90 to 144.10)	-50 (-58.71 to -41.29)

95% confidence intervals in parentheses

CONCLUSIONS

It is clear that we have not yet discovered a method for transferring estimates of WTP for protection of groundwater from nitrate contamination from one site to another. This is despite designing the three studies so that the same variables were used in each. While we have not studied reasons for this failure, it may be helpful to speculate about some of the possible reasons.

The most plausible explanation is that the residents of the three study areas have very different perceptions of the likelihood of nitrate contamination in their area and different perceptions about the possible harm that such contamination might cause them and their families. Further, the three study sites are in different regions of the country and focus group discussions revealed substantial differences in people's receptivity to the idea of government taking action to solve such a problem if it developed. Thus, it is possible that the underlying "true WTP" is substantially different among this group of sites and, by extension, could be expected to be substantially different from what would be found in other parts of the United States.

The finding that transferred WTP estimates differ greatly depending on the transfer method used suggests that benefits transfers might be manipulated to produce results in keeping with the prior desires of policy analysts. That is, if a high estimated WTP is desired, one can choose a study site and transfer method that is more likely to produce a high WTP. Similarly, if one desires a low WTP value, other sites and transfer methods can be used to achieve that result. The lack of a clear-cut, proper method for performing WTP transfers leaves open the possibility for intentional manipulation as well as unintentional bias. It may not always be easy to determine when these errors have occurred.

The design of the study reported in this paper also presents a problem for those wanting to apply its results for benefit transfer. The results can be used for benefit value transfers, although the estimated WTP values differ greatly among the three sites and between the probit estimates of the dichotomous choice question and the tobit estimate of the open-ended responses. But, those wishing to use a benefits function transfer will find that many of the key independent variables can be obtained only by a survey of the residents of a site. Such variables as perceived changes in water safety with the proposed program, or concern about groundwater are not available from public records or census reports; they rely on primary data that must be gathered as a part of the study. If a survey is to be conducted to gather such information, it will cost only a little more time and money do a WTP study at the site and estimate WTP directly. This does not avoid the time and money costs of conducting a survey--the primary reason for considering benefits transfer methods in the first place.

Finally, the reader is cautioned to remember that this study focused on developing a protocol for transferring WTP to avoid nitrate contamination of groundwater. Transfers of WTP estimates for other nonmarketed goods and services may be more successful and reliable. Our lack of success does not condemn all benefits transfers. And, we are continuing our efforts to develop an acceptable transfer method for WTP for avoiding groundwater contamination.

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Amenity Impacts on Rural Land Values: Geographic Information Systems Data Incorporated into a Hedonic Property Model

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Amenity Impacts on Rural Land Values: Geographic Information Systems Data Incorporated into a Hedonic Property Model

Abstract

Geographic Information Systems (GIS) data are used to measure recreational and scenic amenities associated with rural land. A hedonic price model is specified with the GIS measures and used estimate the impact of amenity and agricultural production land characteristics on price per acre for a sample of Wyoming agricultural parcels. Results from the hedonic model indicate that the specification performed well and that the sampled land prices are explained by the level of both environmental amenities as well as production attributes. Statistically significant amenity variables included distance to town, scenic view, elk habitat and sport fishery productivity. This analysis permits a better understanding of regional and national rural land markets.

Introduction

Agricultural land values can be estimated by summing the discounted productive rents. This approach may reflect soil quality, capital improvements, water supply and location to markets. Agricultural land also provides land for current and future development, recreation, access to public lands, wildlife habitat, and open space. Land, following Xu, Mittelhammer and Barkley, can be viewed as an input to production; space for amenities (provision of public goods via place); fixed and taxable (provision of public goods via net revenue); and as an asset (capital good). Sale price should be the outcome of the total economic value of a parcel, given existing and efficient markets.

The demand for agricultural land is in part the demand for productive capacity by agriculturalists. Rural land prices may also reflect households' demand for homes with rural amenities. Agricultural land is being converted into nonagricultural uses across the U.S. (Vesterby, Heimlich and Krupa) and the Rocky Mountain region. Rocky Mountain counties containing or bordering national forest wilderness areas experienced population gains from 1970 to 1985 (Rudzitis and Johansen). Population in Utah, Colorado and Idaho grew by 10 to 15 % from 1990 through 1995 (US Census, 1996). Mountain counties in western Wyoming grew by 7 to 18 % during the same period (Woods and Pole). Rural amenities in the Rocky Mountain region include abundant public lands, recreational opportunities, wildlife, and open spaces.

Growth affects agricultural land in terms of aggregate producer output and income. It can impact production practices via nuisance regulations or land use laws. Growth may affect the viability of input suppliers. Public goods associated with agricultural land (wildlife, scenery, open space), and the economic as well as fiscal base of rural counties, may be affected. Agricultural land is a rural good, potentially demanded in many input markets.

It is important for landowners, land demanders and land policy analysts to understand what factors drive land prices. Such knowledge may provide insight into circumstances prompting the conversion of agricultural land to other uses and putting agricultural lands at risk for development. Geographic Information Systems (GIS) permit a quantitative means of affixing land characteristics to their location. This paper demonstrates how GIS data can be used to assess marketable attributes of agricultural lands in Wyoming.

Summary Theory of Land Value

Land ownership can be viewed as consisting of a bundle of property rights and related use values. Specific elements of the bundle may be demanded in different markets. Agricultural rents from production can be understood as follows:

$Q_i = f(L, X)$ where **(1)**

$\boldsymbol{Q_i}$ denotes output level of commodity $\boldsymbol{i}$.

$\boldsymbol{L}$ is the land input, and

$\boldsymbol{X}$ is a vector of all other inputs.

$P_L=\sum_{i=1}^{n}\left[(P_iQ_i)-P_xX\right]$ denotes the rent to land at a given point in time, where **(2)**

P_i and P_x are output and input prices respectively.

The production function can be refined to account for soil fertility factors as well as climatic and location factors affecting the contribution of the land input, ***L***, to production of a given commodity. More elegant and comprehensive discussions of agricultural land value theory are found in Randall and Castle; and Miranowski and Cochran.

Equations (1) and (2) do not include amenity values. Wildlife habitat, such as big game for hunting or viewing on-parcel, provides opportunities for securing additional rents. Water and angling opportunities offer returns to fee fishing for the landowner.

If the market for land is driven by residential demand, wildlife enjoyment and fishing may be important household utility arguments. Aesthetic considerations, such as scenery and open space, are attributes of land that may provide homeowner satisfaction as well. Household production theory provides a means of conceptualizing land as an input to the production of household satisfaction. It is given as follows:

$Z_i=f(L,M,N,K)$ where **(3)**

Z_i is the output of concern, i.e. place to live

N is the labor input,

K is the capital input,

L is the land input and

M is a vector of other material inputs.

Land may have many attributes that could contribute to the quality of ***L***. The individual acts like a firm in minimizing cost subject to technical constraints in Z_i and ***K***. The individual then seeks to maximize utility subject to the cost constraint as

$U = v(Z_i)$ given $C = g(P_l, Pm, Pn, Z_i, K)$ where **(4)**

U is a separable utility function,

C is the cost function consisting of a vector of prices, and represents total expenditures on the inputs of Z_I,

P_l is the price that pertains to land,

P_m is the price that pertains to other material inputs,

P_n is the price that pertains to labor;

Z_i is the output of interest; and

K is the capital input.

Land attributes enter into (4) via the original household production function (3). See Lancaster for theoretical origins, and Deaton and Muellbauer for a more rigorous treatment, of household production theory.

Hedonic price models relate land attributes to the price of land. The land itself is an input that is being competed for in multiple markets. Hedonic price models, including GIS delineated variables, permit inferring the impact of land attributes on land values.

Theory of Hedonic Price Valuation

The hedonic technique is based on the premise that goods traded in the market are made up of different bundles of attributes or characteristics. These goods are not homogeneous and can differ in numerous characteristics (Palmquist). Market data can be used to analyze the effects that different characteristics have on the price of agricultural lands. Where market data are incompletely specified, the relevant land characteristics can be measured by GIS. Benefits of a change may be measured from the underlying demand for the characteristic or characteristics of interest.

Both Rosen and Bartik indicate that the differentiated product (**z**) can be represented by a vector $z = (z_1, z_2, \ldots, z_n)$, which is the marginal bid function. These z_i represent the exogenous variables that shift land demander budget constraints, given that unobserved tastes do not shift with varying levels of the z_i.

The z vector for this analysis is based on two sets of characteristics, agricultural production attributes, z_{ag}, and amenities attributes, z_{am}. The observed price for z in the market is defined as a hedonic function of its characteristics represented by

$P = P(z_{ag_1}, \ldots, z_{ag_n}, z_{am_1}, \ldots, z_{am_n})$.

The marginal price of any z_{ami} can be estimated from this function.

The underlying demand function for z_{am} needs to be correctly specified. The demand for agricultural land can be considered as a factor demand model associated with a production function which includes agricultural outputs, consumptive value outputs and residential sites. The price a prospective buyer is willing to pay is a function of output prices, non-land input prices, production skills and site characteristics. This specification of the demand for land provides guidance for the hedonic price function specification.

Selective Review of Land Value Models

Gertel and Atkinson investigated several farmland price models. They found that a multivariate state space approach was superior to other price forecasting models. Their model sets average farmland price per acre as a function of lagged farmland prices, returns to assets and real interest rates. No consideration was given to farmland attributes.

The literature examined reveals various components of land values. Garrod and Willis examined neighborhood or environmental characteristics of countryside parcels in the UK using a hedonic price model. Measured attributes were compared to perceived attributes. The view, and presence of water were important. McLeod used a bid-price approach to determine marginal willingness-to-pay for urban residential properties in Perth, Australia. River view as well as water and park access were important. Elad, Clifton and Epperson estimated a hedonic model for rural Georgia land. They found that residential, agricultural and locational factors were significant deteminants of land price. They used mean hedonic estimates as variables in a bid-price function. Residential use per acre values exceeded those for agriculture use.

Spahr and Sunderman (1995) used Wyoming ranchland sales data to model the contribution of scenic and recreational quality to land price. Low, medium and high quality, based on the judgement of area appraisers, are represented by dummy variables in their statistical model. These variables are statistically significant with high scenic quality contributing to higher sale price. Spahr and Sunderman (1998) examined agricultural land prices in the west using a hedonic approach. They found that taxes on agricultural lands encouraged speculation where non-scenic subsidized scenic parcels via property taxes. The scenic value variables were dummy variables multiplied by the deeded acres across little, good, or great scenic levels. Scenery was significant in explaining land values.

A hedonic rural land study using GIS was provided by Kennedy et al. The analysis identified rural land markets in Louisiana based on economic, topographic and spatial variables. GIS was used for building distance to market and soil type variables. No nonagricultural amenities or open space variables were included in the estimation.

Conceptual Model

Let $P = f(Zag_i, Zam_i)$ where **(5)**

P is the total price of the land parcel,

$\boldsymbol{Zag_i}$ is a vector of agricultural production related variables,

$\boldsymbol{Zam_i}$ is a vector of amenity related variables and

i is either a production agricultural demander, **PA**, or a household demander, **HH** .

The model (5) is thought, *a priori*, to result from the following relationships:

$\partial \mathbf{P}/\partial \mathbf{AG_{PA}} > 0$; $\partial \mathbf{P}/\partial \mathbf{AG_{HH}} \geq 0$; $\partial \mathbf{P}/\partial \mathbf{AM_{PA}} > 0$; and $\partial \mathbf{P}/\partial \mathbf{AM_{HH}} > 0$.

Any given rural land parcel is being competed for in alternate markets defined by intended land use. Rural land attributes are preferred by all demanders of land except in the case of some $\boldsymbol{Zag_i}$ attributes possibly not adding to utility of **HH** demanders. The presence of agricultural production characteristics have a mixed effect depending on the demander profile. Some of the agricultural production factors will be inconsequential in household demand. It is expected that the presence of amenities raises land prices in all cases. This is owing to the land purchaser's opportunity to capitalize on rents from activities such as fee hunting and fishing as well as enjoyment of aesthetic values.

Data

Study Area

Wyoming is a rural state. It consists of irrigated basins and forested range in the west as well as desert and high plains in the central and eastern part of the state. The state is divided into two regions for this analysis. A random sample of available agricultural land sales data is taken for each region. The regions roughly follow the Bureau of Land Management (BLM) Ecoregions as reported in USDA/USDI. Region 1 (BLM Ecoregion 7 and 8, south part) includes counties in the west part of the state. These counties are directly south and east of Yellowstone and Teton National Parks. The Snake, Bighorn, New Fork, and Green River basins, known for their blue ribbon trout fisheries, are located in these counties. Region 2 (BLM Ecoregion 8, central part and Ecoregions 4 and 5) covers the central and east part of Wyoming. Federal lands are found in both regions: US Forest Service lands dominate in Region 1 with BLM as the major federal land agency elsewhere.

Population change on non-incorporated lands has not occurred uniformly across the state. Counties with more public lands tended to grow the most. The western portion of the state grew faster than the remainder from 1990 through 1995 as seen in Figure 1.

Generally, in-migrants to western wilderness counties tend to be better educated, have professional occupations, have higher incomes, be younger and have lived previously in more populated places than area residents (Rudzitis and Johansen). These immigrants seek amenities in terms of improved climate, recreation, scenery, and environmental quality (Rudzitis and Johansen; for a Wyoming case see McLeod et al.). They are in a favorable position to out compete agriculturalists for rural land. This is revealed by ranchettes, 35 + acre residential fragments of former ranches, found all over the western US and particularly in the Rocky Mountain region (Long).

Wyoming agriculture largely consists of livestock and forages with some crop production. Region 2 has the most crop acres. It has the highest crop and livestock production returns compared to the remainder of the state. It is the more important agricultural region of the two, as measured by agricultural receipts (see Figures 2 and 3).

Agricultural Production Determinants of Value

Production characteristics of Wyoming agricultural land are taken from land sales between 1989-95. Farm Credit Services in Wyoming and Nebraska as well as the Wyoming Farm Loan Board and the Wyoming BLM provided the data. The data consist of appraisals for transacted sales. Appraisals reported individual tract descriptions including values established by type of land and structural improvements as well as public and private grazing leases and permits. Land characteristics, and the chosen measures of each used in the hedonic price model, follow Chicoine; Torrell and Doll; Xu, Mittelhammer and Barkley; Xu, Mittelhammer and Torell; and Spahr and Sunderman (1998).

Nonagricultural (Amenity) Determinants of Value

Integrating GIS data into a hedonic framework permits modeling the presence of amenities on agricultural land prices more accurately. GIS protocols are developed for quantifying amenity resources such as wildlife habitat, trout habitat, accessibility, and scenery.

The consumptive and non-consumptive values of wildlife habitat for each land sale are represented by the area of select habitat types for elk. Elk are chosen due to their popularity in wildlife hunting and viewing. The importance of elk is evidenced by estimated expenditures for all elk hunters in Wyoming growing by 22.6% from 1990 through 1995, with 1995 hunter expenditures exceeding $29 million (Wyoming Game and Fish Department). See also willingness-to-pay measures for Rocky Mountain region elk hunting using contingent valuation methods by Brookshire, Randall and Stoll; and Sorg and Nelson that further support the value of elk hunting opportunities. Elk habitat measurements are based on GIS coverages created by the Wyoming Game and Fish Department.

Trout are chosen as a common and desirable fish to represent availability of water-related recreation. Sport fishing expenditure estimates in Wyoming grew by 11.7% from 1990 through 1995 with 1995 angler expenditures being over $225 million (Wyoming Game and Fish Department). Willingness-to-pay measures for Rocky Mountain region trout fishing using contingent valuation methods by Dalton et al.; and Duffield and Allen further indicate the value of regional trout fisheries. Stream coverages, provided by the US Geological Survey, are combined with information on trout fishing quality, available from the Wyoming Game and Fish Department.

Accessibility to towns is important in that it provides cultural and shopping opportunities to rural residents. Proximity to incorporated towns with greater than 2,500 individuals is measured to represent the accessibility of the purchased parcel. The particular town population is chosen due to size thresholds that are related to the presence of various retail trade and service opportunities (Taylor and Held). Road coverages come from the US Census Bureau TIGER files and are used to identify the roads travelled and town locations.

View is chosen to explore the aesthetic values related to land prices. The scale of view in Wyoming (as well as in the Rocky Mountain and Great Basin regions) is generally more extensive than other views in the US. Views across plains and valleys, of forested hillsides, of snow capped peaks, or to horizons framed by bluffs and mesas may contribute value to agricultural parcels. See Spahr and Sunderman (1998); Garrod and Willis; and

McLeod for examples of previous hedonic price models that include scenery and aesthetic land values.

The development of a protocol for estimating scenic value or view composition, using GIS, is an important component of the proposed work. The view variables are based on view cognition and preference studies (e.g. Kaplan, Kaplan and Brown; Hammitt, Patterson and Noe). Photograph-like simulations of the view, as seen by an observer standing at the centroid of a parcel, are used for measurements of the view composition. Digital Elevation Models are adjusted for vegetation heights as per Driese, Gerow and Reiners.

A measure of diversity is used to indicate the view composition. Simpson's Index is taken from the ecology literature and applied to views of landscapes. The view composition rather than types of species is used in the calculation. Simpson's Index (Barbour, Burk and Pitts) is calculated as follows:

$$D = 1 - \sum_{i=1}^{l} (p_i)^2 \text{ where} \qquad \textbf{(6)}$$

D is the diversity index ranging from 0 to 1 (0 being no diversity and 1 being maximum diversity),

l is land coverage type, and

$\boldsymbol{p_i}$ is the proportion of land area coverage type which can be seen from the centroid of the parcel in a 360° panoramic view.

The total area of land which can be viewed from the centroid in all directions is estimated. The GIS coverage for each of ten different land coverage types is overlaid on that area. The area of each land coverage type is then divided by the total potential view area from the centroid to estimate p_i. Coverage categories include coniferous, deciduous, shrubland, riparian, prairie, water, incorporated, alpine, barren and disturbed lands.

The variables used in estimating the hedonic price model are provided in Table 1. The dependent variable of the model is price per acre, **CDACRE**, or average within parcel price. Measures of agricultural productivity thought to affect price are **PASTMEDW** (grazing lands); **IRIGAUAC** (irrigated croplands); **TOTAUMS** (operation size); **IMPDOLAC** (on-parcel improvements); and leased land (**RRUAPER** and **PUBAUMS**). The former is railroad land, which follows a checkerboard dispersion with other private, state, and federal lands. This land is privately owned, not designated for multiple use and is available for purchase. The average value of railroad grazing leases tends to be greater than or equal to those found on public lands in Wyoming for the study period 1990-1995 (Bastian, Foulke and Hewlett; Bastian and Hewlett).

Important amenity variables are urban access (**TOWND**); view (measured by **SIMPINDX**); on-parcel trout fishing opportunities (measured by **FISHVALU**); and **ELKACPER** for wildlife viewing and hunting on-parcel. Region may be an important influence on amenity value. Interaction terms are constructed for view as well as for fishing and elk habitat. **TREND** is used to ascertain time-related movements of price.

Results

An OLS model is used on the basis of results from Cropper, Deck and McConnell. Other functional forms of the model, such as a log linear or quadratic specification, are estimated but without improvements in explaining the variability of price per acre. The R^2 estimate and F-statistic both indicate a statistically significant proportion of the variation in price per acre is explained by the regression. Nonlinear forms of the explanatory variables, such as **ELKACPER** and **TOWND**, are tried but do not improve the explanatory power of the model. Variables are constructed on a percent or per unit basis to correct for anticipated heteroscedasticity problems.

The model described above is initially estimated using Ordinary Least Squares (OLS) regression techniques. Multicollinearity diagnostics are estimated. The conditional index scores exhibited no significant multicollinearity problems with the model (all scores < 20). It was hypothesized that serial correlation could be a major source of heteroscedasticity in the model given that the sales data sample was drawn from multiple years coupled with a price discovery mechanism for land which is often heavily influenced by past sales information. The Durbin-Watson statistic estimated for the OLS regression indicated inconclusive serial correlation. The Breusch-Pagan statistic shows the presence of heteroscedasticity, not surprising given the cross sectional data set. White's consistent estimator of the covariance matrix is employed to correct for heteroscedasticity. The correction does not change the OLS coefficients nor necessarily change the size of the standard errors (White).

The signs on the significant GIS constructed amenity value measures variables meet *a priori* expectations, save **REGELKPR**. **REGELKPR** has a negative coefficient indicating decrease in western Wyoming ranch or farmland value due to the presence of elk habitat. Possible rents extracted from fee hunting for elk in western Wyoming are diminished due both to elk occupying public land during the hunting season and the large amount of public land there (81% of region 1). Elk are a source of property damage to fences and hay stacks and may be viewed as a nuisance. Elk habitat **(ELKACPER)** state-wide is positively related to sale price, significant at α=0.101 level. Elk state-wide offers rent seeking opportunities for rural landowners due both to scarcity and trespass. The central and eastern part of the state have less elk and less public land (proportionately more privately controlled land). Variables signifying trout habitat are significant in the western part of Wyoming (**REGFISH**) at α=0.01 level but not state-wide (**FISHVALU**). The latter outcomes indicate the regional prominence of the afore-mentioned trout streams in comparison to the balance of the state. The most interesting result of the amenity variables is the significant and positive coefficients of scenic amenities state-wide (**SIMPINDX**) at α=0.01 level and in region 1 (**REGSIMP**) at α=0.000 level. The view could improve owner utility as well as result in future gains should the land be developed residentially.

Distance to social amenities (**TOWND**) is significant at the α=0.07 level. It indicates that the more distant and rural the agricultural property, the higher its per acre price. This supports the potential demand both by agricultural interests due to less urban-originated nuisance claims arising from agricultural practices. The possible demand by amenity seekers who enjoy untrammeled trout streams, elk habitat and scenic views is also suggested.

The signs on the significant agricultural production variables meet *a priori* expectations. The agricultural production variables associated with grazing (**PASTMEDW**) and irrigated crop production (**IRIGAUAC**) are significant at the α=0.01 level. Capital improvements (**IMPDOLAC**) are significant, at the α=0.05 level, in explaining sale price. **RRAUPER** is positive and significant at the α=0.01 level, indicating the importance of secure (private) grazing leases. Ranch or farm size (**TOTAUMS**) has a negative coefficient and is significant at the α=0.01 level. The sign is indicative of the diminishing marginal value (measured on a per acre basis) associated with increasing size. These findings are consistent with Torell and Doll; and Xu, Mittelhammer, and Torell.

While the variable associated with public forage (**PUBAUPER**) was not significant, it is interesting to note that the sign is negative. This result is compatible with previous research. Torell and Fowler found that proposals for increasing grazing fees on federal lands and actual increased grazing fees on New Mexico State trust lands lead to a substantial percentage decline in ranch values for ranches highly dependent upon public land forage. Bastian and Hewlett concluded that as the public originated percentage of total forage for a ranch increased beyond 24% the price per animal unit declined for ranchlands sold during 1993 through 1995.

Non-agricultural interests (amenity seekers) would not be expected to associate value with federal grazing leases. Subleasing of federal allotments is generally prohibited and opportunities to secure resale or rents by non-grazing interests are minimal.

TREND is positive and significant. Wyoming ranch and particularly farm land prices rose during the study time period (Bastian, Foulke and Hewlett; Bastian and Hewlett). This phemonena does not appear to have any serious econometric implications given the Durbin-Watson statistic.

Conclusions

Traditional economic approaches to estimating agricultural land values have been related to the sum of the discounted rents over time. These have been captured through agricultural production activities, location to markets, and capital improvements. Recent trends point to agricultural lands being demanded by non-agricultural interests. Household production theory and hedonic modelling techniques offer a richer set of testable hypotheses regarding agricultural land values.

The demand for amenities such as outdoor recreation, scenery and open space are expected to grow as population migration to less urban areas continues. These growing pressures will increase the competition for agricultural lands. It is important to understand what factors are driving land prices, prompting the conversion of agricultural land to other uses and putting agricultural lands at risk for development. Results of this study indicate agricultural lands, which include wildlife habitat, angling opportunities and scenic vistas, command higher prices per acre than those only possessing agricultural production capacity.

Past research suggests attributes other than productivity that are related to agricultural land values. The contribution of this study is to utilize estimated variables derived from GIS measures, the values of which are uniquely specific to individual land parcels. The GIS variables provide a means to quantify amenity attributes and the opportunity to include them in a hedonic price model. The results point to an improved hedonic price model specification for agricultural lands, particularly for the Rocky Mountain and Great Basin regions. The GIS data development provides more explicit variables and model specifications than qualitative representations such as ordinal ranking of land attribute levels or dummy variables signaling the presence of amenities.

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Table 1. Variable identification, description and hypothesized sign.

Variable	Hypothesized sign	Variable Description/Definition
CDACRE	**(dependent)**	Total ranch price in dollars divided by deeded acres (average per acre price by parcel).
PASTMEDW	**Positive**	Productivity rating of all pasture and meadow lands on parcel, measured in aums per acre.
IRIGAUAC	**Positive**	Productivity rating of all irrigated lands on parcel (both sprinkler and gravity irrigated), measured in aums per acre.
TOTAUMS	**Negative**	Total carrying capacity of property, including deeded acres and assured leases, measured in aums.
RRUAPER	**Positive**	Percentage of total aums of carrying capacity coming from railroad leases.
PUBAUMS	**Indeterminate**	Total aums coming from BLM or state range which are an assured lease with the sale of the property divided by total aums and multiplied by 100. Note: This percentage can be more than 100.
SIMPINDX	**Positive**	Simpson's diversity index multiplied by 100. This number can range between 0 and 100.
STRMAC	**N/A**	Meters of stream on the property divided by deeded acres.
FISHPROD	**N/A**	Fish productivity average index on the property. The index comes from a Wyoming Game and Fish coverage.
FISHVALU	**Positive**	STRMAC multiplied by FISHPROD, providing a measure of fishing density per acre.
IMPDOLAC	**Positive**	Total dollar of improvements divided by deeded acres.
ELKACPER	**Positive**	Acres of spring-summer-fall and winter yearlong elk habitat / deeded acres.
TOWND	**Negative**	Distance from edge of property to nearest incorporated town of 2,000 inhabitants by road.
TREND	**Positive**	Trend variable for years in sample of 1989-1995.
REGN	**N/A**	0 or 1 dummy variable for two regions in state, 1 being high amenity Western region of state, O being rest of state.
REGSIMP	**Positive**	Interaction variable, SIMPINDX*REGN.
REGFISH	**Positive**	Interaction variable, FISHVALU*REGN.
REGELKPR	**Positive**	Interaction variable, ELKACPER*REGN.

Table 2. Means, minimums and maximums for dollars per acre for agricultural land and agricultural production and GIS amenity variables in Wyoming (N=138).

Variables	Mean	Std. Dev.	Minimum	Maximum
CDACRE	430.655	442.630	28.538	2602.230
PASTMEDW	1.271	1.465	0.000	6.000
IRIGAUAC	1.600	3.493	0.000	12.500
TOTAUMS	1445.347	1990.008	96.000	12480.000
RRAUPER	0.317	2.991	0.000	33.753
PUBAUPER	6.388	15.776	0.000	83.034
SIMPINDX	45.430	11.966	3.077	61.857
REGSIMP	22.830	26.292	0.000	61.857
FISHVALU	2.254	5.578	0.000	43.839
REGFISH	1.604	5.115	0.000	43.839
IMPDOLAC	36.315	110.141	0.000	845.000
ELKACPER	13.352	31.504	0.000	100.000
REGELKPR	10.047	28.224	0.000	100.000
TREND	4.920	1.529	1.000	7.000
TOWND	34.480	27.546	0.000	110.237

Table 3. Coefficient estimates of hedonic price model.

Variable	β - Value	t-statistic	Prob.
Intercept	-360.952	-2.934	0.004
PASTMEDW	64.907	2.667	0.009
IRIGAUAC	40.018	3.801	0. 000
TOTAUMS	-0.038	-4.179	0.001
RRAUPER	13.012	3.790	0.000
PUBAUPER	-1.549	-1.131	0.260
SIMPINDX	5.527	3.897	0.000
REGSIMP	4.263	2.045	0.043
FISHVALU	4.057	0.983	0.327
REGFISH	28.456	2.627	0.010
TREND	46.936	2.613	0.010
IMPDOLAC	0.707	2.138	0.035
ELKACPER	0.751	1.649	0.101
REGELKPR	-2.780	-2.512	0.013
TOWND	1.847	1.831	0.070

R^2	0.6040	**N = 138**	
Adj – R^2	0.5589	**Breusch-Pagan X^2**	154.2242*
F-statistic	13.40	**d.f. = 123**	
Durbin-Watson	2.2110**		

* Results adjusted using White's consistent estimator. OLS results are given, but with revised, robust covariance matrix (Greene, 1998).

** Durbin-Watson inconclusive for autocorrelation at α=0.05 & 0.01.

Figure 1. Wyoming rural population growth by region for 1990-1995.

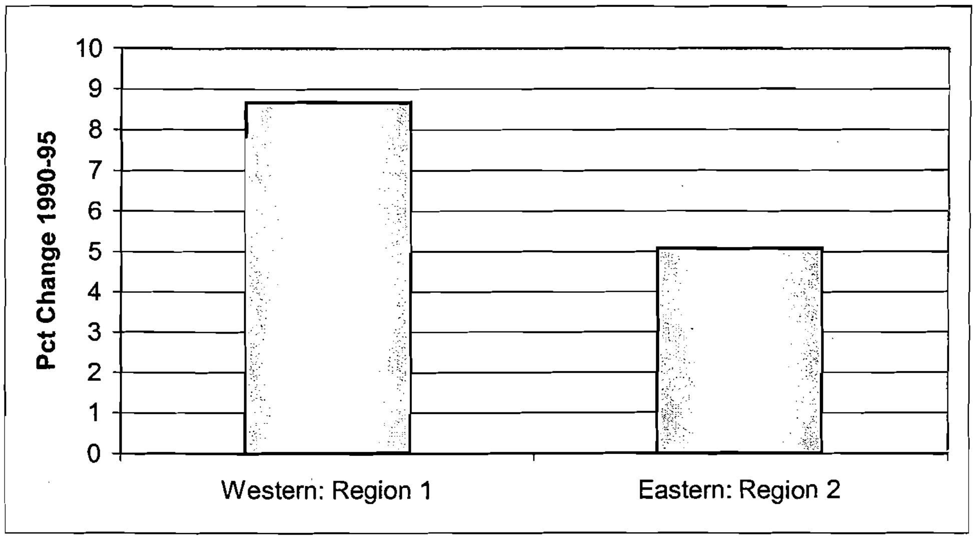


Figure 2. Agricultural receipts for livestock and crops by region, average for 1990-1995.

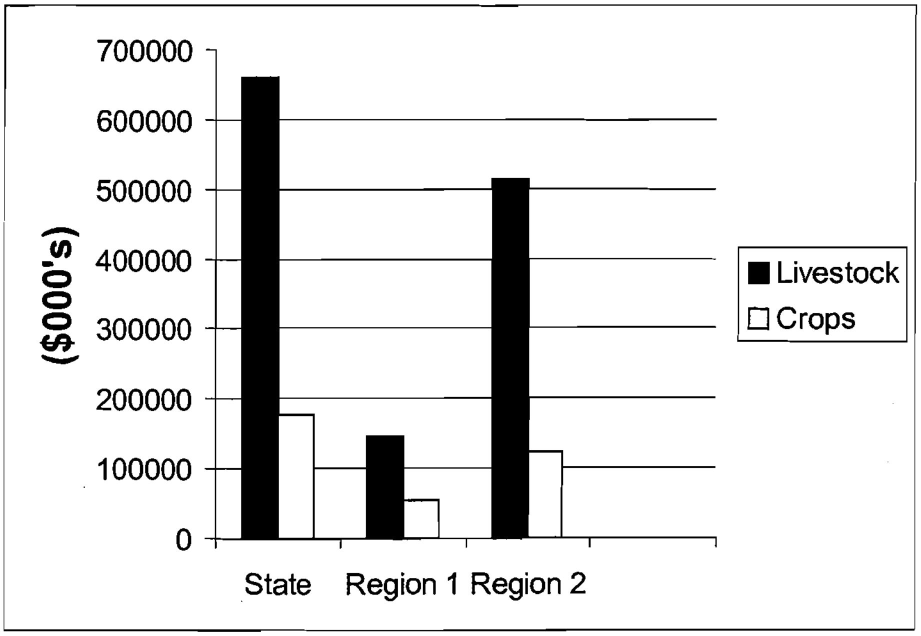
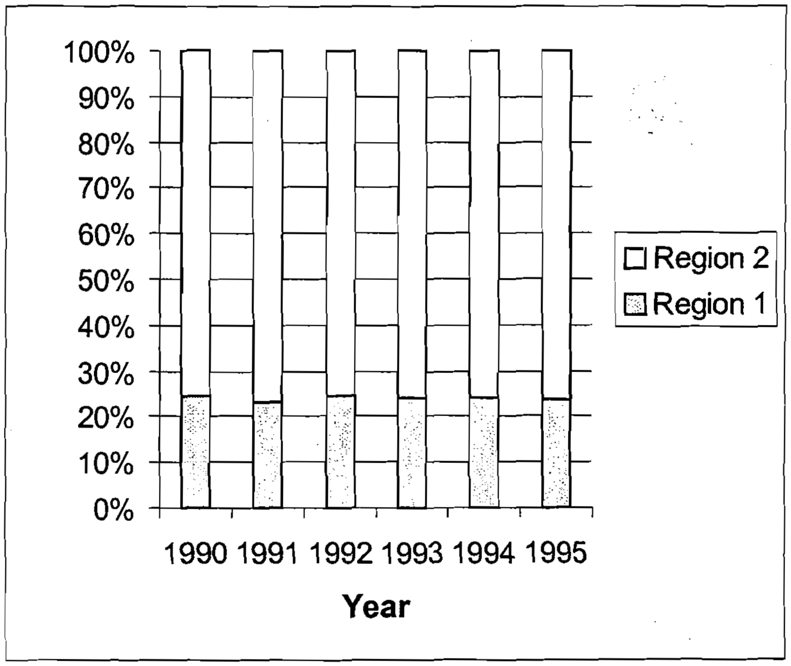


Figure 3. Percentage of total agricultural receipts in Wyoming, by region, 1990-1995.



VALUING VISIBILITY IN NORTHEASTERN WILDERNESS AREAS

T. Stevens, I. Porras, J. Halstead, W. Harper, B. Hill and C. Willis

The 1977 Clean Air Act requires the U.S. EPA, the states, and federal land managers to protect and restore visibility in wilderness areas (Harper, 2000). However, despite national reductions in sulfur dioxide emissions, visibility in most of the northeastern wilderness has declined substantially since the 1970's. As noted by Hill, et al., (2000), human induced smog conditions have become increasingly worse and average visibility in Class 1 airsheds, such as the Great Gulf Wilderness in New Hampshire's White Mountains is now about one-third of natural conditions. Deregulation of electricity production is likely to result in further degradation as consumers switch to low cost fossil fueled generation, and although EPA regional haze rules attempt to address this problem, many policy makers question whether the value of improved visibility is worth the cost.[1]

This paper focuses on several of the problems associated with the valuation of atmospheric visibility in wilderness areas. One problem is that different forms of the stated preference valuation approach, such as contingent valuation and conjoint or choice analysis may produce very different results (Stevens, et al., 2000). Results may also differ depending on

[1] The EPA regional haze rules were recently overturned in Federal Court. However, the EPA has appealed and the current administration plans to take the case to the Supreme Court (Harper, 2000).

whether valuation is conducted onsite or offsite, or by mail or in person. Of particular importance is that little is known about the geographical extent of the 'market' for visibility; is it a local, regional, or global public good? Finally, do visibility value estimates adequately exclude the value of joint products like health and ecosystem effects associated with atmospheric pollution?

We begin with a brief review of previous studies. A case study of visibility in the Great Gulf Wilderness of New Hampshire is then presented and discussed.

Background and Previous Studies:

Most previous studies of the value of visibility have used the contingent valuation method (CVM). One of the first studies was conducted by Rowe, et al. (1980) who found that non-residents were willing to pay about $4 per day to preserve visual range in southwestern Colorado. Schulze et. al. (1983) reported that residents of Los Angeles, Denver, Albuquerque and Chicago were willing to pay $3.75 to $5.14 per month to preserve visibility in the Grand Canyon. Crocker and Shogren (1991) estimated that residents were willing to pay about $3.00 per day to preserve visibility in the Cascades of Washington State. And, Chestnut and Rowe (1990) found that respondents were willing to pay $4.35 per month to avoid a change in average levels of visibility in the Grand Canyon, Yosemite and Shenandoah National Parks.[2]

With respect to wilderness areas in the northeast, the Appalachian Mountain Club (AMC) administered a survey in the summer of 1996 to ascertain visitor's perceptions of visibility in the White Mountain National Forest. This survey was administered to individuals at three sites: The

[2]Many of these studies built on research and ideas developed or presented at a 1982 conference on visual values (Rowe and Chestnut, 1983).

Pinkham Notch visitors' center at the base of Mt. Washington, the Cardigan lodge at the base of Mt. Cardigan and the Mt Washington Observatory (at the top of Mt. Washington). This survey asked respondents to rate photographs of Mt. Jefferson, a mountain in the Class 1 Presidential Dry River airshed, at various visibility conditions. Each photograph was correlated with a measurement of optical extinction measured by a nephelometer at the site where the photograph was taken. Results of this survey show that individuals were able to consistently perceive different levels of visibility. That is, respondents were clearly able to differentiate between improvements and degradations to visibility (Hill, 2000).

Although much has been learned, results of previous research suggest that several important questions remain unanswered. The first issue refers to the valuation technique used. As noted by Brookshire, et al.(1982), results should be tested by using valuation techniques other than the traditional CVM. Second, relatively little is known about the relationship between the onsite and offsite value of visibility or about the effects of location (distance) on the value of visibility. The results of location analysis might help to resolve two of the major problems in the valuation of environmental assets: the extent of the market area associated with damage assessments and whether benefit estimates derived from one region can be transferred to other areas. And, very few studies have included analysis of the potential problem of joint products which may be a very important factor in estimating the value of visibility itself.

Methods:

A case study of visibility in the Great Gulf Wilderness in New Hampshire was undertaken during the winter, spring and summer, 1999. Visibility at the study area, which is about one quarter mile northeast of the Mt. Washington summit, is commonly impaired by regional haze that is largely a product of fossil fuel energy production (Hill, et al., 2000).

Three surveys were used to measure the value of visibility in the Great Gulf Wilderness region. The first survey was administered onsite by a trained interviewer who used a personal computer (laptop) to present respondents with computer modeled images derived from the WinHaze Visual Air Quality Program. This program allowed us to hold weather conditions constant (cloud cover) while changing visibility only.

The second survey was identical in all respects except that it was administered offsite to individuals residing in the Northampton/Amherst area in Western Massachusetts (about a 3 to 4 hour drive from the study site). The third survey which was conducted by mail involved a random sample of 1,000 New England residents.

A split sampling approach was employed throughout; in each of these surveys one half of the respondents received a contingent valuation question that asked for their willingness to accept reduced visibility in exchange for lower electricity bills. The other respondents were asked to rate, on a scale of 1 to 10, the status quo and a scenario with less visibility and lower monthly electricity bills.

This sampling strategy allows us to test for differences in economic value estimates due to respondent's place of residence, survey type (mail or personal), type of valuation question (contingent valuation or conjoint/choice), and whether the respondent was contacted onsite or offsite.

The first section of the surveys asked respondents to rate several pictures according to the amount of haze in each. Each picture was a view taken from Camp Dodge, directly across from the Great Gulf Wilderness that had been altered by WinHaze to simulate different levels of atmospheric pollution, all else held constant (cloud cover, etc). Respondents to the personal survey were asked to rate 15 pictures while mail survey respondents rated 4 pictures.

The CVM or ratings (conjoint/choice) question was then presented. Each respondent viewed two pictures in this section: picture A represented the status quo visibility and electric bill while picture B represented reduced visibility and a lower electric bill. The CVM and conjoint (choice) questions were asked as follows:

INSERT QUESTIONS

Picture A, which represented the base scenario, or status quo, describes the average visibility level at the site during the summer months. Picture B represented one of four visual range reductions. The electric bill reduction was 20 percent of the respondent's total monthly bill in the personal survey and one of 1/4th, 1/3rd, or 1/2 of the monthly bill for mail survey respondents.[3]

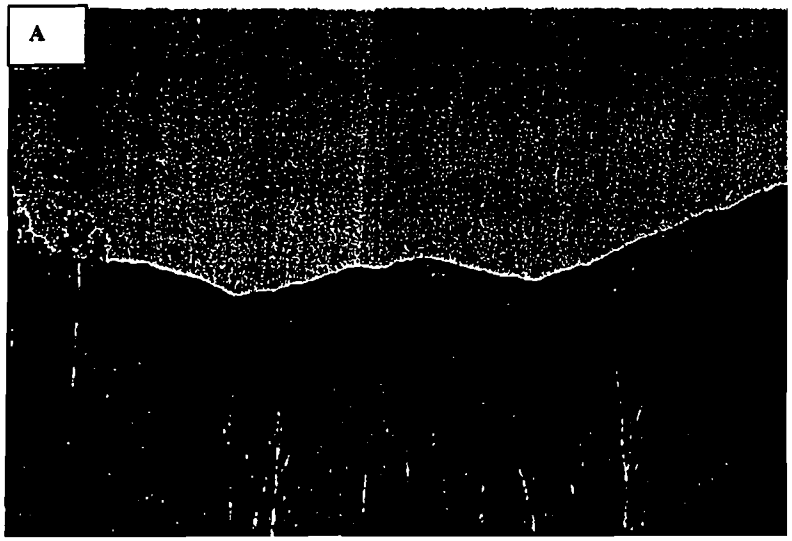
A series of follow up questions were asked to obtain information about each respondent's socio-economic characteristics, motives involved in answering the valuation question, and plans, if any, to visit the wilderness area in the future.

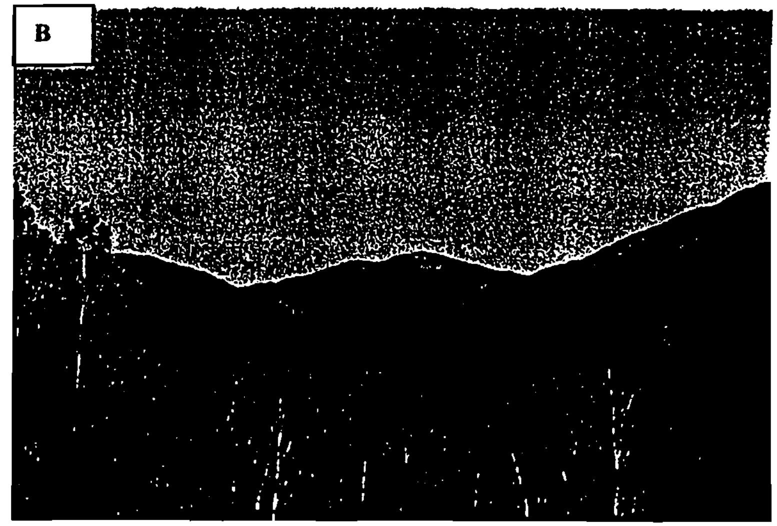
Although previous efforts to obtain willingness to accept (WTA) estimates for environmental commodities have generally been unsuccessful (Hanley, et al., 1997), there are three reasons why a WTA format was employed in this study. First, from a theoretical

[3] Twenty percent is the average savings expected from deregulation.

Section 2. For the next question, consider the following: Currently, many states are debating the issue of deregulation of the electric utility industry. If deregulation occurs in your state, you may be able to choose your own power provider. Assume for the purposes of this question that cheaper power (that is, less than what you currently pay) is available through a mid-western power company. Further, this power company produces electricity by burning coal. Increased demand for this company's cheaper power will contribute to air pollution and poor visibility in the White Mountains of New Hampshire.

- **Please enter your estimated average monthly electric bill US$____________**





Now suppose picture A represents the level of visibility most often experienced in this region during the summer months. Further suppose that you are faced with a situation where the visibility level changes to that in picture B. For the purpose of this question, assume that visibility would change ONLY in the White Mountain National Forest in New Hampshire.

- **Would you be willing to accept this new level of visibility (indicated by picture B) in the White Mountain National Forest if your monthly electric bills were reduced by _____?**

  YES NO

- If your answer was NO, please explain why ____

- If your answer was YES, please describe the factors you considered in making this decision ____________________

Section 2. For the next question, consider the following: Currently, many states are debating the issue of deregulation of the electric utility industry. If deregulation occurs in your state, you may be able to choose your own power provider. Assume for the purposes of this question that cheaper power (that is, less than what you currently pay) is available through a mid-western power company. Further, this power company produces electricity by burning coal. Increased demand for this company's cheaper power will contribute to air pollution and poor visibility in the White Mountains of New Hampshire.

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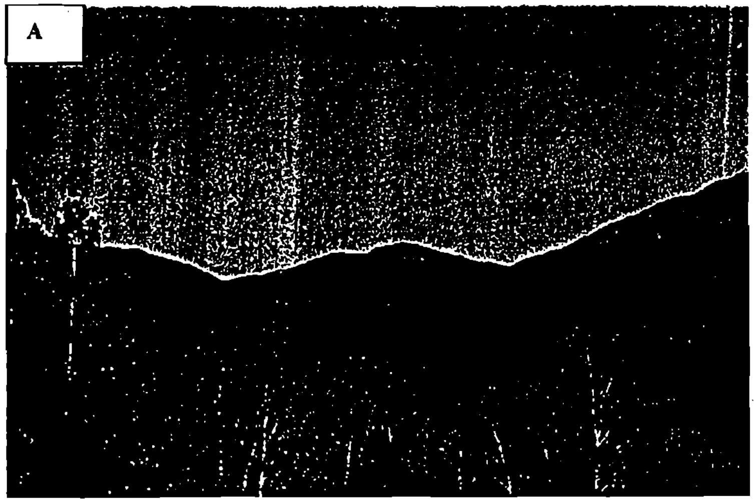

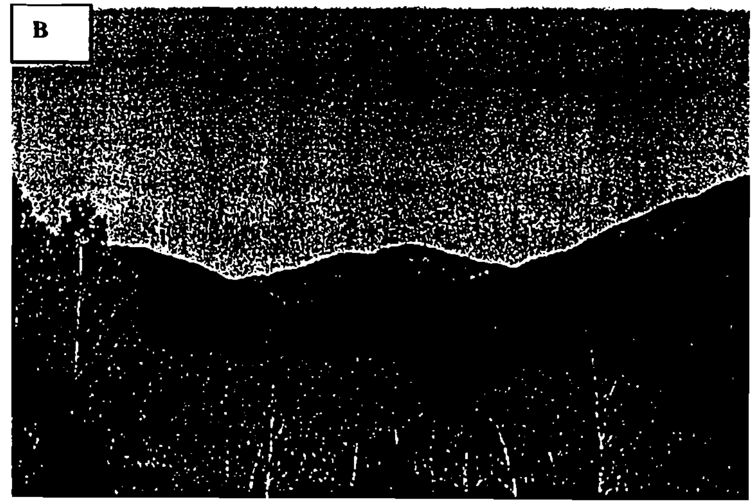

Now suppose picture A represents the level of visibility most often experienced in this region during the summer months. Further suppose that you are faced with a situation where the visibility level would change to that in picture B. For the purposes of this question, assume that visibility changes ONLY in the White Mountain National Forest in New Hampshire.

- **How would you rate the situation in photograph A on a scale of 1 to 10, with 1 being totally unacceptable and 10** indicating that you would definitely be willing to accept this level of visibility along with no change in your average monthly electric bill?

1 2 3 4 5 6 7 8 9 10

- How would you rate the situation in photograph B on a scale of 1 to 10, with 1 being totally unacceptable and 10 indicating that you would definitely be willing to accept this level of visibility along with a decrease of _______ in your average monthly electric bill?

1 2 3 4 5 6 7 8 9 10

- **If you rated picture B as a 1, (that is, the diminished visibility with a decrease in your electric bill was totally unacceptable), please take a moment and tell us why you felt the situation in picture B was totally unacceptable.** ____________________

- **If you gave B (diminished visibility with a decrease in your electric bill) a higher rating than A, please describe the factors you considered in your decision**

____

perspective, property rights to a clean environment are often assumed to belong to the public, and consequently environmental losses should be evaluated using a WTA measure (Harper, 2000). If as suggested by Kahneman, et al. (1990), individuals value losses more highly than gains, willingness to pay estimates could severely understate value. Second, given deregulation of electricity generation, acceptance of an increase in air pollution in exchange for cheaper electricity is, in our view, a very realistic scenario. Third, few, if any, comparisons of WTA derived from the CVM and conjoint or choice techniques have been conducted.[4]

Results:

Characteristics of individuals responding to each survey are summarized in Table 1. Respondents to the mail survey tended to be older and have more income as compared to personal survey respondents. One reason for this difference is that personal interviews were conducted on randomly selected individuals who were contacted onsite or offsite at libraries and cafes in the college towns of Amherst and Northampton, MA. On the other hand, the mail survey was sent to a randomly selected list of households in the entire New England region. It is important at this juncture to note that none of the samples are representative of the population as a whole, and therefore the results should not be extrapolated beyond the sample itself.

Results from each survey in terms of the percentage of respondents accepting reduced visibility in exchange for lower monthly electricity bills is shown in Table 2. For the conjoint responses, three alternative criteria were used to define acceptance; scenario B ranked equal to or

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[4]Since the conjoint method avoids pricing the environmental commodity directly, we hypothesize that conjoint or choice analysis might be more reliable in WTA applications.

greater than A, scenario B ranked greater than A, and scenario B rated a 10 (definitely accept), but not equal to A. Table 2 also shows average electricity bill compensation. It is important to note that relatively few respondents were willing to make a tradeoff between electricity bills and reduced visibility and that willingness to accept was quite sensitive to the criteria of acceptance assumed in the conjoint format.

That relatively few respondents were willing to accept a tradeoff between visibility and electricity cost is not surprising. In this study average electricity bill reductions ranged from only \$7.41 to \$ 29.14 per month. However, it is important to stress that the scenarios presented are thought to be very realistic given projected conditions for electricity deregulation in New England (Harper, 2000).

To test for the effects of valuation technique, respondent's location, and type of survey (mail or personal), the two logit model set forth in Table 3 were specified. All data derived from the surveys were pooled and dummy variables were included to test for the effect of respondent's residence, whether the survey was a choice or CVM format, whether it was conducted on or offsite, and whether by mail or in person. The dependent variable in the first model is defined as those rating scenario B>A in the conjoint format and yes in the CVM. The dependent variable in the second model takes on a value of one if respondents rated B $\geq$A or answered yes to the CVM question.[5]

The specifications presented in Table 3 are not rigorously grounded in economic theory. Rather, we view these specifications as similar to Meta Analyses in that we are primarily attempting to examine the influence of location and survey method (personal, mail, onsite, offsite,

[5]There were not enough observations to model B = 10 respondents.

etc.) on whether or not respondents would accept a reduction in visibility in exchange for cheaper electricity.

As shown in Table 3, WTA reduced visibility is expected to increase with compensation and visibility. We also expect that the probability of accepting a visibility reduction will be less for those who plan future visits to the site and for those interviewed onsite.[6] It is also important to note that one-half of all respondents were interviewed personally, forty percent received a choice survey, 21 percent were interviewed onsite, about 8 percent lived in New Hampshire, and more than two-thirds had plans for future visits. And, only about 15 to 20 percent were willing to trade reduced visibility for cheaper power, depending on model specification.

Results obtained from the models are presented in Table 4. WTA reduced visibility increases, as expected, with compensation and visibility.[7] However, residents of New Hampshire were more likely to accept reduced visibility, all else held constant. One possible explanation for this is that individuals who are most familiar with the resource being valued (live relatively nearby in New Hampshire) are less concerned about visibility.[8] However, respondents planning future visits to the wilderness area were less likely to accept reduced visibility. Whether the survey was conducted in person or onsite was not a statistically significant factor. However, conjoint respondents were less likely to accept reduced visibility in model 1, but not in model 2.

That the CVM and conjoint models can produce different results should not be too surprising. Although few comparisons of these techniques have been published, most previous

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[6]Those onsite presumably have more at stake.

[7]This suggests that the models pass the so called scope test.

[8]This is basically a diminishing marginal utility argument..

empirical comparisons suggest substantial differences (see T.H. Stevens, et al., 2000). There are several reasons for this. First, when compared with the CVM, many conjoint questions provide more information about substitutes. Second, from a psychological viewpoint, respondents may react differently when choosing among options then they do when making dollar valuations (Irwin, et al., 1993; Brown, 1984). Third, Alberini, et al., (1997), Wang (1997), Elkstrand and Loomis (1997) ,Champ, et al. (1997) and others have shown that value estimates can vary widely depending on how respondent uncertainty is included in the analysis.

In the case study considered here, the CVM and conjoint questions presented respondents with the same set of substitutes, but conjoint responses were counted as "yes" in two different ways; if B>A or if $B \geq A$. And, this difference seems to be responsible for whether the conjoint results are or are not different from CVM results. In other words, the way in which respondent uncertainty is handled appears to be responsible for the disparity between the CVM and conjoint results in this study.

Estimates of the median economic value of visibility derived from the logit models are presented in Table 5. All median values were calculated by:

$$(1) \quad \text{Pr Accept} = \frac{1}{1+e^{-(a + b\text{Ln Compensation})}}$$

where 'a' and b are estimated parameters (see Table 4). The estimated visibility values suggest that the average respondent is not willing to make a tradeoff between energy cost and visibility. The average respondent's monthly electricity bill was approximately $70, substantially less than the median WTA estimates of $1253 and $620 per month derived from models 1 and 2, respectively. And, the median value estimates are very sensitive to whether model 1 or model 2 is used, whether the respondent lives in New Hampshire, or does not plan to visit the site.

Another issue concerns what it is that respondents were valuing. Responses to the follow up questions indicate that many individuals were not just valuing visibility; rather, air quality as a whole was valued. Many respondents linked their WTA response to health problems, now or in the future. Visibility per se did not seem to be the main concern in many cases, regardless of the respondent's geographical location. For example, consider the following quotes from the follow up questions:

> "This 'haze' would in fact be potentially dangerous pollution in the form of air born particulates accompanied by large amounts of invisible sulfur dioxide and some heavy metals. This pollution would be spread and/or funneled by the prevailing winds over a large area. It is the <u>long term effect</u> of these pollutants that is <u>unacceptable</u>. The technology exists to significantly reduce this emission".

> "It will increase sickness and allergies"... "With the increase of haze in the air, more health problems will result. Since I live in Vermont, this will affect my personal health."

> "To me visibility *per se* is cosmetic; what truly concerns me is the contents of that air and its long term effect on human existence..."

Other respondents were more concerned about the effects of the increase in pollution on the ecosystem and wilderness. Context is important here, and respondents felt affected by their environmental "responsibility". For example:

> "This condition is unhealthy for the living things. I am willing to pay a little more to protect the environment"... "Only a small amount of haze can have an enormous impact on the forest ecosystem."... "Endangered species/wild animals that depend on the wild will be likely to migrate or disappear".

> "Clean air and clean water are priceless. I do not think that money is the issue at stake. The health and well-being of humans as well as most other animals and plants is dependent upon the quality of the environment in which we live. To put a

price on environmental quality and destroy the resources on which we depend is absurd."

"Preserve these treasured landmarks"... "Preserving the pristine conditions of National parklands should be a national priority. One that does justify cost to consumers"... "Too much haze for a non-city vacation spot."

Some respondents were also concerned about the effect that visibility might have on the tourism, recreation activities and property values in the White Mountains:

"As a landowner in the White Mountains I wouldn't accept any increase in air pollution."... "If visibility is poor the usual number of tourist do not come to Maine, New Hampshire or Vermont, there the ripple effect will be seen in less revenues for the states, hotels/motels, restaurants, etc."

Finally, some respondents were totally against energy providers using coal, and advocated the use of alternative forms of electricity that provide the same benefits (reduced costs) without increasing pollution. Some respondents did not believe the assumption that the reduction in visibility would only occur at the White Mountains of New Hampshire and were concerned about the effects of the increased pollution in their own area.

"Why should the level of visibility be less than it is in the picture A?. There shouldn't be any pollution. Alternative renewable energy sources are available now, which would eliminate pollution and be cheaper than fossil fuels to produce. The use of solar energy and its applications to solar thermal electric and solar photovoltaic electricity, wind energy and hydropower could easily replace fossil fuels and nuclear energy. This would result over a period of just a few years in the elimination of pollution globally and actually reduce the cost of electricity."

Since many respondents valued air pollution in general as opposed to visibility only, the valuation results presented in this study are likely to be biased upward. However, it may be impossible, at least in a field survey (as opposed to an experimental setting) to separate the effects of visibility from the problems of air pollution in general.

Summary and Conclusions:

The findings that emerge from this study can be summarized as follows. First, most respondents were not willing to accept cheaper electricity in exchange for reduced visibility over the range examined in this study. In fact, the estimated economic value of visibility suggests that compensation for improved visibility via lower priced electricity is simply not feasible; the necessary compensation is likely to be greater than the average respondent's actual electricity bill. If respondents are well informed, we might therefore infer that deregulation will not result in a substantial increase in pollution as a result of greater household demand for the cheapest source of electricity.

Second, the effects of location appear to be more complex than previously imagined. Respondents living nearby seem to value visibility less than those living further away, all else held constant. Perhaps absence does make the 'heart grow fonder'. On the other hand, valuation did not differ among those interviewed on or off site, yet those planning future visits were much less likely to accept reduced visibility.

The "market area" for visibility at popular unique sites, such as the Grand Canyon and Yosemite is known to be very large. Although much less is known about the extent of the market for less unique wilderness areas, like the Great Gulf in New Hampshire, this study suggests that its market area may also be quite extensive. On the other hand, conclusions about the effects of location are clouded by the finding that many respondents did not believe that air pollution would be limited to the study site.

Third, the CVM and conjoint models can produce very different results. However, in this study the difference seems to be a result of the criterion used to define a "yes" response in the conjoint format. Twenty percent of conjoint respondents were WTA the tradeoffs presented in this study when a yes response was defined as B$\geq$A; 8 percent of conjoint respondents were WTA if the criteria is B>A; and only about two percent indicated that they would <u>definitely</u> accept (B=10 and B$\neq$A). We therefore believe that future studies should include tests for sensitivity to the valuation question format and to respondent uncertainty.

Fourth, we did not find differences associated with whether the valuation question was conducted by mail or in person. Perhaps the NOAA guidelines requiring personal interviews should continue to be reevaluated.

Finally, despite survey pre tests and careful wording of the valuation question, many respondents valued air pollution in general. Consequently, the value of visibility is likely to be overestimated. A conjoint analysis that includes several attributes of pollution, including visibility, might clarify this issue, but the problem of sensitivity of this method to the definition of "yes" responses is likely to remain an issue.

Table 1. Socioeconomic Characteristics of Respondents; Sample Means[a]

Survey	Planned Future Visits (%)	Age (years)	Income (thousands)	Residence (%) MA	CT	NH
CJ, Personal[b] Onsite	NA	NA	NA	NA	NA	NA
CJ, Personal, Offsite	60 (49)	36.7 (12.8)	43.8 (36.2)	100 (-)	-	-
CJ, Mail, Offsite	71 (45)	48.9 (15.7)	67.2 (39.2)	84 (37)	05 (21)	06 (23)
CVM, Personal, Onsite	95 (21)	38.3 (14.6)	38.9 (34.2)	27 (45)	07 (26)	16 (37)
CVM, Mail, Offsite	62 (49)	48.0 (13.9)	52.3 (33.9)	16 (37)	39 (49)	11 (31)
CVM, Personal, Offsite	54 (50)	31.7 (10.3)	22.4 (20.9)	100 (-)	-	-

[a] Standard deviations in parentheses.
[b] Data not available at this time.

Table 2. Summary of Survey Results[a]

Survey	Sample Size	Average Monthly Electric Bill Reduction ($)	Percent Accepting Visibility Reduction B≥A or yes	B>A or yes	B=10[c]
Conjoint, Personal[b] Onsite	NA	NA	NA	NA	NA
Conjoint, Personal Offsite	60	$12.23 (10.27)	25 (44)	12 (32)	5 (-)
Conjoint, Mail Offsite	105	$25.73 (15.95)	18 (39)	6 (23)	1 (-)
CVM, Personal Onsite	87	$7.41 (2.51)	17 (38)	17 (38)	-
CVM, Mail Offsite	102	$29.14 (25.86)	23 (42)	23 (42)	-
CVM, Personal Offsite	59	$11.35 (6.38)	20 (41)	20 (41)	-

[a] Standard deviation in parentheses.
[b] Data not available.
[c] And B≠A.

Table 3. Logit Model Specification

Variable	Definition	Mean	Standard Deviation	Expected Sign
Model 1 Dependent	Rating B>A or yes to CVM	.15	.36	
Model 2 Dependent	Rating B≥A or yes to CVM	.20	.40	
Ln Compensation	Ln $ monthly electric bill reduction	2.62	.76	+
Ln Visibility	Ln miles	2.75	.60	+
Age	years	42.2	15.4	+/-
Income	thousands	47.8	37.1	+/-
MA	Dummy; Massachusetts resident = 1	.60	.49	+/-
CT	Dummy; Connecticut resident = 1	.12	.33	+/-
NH	Dummy; New Hampshire resident = 1	.08	.26	+/-
PER	Dummy; Personal Interview = 1	.50	.50	+/-
Onsite	Dummy; Onsite Interview = 1	.21	.41	-
FVisit	Dummy; Plans for future visit = 1	.70	.46	-
CJ	Dummy; Conjoint (Choice Survey) = 1	.40	.49	+/-

Table 4. Logit Model Results

	Model 1 (B>A)		Model 2 (B≥A)	
Variable	Parameter Estimates	Standard Error	Parameter Estimates	Standard Error
Intercept	-4.80***	1.38	-3.47***	1.13
Ln Compensation	.45*	.27	.39	.23
Ln Visibility	.68**	.30	.44*	.24
Age	.009	.011	-.004	.009
Income	.003	.004	.003	.004
MA	.31	.49	.22	.45
CT	.40	.53	.47	.50
NH	.74	.57	.86*	.52
PER	.37	.50	.29	.41
Onsite	.23	.56	.09	.50
FVisit	-1.18***	.33	-.92***	.28
CJ	-1.25***	.41	.01	.33
N	412		412	
F	37.50***		23.09**	
Percent correct predictions	73.7		65.2	

*** Significant at .01 percent level; ** Significant at .05 percent level; * Significant at .10 percent level.

Table 5. Visibility Value Estimates: Median WTA Per Month[a]

	Model 1 (B>A)	Model 2 (B≥A)
I. Average Respondent	$1253	$620
II. New Hampshire Resident; no visits planned	[b]	$16
III. Average resident; No visits planned	$200	$119
IV. Average Respondent Conjoint model	$6634	—[c]
V. Average Respondent CVM Model	$412	—[c]

[a] Values rounded to nearest dollar.
[b] New Hampshire dummy variable not different from zero (see Table 4).
[c] Conjoint dummy variable not different from zero (see Table 4).

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Interacting Agents, Spatial Externalities and the Evolution of Residential Land Use Patterns

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Abstract

We adapt techniques from interacting particle systems theory to a land use conversion model in which local interactions among spatially distributed agents arise from land use externalities. We show that such a model can explain the observed "sprawl" pattern of exurban residential development as an outcome of growth pressures, exogenous landscape features, and negative development externalities. Empirically, we address the identification problem of distinguishing endogenous interaction effects from unobserved spatial heterogeneity by bounding the interaction effect. Results provide empirical evidence of negative interactions among recently developed residential subdivisions in an exurban Maryland region. (*JEL* R14, R1, C29)

Keywords: land use pattern, spatial externalities, interactions-based models

Economists have generally understood the evolution of urban spatial structure to be the result of economic forces that spur the spatial concentration of economic activity. Recent changes in urban land use patterns, however, are characterized not only by the formation of new "edge cities" around traditional urban centers, but also by scattered, leapfrog residential development in outer suburban and urban-rural fringe[1] areas. Rates of conversion to urban land use have far exceeded population growth rates in most U.S. suburban and exurban areas, leading to a low-density, land intensive development pattern that many refer to as "sprawl." A recent study of fifty-eight U.S. metropolitan areas found that during the 1980's new suburban growth occurred at an average density one-fourth that of the population density in the central cities (Rusk, 1999). Changes in development patterns in exurban areas have been equally dramatic. For example, Calvert County, Maryland, located approximately 30 miles southeast of Washington D.C. and currently the state's fastest growing county, witnessed a 94% increase in population, 191% increase in the number of acres in residential use, and a 145% increase in the degree of fragmentation[2] of the urban land use pattern between 1981-97. This is representative of development patterns occurring in exurban areas throughout the U.S.

While the emergence of multiple urban clusters has prompted a spate of recent research in economics,[3] the evolution of low density, fragmented development patterns in exurban areas has received much less attention. An underlying principal that is sufficiently robust to explain both phenomena is the notion that urban spatial structure is determined by interdependencies among spatially distributed agents. This theme has been developed in the literature by Anas (1992), Anas and

[1] These areas are sometimes called "exurban" areas, a term that we use in this paper to refer to regions that are outside of, but contiguous to one or more urbanized areas.

[2] The degree of fragmentation is measured using a landscape pattern index that sums the edge to interior ratio of all polygons representing urban land areas within the county.

[3] For a recent review, see Anas, Arnott, and Small, 1998.

Kim (1996), Arthur (1988), Chen (1996), Fujita (1988), Krugman (1991, 1995, 1996), Page (1999), Papageorgiou and Smith (1983), Zhang (1993), and others. While these models vary in terms of the hypothesized sources and specification of agent interdependence, they adopt the common theme that urban spatial structure evolves from a "tug-of-war" between attracting and repelling interactions that result from economic linkages among agents.[4] The relative magnitudes of these interactions determine individual agents' location decisions and hence the evolution of urban land use patterns. Because the interactions both influence future location decisions and are a function of past location decisions, the spatial distribution of agents across the landscape is endogenously determined. These interactions-based models can explain the formation of a variety of observed urban spatial patterns, e.g. single cluster, multiple clusters, and dispersion, and are consequently much more robust than the monocentric model that has dominated much of urban economic theory.

Empirical evidence of such agent interactions in the formation and evolution of urban spatial structure has thus far been absent. This is a challenging task, in part because of the many heterogeneous features of the landscape that are likely to influence location decisions (e.g. roads, zoning, natural features). This landscape heterogeneity is ignored by the theoretical interaction models, a simplification that allows for tractable analytical models that demonstrate the potential role of interactions but does not offer a means for identifying these effects using real world data. Empirically, the challenge is to separate the effects of endogenous interactions from spatially correlated exogenous landscape features, which may evoke land use patterns that are observationally equivalent. Because it is difficult to measure such interactions, separating these effects from

[4] The notion of spatial interdependence leading to agglomeration is not new. Beckman (1976) explored the effect of social interactions among spatially distributed households on urban spatial structure. More recently, these interactions have been modeled as arising indirectly through market forces, e.g. transportation costs and pecuniary externalities (Krugman, 1991, 1995), as well as directly through agents' preferences (Page, 1999) or spatial externalities, e.g. knowledge spillovers (Zhang, 1993).

unobserved exogenous heterogeneity is possible only for limited cases. The challenge of econometric identification has been outlined in a separate literature on empirical models of social interactions, most notably by Manski (1993, 1995) and Brock and Durlauf (1999).

The purpose of this paper is twofold. First, we develop a model of an agent's land use conversion decision in which interactions among agents arise from land use externalities, and we investigate whether this hypothesis is consistent with the large-scale fragmented residential patterns observed in U.S. urban-rural fringe areas. To accomplish this, we incorporate interactions among neighboring agents into a spatially explicit economic model of land use conversion by adapting techniques used in statistical physics to model interacting particle systems. Simulation results illustrate that a model with interaction effects and exogenous landscape features can explain the observed fragmentation of residential development patterns as the outcome of growth pressures, exogenously located landscape features, and relatively strong repelling effects generated from negative development externalities.

Second, we address the interaction question empirically using parcel-level data on residential subdivision conversion from an exurban region of central Maryland. The principal challenge is to identify, econometrically, the endogenous interaction effects by distinguishing them from the influence of unobserved spatially correlated variation. We employ an identification strategy suggested by Heckman and Singer (1985) based on bounding the direction of the interaction effect. Due to the positive spatial correlation of exogenous factors, the latter is identified only if the estimated interaction parameter is negative. Empirical results provide evidence of negative interaction effects for residential conversion occurring in rural-urban fringe areas in recent years. Simulations of predicted changes in the development pattern demonstrate the magnitude of these estimated effects. The results underscore the path dependence of land use conversion patterns, which has implications for growth management policies.

I. Recent Patterns of Land Use Change

The traditional development pattern of a concentrated urban core surrounded by residential development and rural hinterlands has undergone dramatic changes in the U.S. in recent decades. Increased migration from urban to suburban and exurban areas, more land consumption per capita, and edge city formation around the periphery of older central cities have led to more complicated patterns of development in which the distinction between urban, suburban, and rural is increasingly blurred. Low density, fragmented residential development at the urban-rural fringe has fueled a concern among policymakers and the public alike about the public service and social costs of such land use patterns. In the November 1998 elections, almost 200 initiatives dealing with growth management and the preservation of open space appeared on local and state ballots across the nation.[5]

To judge the efficacy of the traditional monocentric model of urban economics in explaining these emerging exurban development patterns, we conduct an "experiment" using land use data from a seven county region of central Maryland located between the two historical city centers of Washington, DC and Baltimore, MD. Map 1 portrays the actual spatial arrangement of commercial/industrial development, and high, medium and low density residential development in the seven counties in 1994. Setting the total amount of land use in each type of development at these levels, we spatially reallocate the land use totals according to the predictions of a duo-centric model in which the locations of both Washington D.C. and Baltimore are treated as exogenously given and rents are determined only by each parcel's accessibility to the nearest center. Accessibility is measured as commuting distance along the major roads network.[6] Map 2 portrays what the landscape

[5] Havemann, J. 1999. "Gore Proposal Aims to Tame Urban Sprawl: $10 Billion in Bonds Would Help Finance Communities Open Spaces." Washington Post, January 11, p. A02.

[6] The land market of the Washington, DC metropolitan area also includes parts of northern Virginia, but spatially explicit land use data are not available for these counties.

of the seven counties would look like were the same amount and type of development allocated according to this basic form of the duo-centric city model.

The fundamental similarity between Maps 1 and 2 provides evidence of the power of the basic city-center model in describing past evolution of land use patterns. Yet it fails to capture the exurban "sprawl" pattern characterized by dispersed residential development in the outlying counties. To give this model every possible benefit, we further constrain the land use allocation by current zoning restrictions. This reallocation is biased in favor of the duo-centric model, since zoning neither entirely predates the formation of development patterns nor is truly exogenous in the land development process. In Map 3, residential land use patterns are somewhat less contiguous, but the pattern of scattered development in the exurban areas still remains unexplained. While additional complications are possible, there appears no obvious way to account for the degree of fragmentation solely as a function of distance from exogenously defined urban centers. In what follows, we explore whether an interactions-based model can better account for the observed spatial pattern in the urban-rural fringe.

II. The Agent's Land Use Conversion Decision

The evolution of large-scale spatial land use patterns results from decisions of micro-level agents about individual land parcels. We begin by formulating the decision of a profit-maximizing agent concerning the conversion of his parcel from an undeveloped to a developed state. A parcel is considered "undeveloped" if its current use is in agriculture or another resource producing activity such as commercial forestry, as well as if it is in a natural state. The only developed use of interest to us is residential development, since residential sprawl is the key policy concern. Residential use encompasses 18% of the developed land in the seven county area depicted in Map 1 and accounts for 78% of the changes in land use in that region between 1985-94. More importantly, it accounts for over 90% of conversion in the exurban areas during this time period. In contrast to commercial and industrial development, residential development is not greatly constrained by zoning. With the exception of the Critical Areas Zone, which extends inland 1,000 feet from the Chesapeake Bay mean high tide line, and land that is held by the public sector or in agricultural preservation or land conservation programs, virtually any parcel in the region can be converted to residential use if the conversion meets the minimum lot size requirements and other building codes designated by the county.

In our problem the undeveloped parcel is treated as the decision unit, and conversion implies the subdivision of a previously farmed or forested parcel into multiple residential lots. Development is viewed as irreversible both because reversing development is exceedingly costly and because, once developed, ownership of the parcel passes to many small lot owners. Developed land is supplied as residential lots to households, who make location decisions by choosing a bundle of attributes associated with a particular location to maximize utility.

A. Optimal Timing of Development

To represent this choice problem, first define $A(i,t)$ as the returns to parcel i in the undeveloped use in time period t. We will refer to this as agriculture, broadly defined to include any uses of the land in an undeveloped state. Conversion of parcel i at time $t=T$ requires the agent to expend capital costs to reap expected one-time gross returns where the latter is the sum of the expected sales prices of the subdivided residential lots. We denote δ as the discount factor and the one-time returns from development minus costs of conversion in time T as $V(i,T)$. Then the net returns from developing parcel i in time period T equals the one time net returns minus the present value of foregone agricultural returns and is given by:

$$(1) \qquad V(i,T) - \sum_{t=0}^{\infty} A(i,T+t)\delta^{T+t}.$$

The region of study is one that has experienced considerable growth in incomes and population over the last several decades and is predicted to face continued growth into the foreseeable future. As such, it is likely that most agents expect that if their parcels are not already profitable candidates for development, they will become so at some future time. Therefore, the relevant decision from the agent's perspective is the optimal timing of this development.[7] An agent making a decision between two periods will choose to develop his parcel at time T rather than wait until $T+1$, only if

(2a) $$V(i,T) - \sum_{t=0}^{\infty} A(i,T+t)\delta^{T+t} > 0 \text{ and}$$

(2b) $$V(i,T) - A(i,T) \geq \delta V(i,T+1).$$

That is, the agent develops in period T only if the growth rate in returns to residential use, net of opportunity costs, is less than the interest rate.

The smallest T that satisfies (2) is the optimal time to develop if certain assumptions about the time paths of the functions hold. First, we expect that in our region of study the gross returns to development, $R(i,t)$, are rising over time. This will occur if population and/or income per capita continue to rise in the face of a declining stock of undeveloped land. As we have no particular prior expectations on the time path of $A(i,t)$, we assume that returns to the undeveloped use remain constant over time. With only these assumptions, all parcels will eventually meet the development criteria in (2a). The condition specified in (2b) will be met if the tendency for agents to infinitely postpone development in the hopes of greater future returns is mitigated by residential prices that increase at a decreasing rate and/or development costs that increase over time. The latter may be true, for example, if agents fear growth controls will ultimately be instituted to pass some of the public sector costs of

[7] The optimal timing of development problem has been looked at by a number of authors beginning with Arnott and Lewis (1979). They develop their model in terms of continuous time and an infinite stream of *rents* from development, but otherwise our results are similar.

infrastructure on to the developer.

To give more substance to this specification, consider the vector of parcel characteristics that will affect a parcel's value in residential use, its cost of conversion, and its value in the alternative use. The former will include commuting distance to employment centers, provision of public services, lot size, amenities of the landscape, etc. Conversion costs will vary over parcels according to soils and slopes, amount of tree cover, and availability of public utilities. Agricultural returns will vary with soil types and distance to markets. While these parcel attributes vary over space, they are likely to be relatively stable over time. Characteristics such as aspect or soil type are unlikely to change at all over time. Others can be changed only by significant public actions such as the construction of a new highway or extension of public sewer systems. We assume that in the absence of a public action, these attributes, denoted by the vector $X(i)$, will be temporally constant but spatially varying. Although the parcel characteristics are not varying over time, $V(i,t)$ will vary over time due to growth pressures, denoted by $\gamma(t)$. Defining $V(i,T)$ now as $g[X(i),\gamma(T)]$, the decision rule is to develop in the first period in which:

$$(3) \qquad g[X(i),\gamma(T)] - \delta g[X(i),\gamma(T+1)] - A[X(i)] \geq 0.$$

B. Introducing Endogenous Interaction Effects

Endogenous interactions-based models capture the effect of decisions made by others on an individual's choice over discrete states. Researchers in the social sciences have found it useful to adapt models of interacting particle systems in which the interaction among many individual units at a highly disaggregate level leads to the emergence of a collective pattern at an aggregate level. Models of this sort originated in the physical sciences with attempts to characterize the interactions among atoms or molecules that lead to phase transitions in materials' states. They have been applied more recently to economic and social phenomena, including industry location and city formation (Page, 1999; Krugman, 1996; Arthur, 1988), employment status (Topa, 1996), business cycles (Durlauf, 1994), asset price formation (Brock and Hommes, 1997), and crime rates (e.g. Glaeser, Sacerdote, and Scheinkman, 1996).[8]

To illustrate the nature of these models, consider the social interactions model of Topa (1996) that is adapted from a "contact process" model of contagion. In Topa's adaptation, the probability that an agent unemployed in time *t* becomes employed ("infected") in time *t+1* is a function of the characteristics of the agent and a contagion effect that depends on the employment states of the agent's neighbors in time *t*. Specifically:

$$(4) \qquad \Pr[\eta(i,t+1)=1 \mid \eta(i,t)=0, X(i)] = \lambda I(i,t) + H(X(i))$$

where $\eta(i,t) \in \{0,1\}$ is the employment state of the individual at location *i* in time *t*, *h* is a function of the individual's characteristics which are represented by the vector $X(i)$, λ is the contagion parameter, and $I(i,t)$ is the spillover or interaction variable affecting agent *i* in time *t*. In his application, Topa interprets the interaction variable as information about employment opportunities, measured as the rate of employment among neighbors:

$$(5) \qquad I(i,t) = \sum_{k \in N(i)} \eta(k,t) / \widetilde{N}(i)$$

where the summation is over the set of agents constituting the neighborhood of agent *i* and $\widetilde{N}(i)$ is the number of agents in that neighborhood. Topa uses results from the theory of interacting particle systems to show that for certain ranges of the contagion parameter the hypothesized positive spillover effects (between neighbors' employment states and the employment state of the agent) result in a

[8] For a review of interactions-based models, see Brock and Durlauf (1999).

stationary distribution characterized by positive spatial correlations. Thus he is able to draw a correspondence between his hypothesis regarding positive spillover effects among agents and positive spatial correlation of employment.

The types of physical interaction processes adapted in this literature to describe social and economic phenomenon are at least superficially analogous to our land use problem. They are explicitly spatial and can be formulated in terms of a recursive model of spillover effects in which the probability that a parcel changes states (or becomes "infected") in a given period is a function of the states of parcels within a local neighborhood in the previous time period. However, the land use problem differs from the social interaction models in one important way. Because the focus is on the effects of peer pressure, social norms, or social contacts, models such as those by Brock and Durlauf, by Glaser, Sacerdote, and Scheinkman, and by Topa assume a positive interaction effect among agents in like states. In contrast, land use externalities that are hypothesized to create interaction effects among parcels may be positive or negative for any given distance. This suggests that not only the magnitude of the net interaction effect may vary over distance, but that the direction of the effect may vary as well, leading to potentially more complex structures of interaction.

To examine more carefully how interaction effects may enter the land use conversion problem, reconsider the decision rule developed in (3). We now allow for the possibility that the value of the land in residential use might be affected by the land use of neighboring parcels.[9] Specifically, at time

[9] Spillover effects that influence the value of undeveloped parcels are possible, as well, although we ignore them here. These may arise if agriculture is dependent on a critical mass of farms in an area to support agricultural services and other infrastructure. Additionally, increasing residential development in the surrounding area may lead to restrictions on farming activities because of nuisance complaints from residences.

t, the net returns from conversion may be written as:

(6) $$V(i,t) = g[X(i), \gamma(t)] + \lambda I(i,t).$$

The interaction term in (6) is composed of $I(i,t)$, the proportion of neighboring parcels that are in a developed state at the time the development decision is made, and λ, the interaction parameter. Because neighboring developed land could conceivably have positive and/or negative spillover effects, the interaction parameter, which represents the net effect of these spillovers, could be either positive or negative. Positive spillovers from surrounding development may arise, for example, if people value a sense of community or if there are benefits associated with contiguous residential development, e.g. more public services. But, because neighboring development signals the loss of open space amenities that may be associated with undeveloped neighbors, negative spillover effects may occur due to congestion or aesthetic considerations.

Rewriting the conversion rule in (3), development occurs in the first period in which:

(7) $$g[X(i), \gamma(T)] - \delta g[X(i), \gamma(T+1)] - A[X(i)] + \lambda I(i,T) - \delta \lambda I(i,T+1) \geq 0.$$

Although agents expect that the pattern of surrounding land use will be changing over time, the exact location and timing of these changes is difficult to predict. For this reason, we assume that agents are myopic in their expectations over immediate neighborhood changes in the short run. If so, the last two terms collapse to $(1-\delta)\lambda I(i,T)$.

We make one further modification to (7) by allowing the positive and negative spillovers to exhibit different rates of decay over space. This more general form of the interaction effect is specified by subscripting both the interaction variable and interaction parameter by s. This index denotes the order of the spatial lag, which increases with increasing distance from parcel i. By collapsing the first three terms in (7) into a single function of $X(i)$, δ, and $\gamma(t)$, the conversion rule can be restated as:

$$(8) \qquad W[X(i),\delta,\gamma(T)]+\sum_{s}(1-\delta)\lambda_s I_s(i,T)>0.$$

C. Spatial Implications of Interaction Effects

We employ an interactions-based spatial simulation model[10] to illustrate the large-scale changes in pattern of this system under varying parameter values. The origins of these interactions-based simulation models in economics can be traced back to Schelling's models of racial segregation (1978) and more recently have been employed by economists and other social scientists to study formation of markets, coalitions, and other economic and social phenomena (Tesfatsion, 1997; Epstein and Axtell, 1996). Using the model laid out in equation (8), the evolution of an aggregate land use pattern is simulated over many periods and many spatially distributed agents as the cumulative result of individual conversion decisions made by agents at the parcel level. This approach provides a means of incorporating differing types of spatial relationships among agents as well as exogenous spatial heterogeneity that varies across the landscape. In addition, it allows us to represent the interaction process as a dynamic one, in which recursive interactions exist among neighboring parcels and population growth provides the persistent impetus that drives an evolving pattern of land use change.[11]

[10] This type of model, in which the state of a particular cell is influenced by the states of neighboring cells, is known as a cellular automaton and was originally applied in statistical physics to study particle interaction.

[11] Other applications of interactions-based models, e.g. Brock and Durlauf and Topa, formulate joint conversion probabilities and draw on techniques from interacting particle systems theory to characterize the qualitative aspects of equilibrium solutions to their systems. This approach is neither possible nor appropriate for us. It is not possible because we seek to capture the influence of both attracting and repelling effects and because we believe our interaction effect is limited to a local rather than global neighborhood. In such a case, the mean field theory approximation to the interaction structure that is employed, for example, by Brock and Durlauf, is

The purpose of this exercise is to determine whether spatial interaction effects among parcels *can* generate a spatial pattern of subdivision development that is qualitatively similar to the fragmented pattern typical of exurban development. Parcels are represented by cells that are arranged on a two-dimensional 35 x 35 square lattice and are indexed by i, where $i = 1,\ldots,1225$. As before, each parcel takes only one of two states, undeveloped and developed, where the developed state represents a residential subdivision. In order to focus attention on the spatial implications of the interaction term, we simplify the temporal aspects of the conversion decision. The growth parameter and the unit of time are defined such that one residential subdivision is developed each time period. We assume that agents do not speculate, so that the highest valued parcel in residential use in period t is the parcel that will be subdivided in that period. In the case of "ties," the parcel to be converted is chosen randomly from the group of highest-valued parcels. Once converted, the expected costs from re-converting a parcel back to an undeveloped state are assumed always to exceed the returns of re-conversion, so that development is effectively irreversible.

To further simplify the problem, sources of spatial heterogeneity are limited to the time invariant features influencing the returns to development, $X^r(i)$, and the interaction effect of neighboring developed land, $\sum_s \lambda_s I_s(i,t)$. Given these assumptions, the form of the simulation model based on equation (10) is specified as

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inappropriate; the mean group effect will not be independent of any one agent's choice. To the best of our knowledge, more general results from interacting particle systems theory that do not rely on the mean field approximation (e.g. those employed by Topa) are applicable to systems that exhibit positive interactions only. In any event, the approach is inappropriate, since, given our assumption of continual exogenous growth pressures, the only absorbing state is an uninteresting one in which all the available land has been developed.

(9) $$L(i,t) = \alpha X^{r}(i) + \sum_{s} \lambda_s I_s(i,t)$$

where $L(i,t)$ is the expected value of the parcel in a developed use, $I_s(\cdot)$ is the interaction variable as defined in (5), and λ_s is the interaction parameter. $X^r(i)$ is a scalar, defined as the proximity of parcel i to a city center, and α is the corresponding parameter.

As before, $L(i,t)$ is assumed to be influenced by both positive and negative spillovers from neighboring development, such that the magnitudes of both decline as the distance between parcel i and its neighbors increases. While many assumptions are possible regarding the relative magnitudes of these effects and their rates of distance decay, we limit our consideration to a few cases that are representative of the resulting land use conversion patterns:

1. Positive interactions dominate throughout the extent of the neighborhood:
   $\lambda_s > 0$ *for* $0 < s \leq s_{max}$, where s_{max} = the furthest extent of the interactions.

2. Negative interactions dominate throughout the extent of the neighborhood:
   $\lambda_s < 0$ *for* $0 < s \leq s_{max}$.

3. Positive interactions dominate nearest neighbors and negative interactions prevail beyond:
   $\lambda_s = \lambda^1_s \geq 0$ for $0 < s \leq s^*$, where s^*= threshold distance, and
   $\lambda_s = \lambda^2_s \leq 0$ for $s^* < s \leq s_{max}$.

Multiple simulations[12] were performed with these differing assumptions regarding the values of the parameters λ^1_s, λ^2_s, s^*, and s_{max}. Table 1 gives the values of the parameters used for selected

[12] Given that one conversion occurs in each period and that conversion is irreversible, the simulation reaches a "natural" end point after 1225 time steps. The interest here is in identifying the qualitative pattern that emerges for different parameter values, and we find via trial and error that approximately 100 time steps are sufficient to characterize the emerging pattern.

simulation runs illustrated in Figure 1.[13] In general, varying degrees of clustering and fragmentation emerge, depending on the relative values of the neighborhood interaction and city accessibility parameters. Figure 1A illustrates the case in which the positive influence of accessibility to the urban center and positive spillovers from neighboring development lead to a single, contiguous cluster of residential development around the urban center. This development around the city center occurs in the same spatio-temporal pattern as that predicted by the closed city monocentric model, in which exogenous increases in population cause contiguous outward shifts in the urban residential boundary. So long as commuting distance to the city center is the only factor, this pattern occurs either with positive interactions, or, as is the monocentric city model, in the absence of interaction effects.

Table 1: Parameter Values for Land Use Conversion Simulations

	Neighborhood Interaction $0 < s \leq s^* < s_{max}$		City Accessibility
Figure	λ_s	s^*, s_{max}	α
1A	1	$s_{max} = 3$	1
1B	$\lambda_s^1 = 1$ $\lambda_s^2 = -3$	$s^* = 1$ $s_{max} = 3$	1
1C	-0.5	$s_{max} = 3$	1
1D	-1	$s_{max} = 3$	1

Figures 1B – 1D illustrate the changes in pattern that result with the inclusion of a negative interaction effect. The negative interaction term creates a repelling effect among neighboring development that, in part, counteracts the attractive effects of the city and any positive interactions that may be present. With both positive and negative interactions, varying degrees of clustering occur.

[13] The neighborhood boundary is defined in discrete rather than continuous units. A first order (s=1) spatial lag neighborhood around parcel *i* includes the four contiguous neighbors and the four diagonal neighbors around parcel *i*. Likewise, *s* = 2 refers to a second order spatial lag – i.e. the 16 cells that are contiguous to the 8 cells within the first order spatial lag – and s = 3 is a third order spatial lag.

Figure 1B illustrates one such case, in which smaller clusters of residential development form increasingly further from the city center. In Figures 1C and 1D, where interactions are negative throughout the range, initial clustering around the city center is quickly overwhelmed by negative spillovers leading to a leapfrog pattern of development. Comparing the two figures, increases in fragmentation occur with an increase in the negative interaction parameter. Infill occurs in later periods in both cases. In contrast to Figure 1D, Figure 1C illustrates the case in which infill occurs before the entire region becomes congested, due to the relatively weaker repelling effect.

Although highly stylized, the simulation exercise demonstrates that an interactions-based model that incorporates correlated exogenous landscape features can, *in theory*, explain patterns of fragmented residential development as the result of growth pressures and relatively strong repelling effects generated from negative development externalities. Given the availability of parcel-level data on changes in exurban residential land use patterns over time, we turn next to the question of how this hypothesis regarding the spatial pattern of land use may be empirically tested.

III. Estimation of the Empirical Model

Thus far we have assumed that variation over parcels in the timing of development will occur only due to variation in observable parcel characteristics and surrounding land use. But in reality, landowners are heterogeneous and owners of parcels with the same basic attributes will have different reservation prices. Some owners may be especially good at farming or may have high recreational and aesthetic values for their land; others may be near retirement and looking for a way to liquidate their assets. These idiosyncracies will induce a distribution of unobservable factors that will, in turn, induce a distribution of optimal development times, conditioned on explanatory variables.

To take account of these differences across agents, define ε_i as these unobservable factors associated with the owner of parcel i. Now the net returns from developing parcel i in time period T is given by:

$$(10) \qquad V(i,T) - \sum_{t=0}^{\infty} A(i,T+t)\delta^{T+t} - \varepsilon_i .$$

The optimal timing rule suggests that conversion should take place at time T if this is the first period in which:

$$(11) \qquad W[X(i),\delta(T),\gamma(T)]/(1-\delta) + \sum_s \lambda_s I_s(i,T) - \varepsilon_i > 0 .$$

This implies that agents with large ε's, such as those who are particularly good farmers or those that place a particularly high value on their undeveloped land as a source of direct utility, will convert later than agents with the same type of parcel but smaller values of ε. Given that ε is unobservable and therefore viewed by the researcher as a stochastic variable, the probability that a parcel with attributes $X(i)$ and surrounding land use pattern $\sum_s I_s(i,T)$ will be converted by period T is:

$$(12) \qquad \Pr ob\{\varepsilon_i < W[X(i),\delta,\gamma(T)]/(1-\delta) + \sum_s \lambda_s I_s(i,T)\}$$

Define $\varepsilon^*(X(\cdot), \sum_s I_s(\cdot))$ as the ε that makes the agent with parcel characteristics, $X(\cdot)$, and surrounding land use $\sum_s I_s(\cdot)$ just indifferent between converting and not converting in T. The probability that a parcel with these characteristics will be converted in period T is its hazard rate for period T. This is given by:

$$(13) \qquad \frac{F[\varepsilon^*(X,\sum_s I_s,T+1)] - F[\varepsilon^*(X,\sum_s I_s,T)]}{1 - F[\varepsilon^*(X,\sum_s I_s,T)]},$$

where F is the cumulative distribution function for ε.

Duration (or survival) analysis suggests itself as a convenient approach for estimating the parameters embedded in (13) and for testing hypotheses about these parameters. In this analysis we choose Cox's partial likelihood method for the duration analysis. This approach is useful because it can easily accommodate time-varying covariates – an essential element of our problem. In order to estimate the endogenous interaction parameters, we need to capture accurately the fact that the land use surrounding a parcel is changing over time. In Cox's model, the hazard rate is assumed to have the following general form:

$$(14) \qquad h(i,T) = \omega_0(T)\exp[\beta' Z(i,T)]$$

where $\omega_0(T)$ is the baseline hazard at time T, Z is the vector $[X(i), I_s(i,T)]$, and β is the corresponding parameter vector. The baseline hazard does not vary over space, but only over time, so that the relative hazards of two parcels are affected only by the attributes embedded in the vector Z. Cox's method involves maximizing the partial likelihood function, which is the product of N contributions to the likelihood function, where N is the number of developable parcels. The form of the n^{th} contribution is given by:

$$(15) \qquad L_n = \frac{h(n,T_n)}{\sum_{j=1}^{J_n} h(j,T_n)}.$$

By definition, the n^{th} parcel is the parcel that is converted at time T_n. In (15), $h(n,T_n)$ is the hazard rate for the n^{th} parcel, $h(j,T_n)$ is the hazard rate for the j^{th} parcel evaluated at time T_n, and J_n is the set of parcels that have "survived" in the undeveloped state until time T_n.

Substituting (14) into (15), it is clear that the baseline hazard term cancels out in each contribution to the likelihood function; the estimation procedure produces information only on the βs. While in some settings this is a disadvantage, it helps us to focus attention on the exogenous heterogeneity and the endogenous interaction terms without having to make assumptions about the functional form of $\omega_0(T)$ or measure variables that might affect $\omega_0(T)$ over time. For example, it seems plausible to assume that the baseline hazard is a function of growth pressures (γ) and the interest rate (δ), as well as other variables (e.g. development fees) that vary over time but not over parcels. In the absence of the baseline hazard, the only aspect that matters in estimating the parameters is the order of parcel conversion over time rather than the absolute time of conversion.[14] If all the attributes embedded in the vector Z were time invariant, this would imply a fixed proportional hazard rate for any pair of parcels. However, because we allow the interaction measure to be time-varying, the ratio of the actual hazard rates of two parcels changes as the surrounding landscape changes.

A. The Identification Problem

In expression (13), the vector $X(i)$ contains all attributes associated with parcel *i*, and the stochastic term ε_i captures the existence of idiosyncratic factors associated with agent *i*. In any actual empirical application, though, data on many attributes of the parcel will not be available and these attributes will also reside in ε_i. This raises potential problems because the unobserved heterogeneity associated with individual land parcels is likely to exhibit strong positive correlation over space. The presence of unobserved, but positive spatially correlated features that influence the conversion decision complicates the identification of our endogenous interaction effects.

[14] This allows us to avoid identifying those regional economic factors (such as rising incomes and population) that affect the rate at which housing starts take place in our study area.

This version of the identification problem has arisen, not surprisingly, in the social interactions literature; identification of the effects of social norms and peer pressures on individual choices requires controlling for unobserved heterogeneity (Manski, 1993, 1995; Brock and Durlauf, 1999).[15] The identification problem in the land use conversion model is similar, both in terms of the source of endogenous effects (i.e. associated with neighboring agents' choices) and the correlation of exogenous variables over space. Analogous to the correlated effects among individuals described by Manski, heterogeneous landscape characteristics that vary over space may generate spatial correlation among neighboring land use decisions. If unobserved, these effects will make decisions appear related, even if they are not, and therefore complicate our ability to discern spatial interactions. Although the nature of the development process implies a temporally lagged spatial interaction effect, the presence of time-invariant unobserved heterogeneity creates the same identification problem due to correlated unobservables as that which arises in the simultaneous social interaction models.

Unfortunately, the identification problem in the land use conversion model is further complicated in ways that prevent ready adoption of most of the identification strategies discussed in the literature (Irwin, 1998). As a consequence, exact identification of the interaction parameter is not possible. However, it is possible to adapt a strategy of bounding the interaction effect. This approach is suggested by Heckman and Singer (1985), who illustrate the conditions under which the sign of the endogenous effect is identified in duration models, where the endogenous term in this case is the duration dependence variable. Heckman and Singer (1985) show that a *negative* bias will result in their model if it is estimated without controlling for the effects of unobserved heterogeneity across individuals. They conclude that the direction of the duration dependence is identified under these conditions only if the sign of the estimated duration dependence parameter is opposite that of the bias

[15] The same problem arises in the literature on own-state dependence over time, which seeks to separate "true" temporal state dependence (e.g. habitual effects) from "spurious" state dependence (Heckman, 1978, 1981).

– i.e. *positive*. Due to the negative direction of the bias, the estimated parameter provides a lower bound, so that if the estimated parameter is positive then the true duration dependence effect must also be positive.

In most of the cases considered in the own-state dependence and social interaction literatures, the direction of the bias caused by the unobserved correlation and the true interaction effect are the same. In the social interactions case, Heckman and Singer's strategy is not useful because the correlation among neighboring agents due to unobservables is usually positive (e.g. students perform similarly because they have the same teacher) and the hypothesized interaction effect is always positive. In the land use conversion case, however, this is a feasible approach for testing for the existence of a negative interaction effect. Whatever spatial correlation exists in the unobservable factors is very likely to be positive,[16] so that the resulting empirical estimate of the interaction effect will be biased in the positive direction. This implies that the estimated interaction effect bounds the true interaction effect from above. If the estimated effect is negative, then it must hold that the "true" interaction effect is negative for at least some range of the sample and over some interval of time. If the estimated interaction effect is positive, however, we cannot determine the existence of a true interaction effect.

B. Specification and Data

Data used to estimate the land use conversion model include spatially defined, micro-level data on land parcels in the exurban areas of five counties in central Maryland. The data set was constructed using the Maryland Office of Planning's geo-coded current file of land parcels and historical information from the state's tax assessment data base. Parcels were tracked backwards in time, so that

[16] In the words of Tobler (1979), "Everything is related to everything else, but near things are more related than distant things."

the population of parcels that could be developed in residential use as of January 1991 could be identified. The data set is comprised of all parcels in the exurban[17] areas of Anne Arundel, Calvert, Charles, Howard, and Saint Mary's Counties that were large enough to accommodate a subdivision of at least five houses given current zoning. The year in which conversion takes place is the event date, with parcels tracked from 1991 through 1997. Censoring occurs in 1997.

A measure of neighborhood development is calculated for each developable parcel to capture the potential spillover effects of neighbors on a parcel's conversion probability. The surrounding land use variable is constructed as the percent of the neighboring land in a developed use in the year prior to the conversion decision. Development is defined as all commercial, industrial, and residential uses for which a structure exists on the land parcel, excluding extremely low density uses (defined by a structure on more than five acres). Since this variable changes over time, it is updated for every year from 1991 through 1997.

The *extent* of the relevant neighborhood around a parcel of interest is essentially an empirical question. Choosing too wide a radius will dilute effects, while choosing too narrow a range might miss important changes in spatial externalities with distance. We specify s_{max}, the maximum distance in which we expect to find interaction effects, as equal to 1,600 meters (approximately 1 mile). This is admittedly arbitrary, but other work by Fleming (1999) using semivariogram analysis supports ranges of this order of magnitude for land use interactions in this area. Since different spatial externalities may have different rates of decay, it is possible that the direction of the interaction parameter may change with distance. Within the 1 mile maximum radius, we allow for changing interaction effects

[17] Exurban land is defined using the 1990 U.S. Census definition of urban fringe, which is generally defined as a contiguous territory adjacent to an urbanized area that has a density of at least 1,000 persons per square mile (U.S. Census Bureau, Appendix A: Area Classifications, STF3 Technical Documentation, 1990).

by specifying two non-overlapping neighborhoods, $0 < s \leq s^*$ and $s^* < s \leq s_{max}$, and we vary s^* to see if the results are sensitive to its choice. The variables **DEVLUSE1** and **DEVLUSE2** are measures of the percent of developed neighboring land within the two non-overlapping neighborhoods.

In order to judge the degree to which omission of spatially heterogeneous attributes influences the estimate of the interaction parameter, a series of three nested models is estimated. The models differ in the amount of the exogenous, but spatially correlated, variation for which they account. These exogenous variables represent the types of parcel attributes that might normally be measurable and included in the vector $X(i)$. The dominant factor affecting net returns to development is arguably accessibility to the urban center, following the monocentric model. Distance to Washington, DC is measured by way of the roads network and is included in logarithmic form (**DCDIST**). Costs of conversion will vary over parcels for a number of reasons including the nature of the topography and soils. We define an indicator variable (**COST**) that takes the value of 1 for parcels that have steep slopes (more than 15%) and/or poorly drained soils.[18] Ideally we would wish to measure the opportunity costs of development using cross-sectional data on farm returns, but such data are not available, for confidentiality reasons, at the spatial resolution that we require. To substitute for this, we include an indicator variable (**PRIME**) that takes the value of 1 for parcels that are currently in agriculture and have prime agricultural soils, and 0 otherwise.

In Model A, all sources of exogenous spatial heterogeneity are purposefully left in the error term, and we investigate a naïve model in which only surrounding land use is incorporated to explain the order of parcel conversion. With no other explanatory variables in the model, one would expect these surrounding land use variables to be spatially correlated with a variety of other effects. A

[18] These attributes are defined according to the Maryland Department of State Planning, Natural Soil Groups of Maryland, Technical Series Publication 199, December 1973.

developable parcel in an already highly developed area would be expected to be a prime candidate for development. Given that many landscape characteristics are spatially correlated, whatever characteristics of the surrounding parcels that made them profitable for early development should also make the parcel in question profitable for development. For example, we would expect parcels that have a high degree of accessibility to the urban center to have high values in developed use. Models B and C account for progressively more exogenous heterogeneity. Model B includes both the surrounding land use measures and the distance to city center, **DCDIST**, and Model C incorporates additional observed spatial variable by including the proxies for both high construction costs, **COST,** and high opportunity costs, **PRIME**.

The proportional hazards model of (14) and (15) implies that at most one event happens at a point in time. Since our data is measured annually, there are many observational ties. We use the exact method for handling these ties developed by DeLong, Guirguis and So (1994); this is based on the assumption that ties arise only because the data are measured in discrete rather than continuous time. Results did not vary with other methods for treating tied events, however.

C. Empirical Results

Estimates of the parameters and their standard errors, together with Wald tests of their significance, are reported in Tables 2A and 2B for Models A, B, and C. Two different specifications of s^* are considered ($s^* = 800$ meters and $s^* = 1{,}000$ meters), although the results are qualitatively similar. Where exogenous effects are included, their parameter estimates are significantly different from zero and consistent in sign with intuition. As commuting distance increases, the optimal time of conversion is postponed farther into the future. Likewise, prime agricultural land and land with poor construction qualities have optimal development times farther into the future.

In all but Model A, the estimated coefficients on the interaction effect are negative and significantly different from zero. The outer interaction effect is not significantly different from zero at the 95% confidence level in either version of Model A. Comparing across Models A, B, and C, both the absolute values of the estimated interaction effects and their significance are found to increase as add additional exogenous features are added. Consistent with our expectation, both the inner and outer estimated interaction effects become increasingly negative as increasing amounts of spatial heterogeneity are incorporated in the model and removed from the error term. To the extent that the remaining omitted variables exhibit positive spatial correlation, by far the most likely case, the estimated parameters on the endogenous interaction variables can be interpreted as upper bounds for the "true" interaction effects. These results support the hypothesis that net interactions among neighboring land use parcels are negative.

Table 2A: Results from Proportional Hazards Model of Land Use Conversion, $s^* = 800$m

Model A (s^* = 800m)				
	Parameter Estimate	**Standard Error**	**Wald Chi-Square**	**Pr > Chi-Square**
DEVLUSE1	-1.652442	0.53026	9.71120	0.0018
DEVLUSE2	-0.608436	0.55845	1.18703	0.2759
Model B (s^* = 800m)				
	Parameter Estimate	**Standard Error**	**Wald Chi-Square**	**Pr > Chi-Square**
DEVLUSE1	-1.735931	0.52497	10.93445	0.0009
DEVLUSE2	-2.043245	0.60210	11.51596	0.0007
DCDIST	-3.191968	0.31250	104.33416	0.0001
Model C (s^* = 800m)				
	Parameter Estimate	**Standard Error**	**Wald Chi-Square**	**Pr > Chi-Square**
DEVLUSE1	-1.882006	0.53161	12.53285	0.0004
DEVLUSE2	-2.193089	0.60351	13.20504	0.0003
DCDIST	-3.064087	0.31995	91.71667	0.0001
PRIME	-1.145804	0.39072	8.60002	0.0034
COSTCON	-1.294097	0.29363	19.42313	0.0001
Binary dependent variable = Conversion to residential subdivision in a given year, 1991-97				
No. of observations = 6,813				

Table 2B: Results from Proportional Hazards Model of Land Use Conversion, $s^* = 1{,}000$m

Model A (s^* = 1,000m)				
	Parameter Estimate	**Standard Error**	**Wald Chi-Square**	**Pr > Chi-Square**
DEVLUSE1	-1.394932	0.56622	6.06921	0.0138
DEVLUSE2	-0.793206	0.56624	1.96235	0.1613
Model B (s^* = 1,000m)				
	Parameter Estimate	**Standard Error**	**Wald Chi-Square**	**Pr > Chi-Square**
DEVLUSE1	-1.774276	0.56907	9.72102	0.0018
DEVLUSE2	-2.024421	0.60838	11.07267	0.0009
DCDIST	-3.241554	0.31284	107.36753	0.0001
Model C (s^* = 1,000m)				
	Parameter Estimate	**Standard Error**	**Wald Chi-Square**	**Pr > Chi-Square**
DEVLUSE1	-1.923620	0.57362	11.24566	0.0008
DEVLUSE2	-2.151569	0.61356	12.29679	0.0005
DCDIST	-3.109106	0.32015	94.31103	0.0001
PRIME	-1.116476	0.39058	8.17103	0.0043
COSTCON	-1.296772	0.29363	19.50409	0.0001
Binary dependent variable = Conversion to residential subdivision in a given year, 1991-97				
No. of observations = 6,813				

D. Comparison of Actual and Predicted Spatial Pattern

In what follows we attempt to illustrate, using a small portion of our study area, the empirical model's ability to explain actual land use conversion pattern. Before doing so, we estimate one final model (Model D) in which the endogenous interaction effects are restricted to zero. These results are reported in Table 3. Using parameter estimates from Model C (s^* = 1000m) and Model D, changes in the 1990 land use configuration of northeast Charles County are then predicted. For each parcel that was "developable" in 1990, the time-invariant exogenous attributes and the time-varing neighborhood land use variables are calculated. The estimated parameters from Models C and D are then used to calculate each parcel's likelihood of conversion. In order to translate probabilistic measures of conversion into actual conversion, a constant regional demand for new housing is assumed and the parcel with the highest probability of conversion in each time period is the parcel chosen for conversion. Neighborhood interaction effects are recalculated after each predicted conversion for the unrestricted case. Simulations of both the restricted and unrestricted cases are carried out for 114 rounds of development and the results are then compared with the actual pattern of 114 subdivisions that were developed in northeast Charles County between 1991-97.

Table 3: Results from the Restricted Proportional Hazards Model

Model D				
	Parameter Estimate	**Standard Error**	**Wald Chi-Square**	**Pr > Chi-Square**
DCDIST	-2.412143	0.31628	58.16672	0.0001
PRIME	-0.929100	0.38977	5.68222	0.0171
COSTCON	-1.128687	0.29392	14.74670	0.0001
Binary dependent variable = Conversion to residential subdivision in a given year, 1991-97 *No. of observations = 6,813*				

Maps 4 and 5 show the comparison of the predicted patterns with observed changes in the development pattern in northeast Charles County between January 1991 and December 1997. Each point corresponds to the centroid of a parcel that has either been subdivided or that could be subdivided. In comparing the two predicted patterns to the actual development pattern, the pattern simulated with only the exogenous effects generates a much higher degree of clustered development than the actual development pattern (Map 4). In this case, the location of development is primarily determined by relative accessibility to Washington D.C., located to the northwest of the developable region. Consistent with the earlier simulations of the cellular automaton, the inclusion of the negative interaction effects generates a pattern that is significantly more fragmented and one that appears to mimic more closely the actual pattern of residential subdivision development (Map 5).

In order to quantify the differences among the three patterns, an inter-distance point statistic is used to summarize each pattern of n points.[19] This statistic is a count variable that tallies the number of paired points whose inter-point distance falls within increasing distance ranges. The counts are normalized by $n(n-1)$ and the distance ranges are cumulative. For any range, d, the statistic is given by:

$$H(d) = \sum_{ij} \Phi(d_{ij} \leq d)/n(n-1),$$

where $\Phi()$ is an indicator variable such that $\Phi(d_{ij} \leq d) = 1$ if points i and j are within distance d of each other and 0 otherwise; $d \in \{0, d_{max}\}$, where d_{max} is the extent of the region; and $H(d) \in \{0,1\}$.

To gauge the degree of difference among predicted and actual patterns, the inter-distance point statistics from the actual vs. predicted patterns are calculated for the same intervals of d and plotted against each other. The statistic representing the actual development pattern is mapped against itself for the relevant distance range, $d = 0,\ldots,d_{max}$. The statistics representing the predicted patterns are mapped against the actual pattern statistic for the same distance range, so that the degree of difference between the actual and predicted patterns is evidenced by the degree to which the plot of the predicted pattern statistics differs from the 45° line. This is illustrated in Figure 2 for the predicted patterns generated by the restricted model (Model D) and the unrestricted model (Model C). The statistic corresponding to the unrestricted model lies quite close to the 45° line, suggesting that the spatial pattern predicted by this model is qualitatively similar to the actual pattern. In contrast, the statistic corresponding to the restricted model lies well above the diagonal, suggesting that this pattern has a much higher degree of positive spatial correlation than either the actual pattern or the pattern simulated with the inclusion of the interaction effect. These observations provide further support for a model that incorporates both exogenous landscape features and endogenous interaction effects.

[19] To calculate this statistic, we adopt the methods outlined in the spatial statistics literature (e.g. Cressie, 1993; Diggle, 1984).

IV. Conclusions

That urban spatial structure may be determined by interdependencies among spatially distributed agents is the theme of several recent papers in urban and regional economics. In most of these, theories about the role of attracting and repelling interactions have focused on the formation of urban centers. In this paper, we adopt an interactions-based model to study the influence of endogenous land use interactions and exogenous landscape features on the evolution of land use pattern at the rural-urban fringe. The presence of interaction effects is shown to generate very different patterns of land use conversion than those predicted by models that ignore such spillovers, e.g. the monocentric model. Rather than concentrated development around urban centers or other exogenous features, land use patterns are characterized by various degrees of clustering, scatteredness, and fragmentation, depending on the relative magnitudes of the repelling and attracting effects.

By incorporating the influences of both exogenous landscape features and endogenous interactions, the model permits an empirical test of the interactions hypothesis. We find evidence of negative spillovers among exurban land parcels converted to residential subdivisions. Although an unbiased estimate of the interaction effect is not possible, the results nonetheless provide the first empirical evidence of the role of interactions in the formation of urban land use patterns.

The results also have prescriptive value for policy. Given sufficiently strong repelling effects from negative development externalities, offsetting attracting influences of exogenous features, e.g. from proximity to the central business district and the supply of public infrastructure, may not be sufficient to mitigate leapfrog development. In an era when "Smart Growth" initiatives, aimed at concentrating development, are dominating the land use policy agenda, insights into the underlying mechanisms that induce low density sprawl have particular policy relevance.

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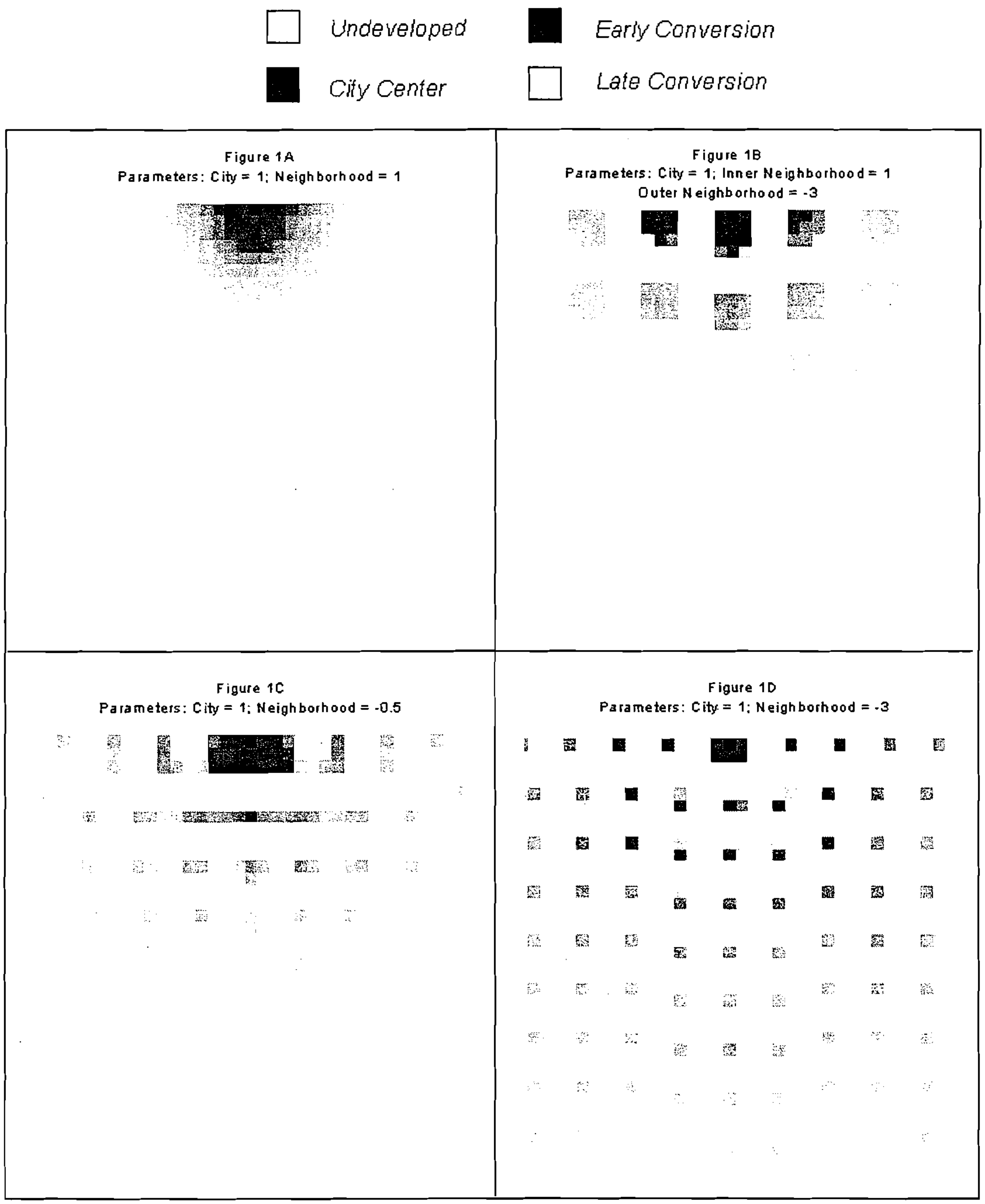
Figure 1

Simulation of Land Use Conversion Model

Color gradient indicates timing of conversion

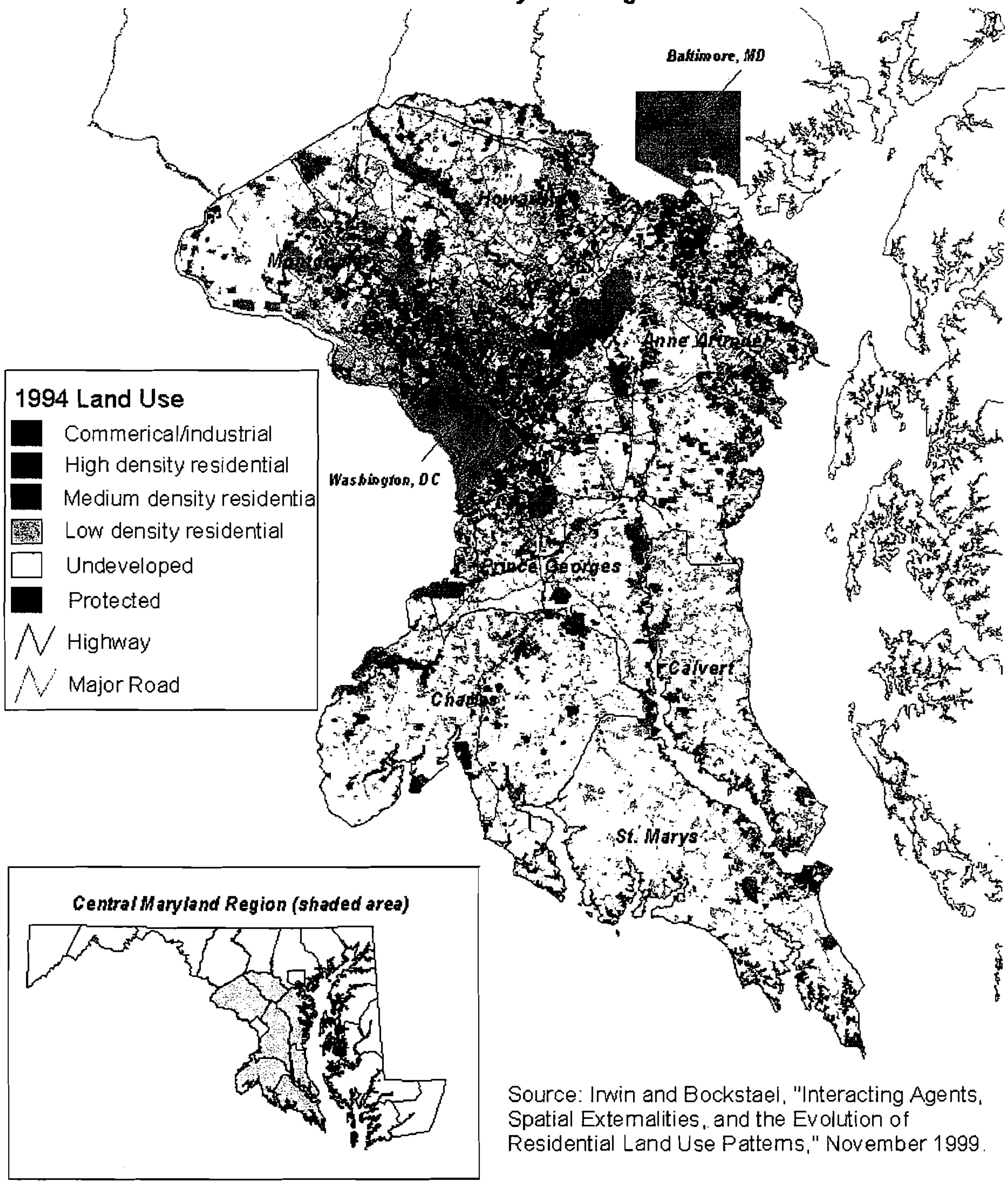


Source: Irwin and Bockstael, "Interacting Agents, Spatial Externalities, and the Evolution of Residential Land Use Patterns," November 1999.

Map 1

1994 Land Use Pattern

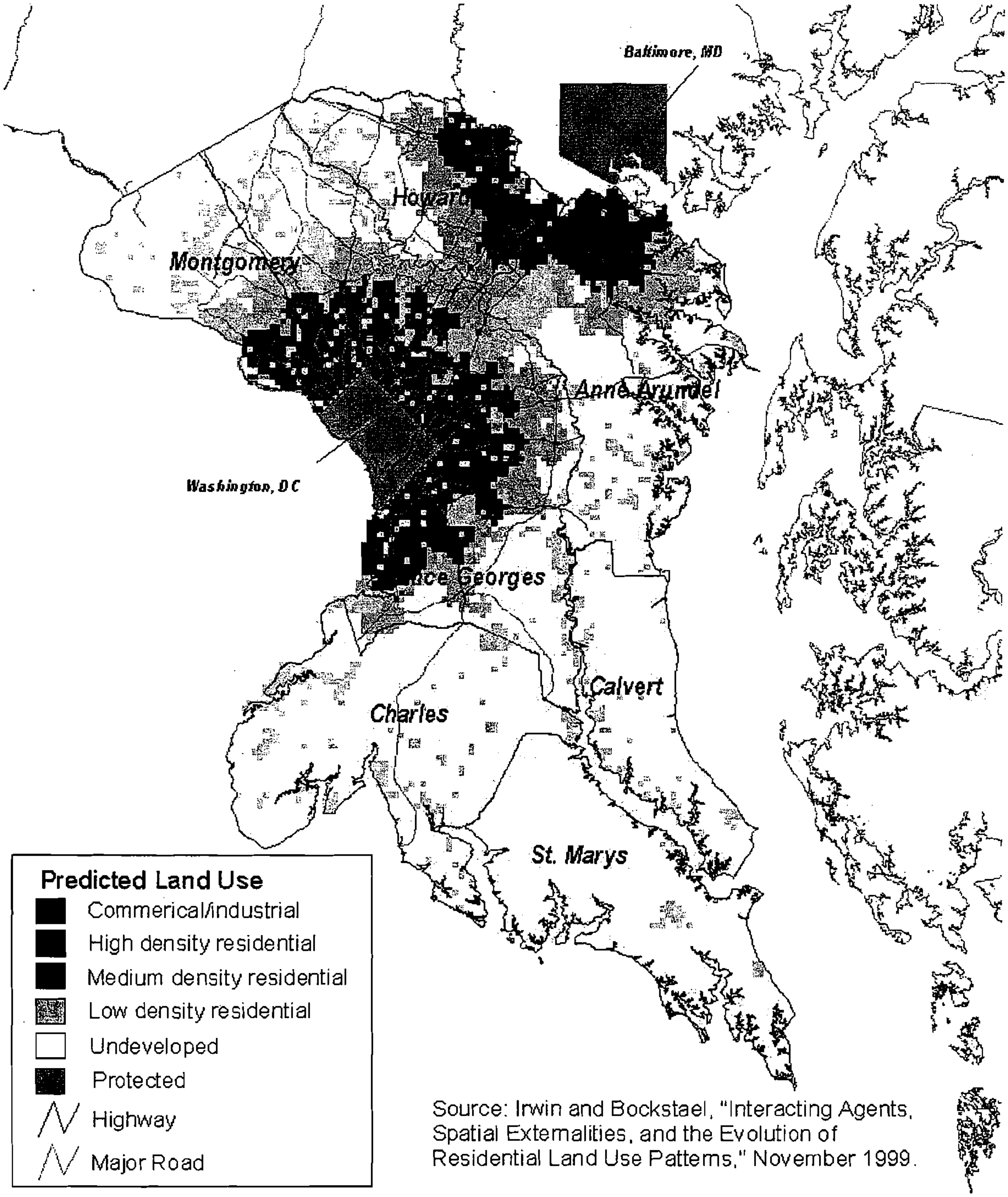
Central Maryland Region



Source: Irwin and Bockstael, "Interacting Agents, Spatial Externalities, and the Evolution of Residential Land Use Patterns," November 1999.

Map 2

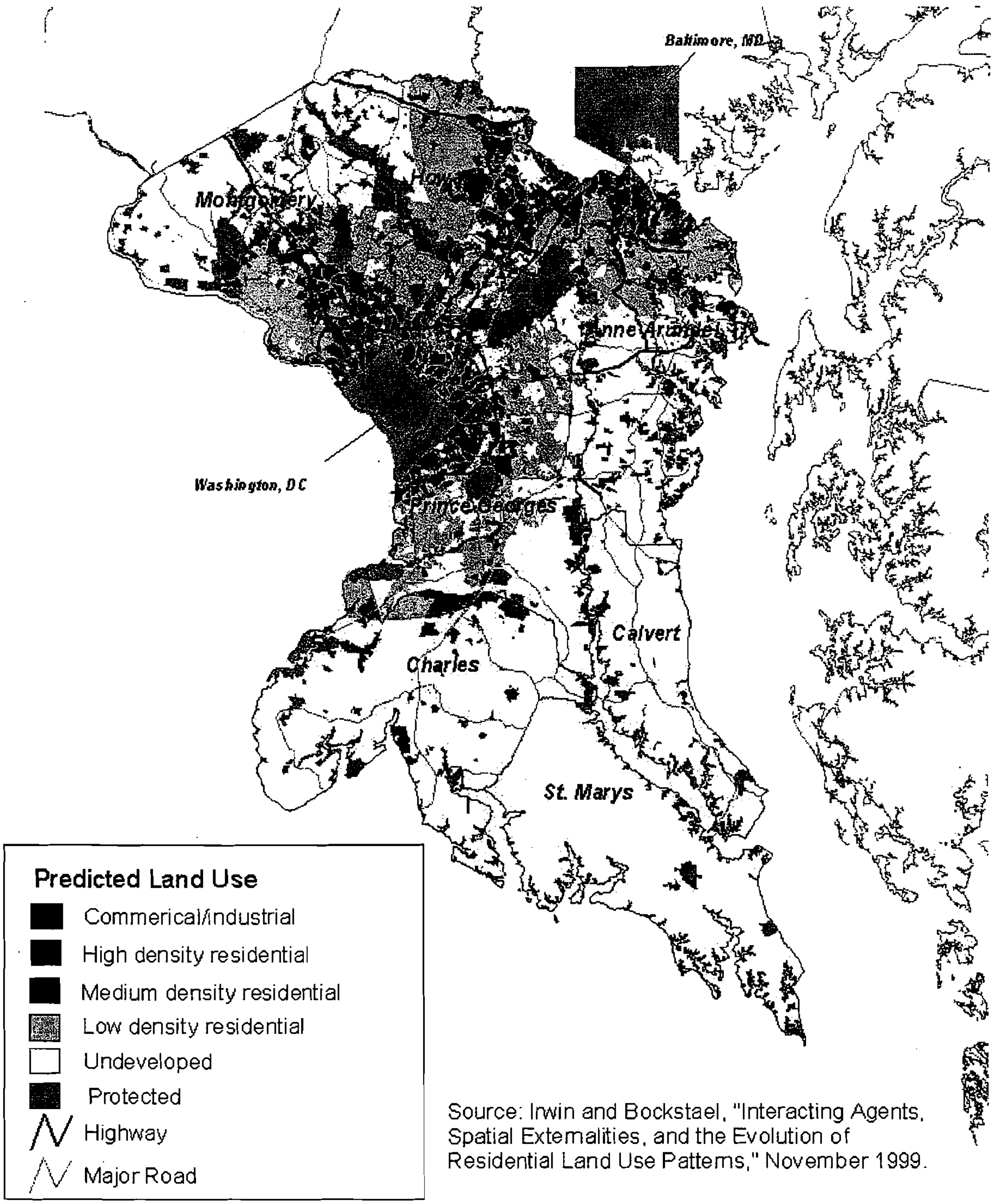
Land Use Reallocation under Duocentric Assumption with Distance Measured via the Roads Network



Source: Irwin and Bockstael, "Interacting Agents, Spatial Externalities, and the Evolution of Residential Land Use Patterns," November 1999.

Map 3

Land Use Reallocation under Duocentric Assumption with Exogenous Zoning



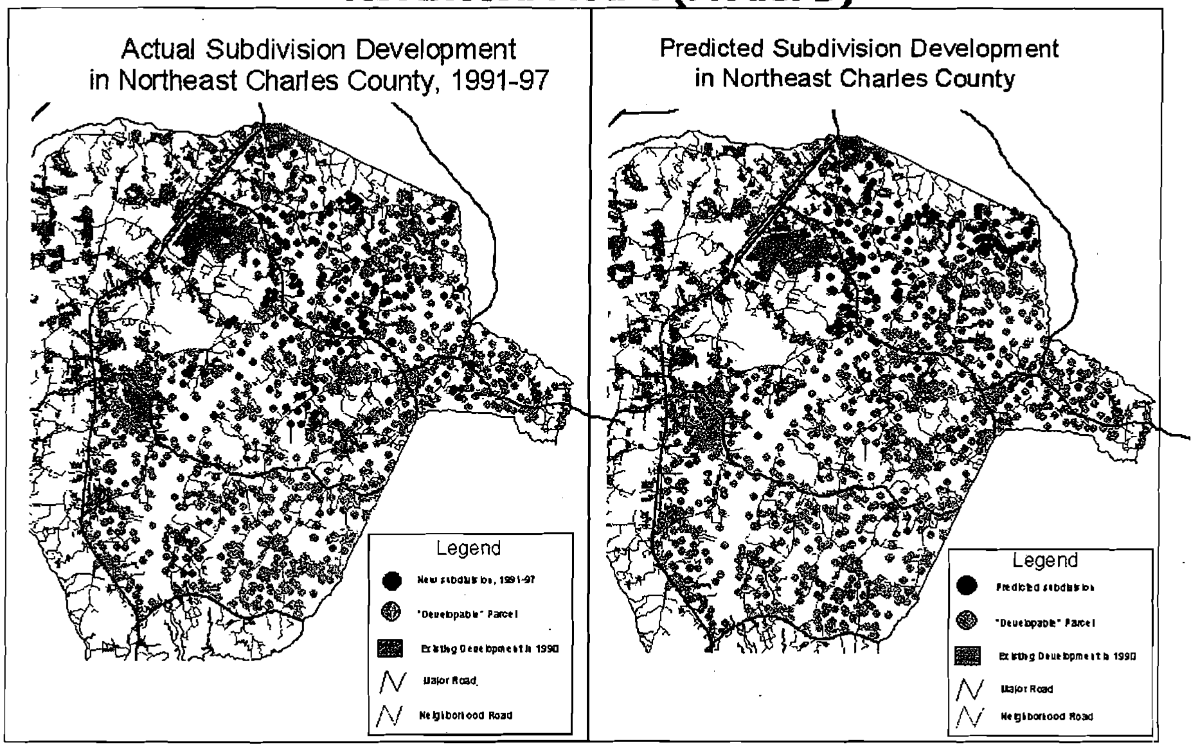
Predicted Land Use

- Commerical/industrial
- High density residential
- Medium density residential
- Low density residential
- Undeveloped
- Protected
- Highway
- Major Road

Source: Irwin and Bockstael, "Interacting Agents, Spatial Externalities, and the Evolution of Residential Land Use Patterns," November 1999.

Map 4

Actual vs. Predicted Development
Restricted Model (Model D)



Source: Irwin and Bockstael, "Interacting Agents, Spatial Externalities, and the Evolution of Residential Land Use Patterns," November 1999.

Implementing an Optimal Experimental Design for a Binary Choice Experiments: An Application to Bird Watching in Michigan

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1. Introduction

Stated preference methods aimed at valuing the attributes of non-market goods, rather than the goods and services themselves, are increasingly popular in environmental economics (Opaluch et al. 1993, Adamowicz et al. 1998). In such studies, respondents are typically presented with scenarios describing two or more sites or resource programs. Respondents are then asked to indicate which of the alternatives they prefer. By varying the attributes of the alternatives, econometric methods can be used to estimate respondents' preferences for the attributes. This paper uses a study of bird watching to address the question of how best to define attribute levels and combine the attributes that make up the alternatives that enter a choice experiment.

By defining attribute levels, combining them into alternatives, and creating choice scenarios, a researcher is implicitly determining the experimental design of the choice experiment. An optimal experimental design maximizes the statistical information that can be obtained from the data on the basis of design criteria. A design that seeks to minimize the covariance matrix will require fewer observations to achieve any level of precision than would be necessary otherwise. Optimal designs are therefore of special interest to researchers who are trying to estimate models with relatively small sample sets.

In the design of a typical choice experiment, researchers select fixed levels for each of the attributes that will be used in the study (Rae 1985). The alternatives that enter the choice experiment are then defined by vectors of the attribute levels. The alternatives are sometimes formed by randomly combining the attribute levels (Buchanan et al. 1998). In other cases, the alternatives are formed by taking the full factorial combination of each of the levels, although this often results in a very large number of alternatives. To reduce the number of alternatives, some researchers rely on fractional factorial designs such as a main-effects plan (Louviere 1988). Unfortunately, these experimental designs need not be optimal for the discrete choice methods commonly used in such studies (Kuhfeld et al. 1994). The research reported here is guided by a recently developed optimal experimental design for binary logit choice experiments (Kanninen 2000). Our experimental design, as well as the survey approach, differs from a traditional design because the attribute levels are selected and updated as a part of the design.

For binary logit choice experiments with linear utility functions, D-optimal plans involve setting all but one of the attributes at extreme values, and then using the remaining attribute to balance the design (Kanninen 2000). One well known problem with the D-optimality notion is that one needs to know the value of the true parameters in order to determine what a D-optimal design would be. A key feature of the D-optimal design for binary logit choice probabilities is that the D-optimal split in the response probabilities depends on the number of attributes in the study, but the D-optimal response probabilities *do not* depend on the vector of parameters for the utility function (Kanninen 2000). Thus, once all but one of the attribute pairs are set at their upper and lower bound levels, the remaining variable can be used to balance the design to achieve the D-optimal response splits. Naturally, the optimal levels of the balancing variable will depend on the true, yet unknown, parameter values. However, during survey implementation a researcher can monitor the survey responses and repeatedly adjust the level of the balancing variable to move in the direction of the D-optimal design – a process which does not require prior knowledge of the true parameters. We refer to this novel survey approach as "sequential updating" of the attribute levels, or as the "updating" approach. The research presented here is the first to develop and implement the updating approach for a choice experiment. The data from the updating approach is also used to determine whether the theoretically prescribed D-optimal design points could be approximated in practice, and to assess whether gains in efficiency were possible relative to a standard orthogonal design.

2. Experimental Designs for Choice Experiments

In the non-market valuation literature, researchers have developed techniques for setting bid amounts to improve the efficiency of valuation estimates (Alberini 1995, Cooper 1993, Kanninen 1993). There is also an extensive literature that addresses ways of improving the efficiency of experimental designs for marketing applications (Lazari and Anderson 1994, Kuhfeld et al. 1994, Louviere and Woodworth 1986). However, much of the existing knowledge on experimental designs for conjoint studies and discrete choice experiments is based on linear models with a continuous dependent variable. Design plans for these types of models are available in the literature (Addelman 1962, Plackett and Burman 1946, Montgomery 1991). Several writers have acknowledged the current shortcomings of our understanding of optimal designs for discrete choice experiments and have argued for more research and increased awareness of the effects of choice experiment designs (Carson et al. 1994, Kuhfeld et al. 1994, Adamowicz et al. 1998, Hensher 1999).

Here, the criteria of D-optimality is used to compare the efficiency of alternative experimental designs. While there are several measures of design efficiency, D-optimality has become a commonly used design-efficiency criterion (Kanninen 2000, Zwerina et al. 1996, Alberini 1995, Kuhfeld et al. 1994). Moreover, D-optimality was recommended by a panel of choice modelers as the appropriate design criteria (Carson et al. 1994). D-optimality is achieved by maximizing the determinant of the Fisher information matrix.[2]

One practical difficulty with optimal experimental designs is that they typically depend on the unknown vector of parameters to be estimated using the data collected in the design. To address this problem, some researchers have developed computer-based algorithms to assess the D-efficiency of a design and search for more efficient designs (Kuhfeld et al. 1994, Zwerina et al. 1996, Cook and Nachtsheim 1980). The computer algorithms can then be run under a variety of priors on the estimated parameters to compare alternative designs. However, in all of these cases, the researcher sets the number of levels for each attribute as well as the values of these levels. The search algorithms merely seek efficient combinations of the predetermined attribute levels. Determining the level of the attributes is not explicitly a part of the design process.

Alternatively, Kanninen (2000) used an analytical approach to derive an optimal experimental design for multinomial and binary-logit choice experiments. Kanninen's approach takes into account the discrete nature of the dependent variable and develops criteria for determining the efficiency of the design. Unlike traditional designs, this approach allows the number of attribute levels and the attribute levels themselves to be part of the design by making them explicit design parameters.

The D-optimal approach is summarized here for the case of the binary choice experiments based on logit choice probabilities. Kanninen developed the D-optimality conditions for an underlying utility function that is linear. Thus, all interactions and second order effects are assumed to be negligible. Each variable is also assumed to be bounded from above and below. Following a typical specification of a random utility model, the utility

[2] The Fisher information matrix inverted and its sign reversed yields the covariance matrix for the maximum likelihood estimators.

function is assumed to have random errors with an extreme value distribution. Hence, the probability of a respondent choosing alternative A among the alternatives A and B in choice scenario j is given by:

$$P_j = \frac{\exp(\theta_j)}{1+\exp(\theta_j)} \qquad \text{Equation 1}$$

The vector of attributes, Q, enter the utility function linearly and thus:

$$\theta_j = \beta_1(q_{1j}{}^A - q_{1j}{}^B) + \beta_2(q_{2j}{}^A - q_{2j}{}^B) + \ldots + \beta_m(q_{mj}{}^A - q_{mj}{}^B), \qquad \text{Equation 2}$$

where $(q_{mj}{}^A - q_{mj}{}^B)$ represents the difference in the level of site attribute m between the two alternatives A and B in choice scenario j. The binary logit model is estimated by maximizing the log-likelihood function:

$$\ln L = \sum_{j=1}^{n} y_j \ln P_j + (1-y_j)\ln(1-P_j) \qquad \text{Equation 3}$$

and $y_j = 1$ when respondent to scenario j prefers site A and =0 otherwise.

D-optimality is achieved by maximizing the determinant of the Fisher information matrix. The Fisher information matrix is:

$$I = \begin{pmatrix} \sum w_j & \sum w_j x_{1j} & \cdots & \sum w_j x_{mj} \\ & \sum w_j x_{1j}^2 & \cdots & \sum w_j x_1 x_{mj} \\ \bullet & & \ddots & \vdots \\ & & & \sum w_j x_{mj}^2 \end{pmatrix} \qquad \text{Equation 4}$$

where:

$$w_j = P_j(1-P_j), \quad x_{ij} = q_{ij}{}^A - q_{ij}{}^B. \qquad \text{Equation 5}$$

Kanninen (2000) has shown that the determinant of I is proportional to the $P_j(1-P_j)$ terms and is increasing in the θ_j's. Since the determinant of I must be maximized to achieve the D-optimal solution, these two components exert distinct pressures on the resulting D-optimal designs. The terms involving the θ_j's alone would be maximized when the θ_j's take on extreme values. Since the empirical model is based on differences in attribute levels and an underlying utility function that is linear, these differences should be as large as possible. Alternatively, maximization of $P_j(1-P_j)$ alone would require P_j to be equal to 0.5. Thus the D-optimal design then must strike a balance between these opposing forces.

Having analytically solved the problem, Kanninen (2000) demonstrated that the D-optimal design calls for only two levels for each attribute. The attribute levels of the variables are set as far apart as possible, i.e., at the upper and lower boundaries for each attribute. The attribute levels are then combined into alternatives by following a 2^m orthogonal main effects plan. The number of choice scenarios is determined by the number of alternatives from the main effects plan. The choice scenarios are then created by pairing each of the main effects alternatives with its opposite. That is, if q_{mj}^A takes the lower bound level for attribute m, then q_{mj}^B is set at its upper bound level. Finally, the D-optimal design requires that the levels for one of the variables be adjusted so that the choice probabilities match the D-optimal response probabilities. This "balancing variable" must be a continuous variable. Importantly, the D-optimal balance in the response probabilities depends on the number of attributes, m, but does not depend on the unknown β. Of course, the D-optimal levels for the balancing variable do depend on β.

3. The Updating Approach

While the D-optimal design for a binary logit choice experiment seems straightforward, one needs to know β to set the D-optimal design points for the balancing variable. However, the fact that the D-optimal response probabilities do not require knowledge of β, suggests a sequential trial-and-error survey method for approaching a D-optimal design. The "updating approach" proposed here starts with choice scenarios derived from a main effects plan as described above. To begin the data collection, the researcher sets the levels of the balancing variable to try and achieve the D-optimal response probabilities based on a prior for β. Then, as survey data is collected, the response probabilities can be monitored. Based on the running average response probabilities for each scenario, the levels of the each choice scenario's balancing variable can be adjusted to move toward the desired response probabilities. Naturally, the better the prior on β, the more efficient the design. In addition, the resulting model efficiency depends on how quickly and how closely the optimal response categories can be approximated.

Below, the implementation of the updating approach is described. The design and the results of the empirical model using the updating approach to survey data collection will be compared to the D-optimal design to evaluate the relative efficiency of the updating approach. In addition, the efficiency of traditional orthogonal designs based predetermined, fixed attribute levels will be compared the updating approach to examine the extent of efficiency gains.

4. Application

For the present research, Kanninen's (2000) optimal experimental design approach was applied to a binary-choice experiment in which birders were surveyed regarding their site preferences. The context of the choice experiment was the selection of a preferred hypothetical birding site for a one-day spring birding trip. Qualitative research with birders revealed the main attributes of birding sites that birders care about (Steffens 1999). Among these, six attributes were selected for the choice setting: the number of warbler species, the number of rare or unusual species, the number of other species, abundance category of warblers (indicating how likely birders are to see a species), habitat diversity, and site entrance fee as the balancing variable.

Members of the American Birding Association in Mid-Michigan were randomly recruited to participate in a study of their bird watching site choices. Personal interviews were conducted with sixty members with an the adjusted response rate was 82% (Steffens 1999). Each respondent was given eight binary choice questions yielding a total of 480 binary choices. The choice experiments elicited the birders preferred site among two hypothetical alternatives. The order in which the scenarios were presented to the respondents was randomly selected. Complete details on the survey and the questionnaire are provided in Steffens (1999).

Setting initial attribute levels[3]

The optimal design requires boundary levels to be set for five of the six attributes and starting values for the balancing attribute, the sixth attribute. For the six variables, a 2^6 main effects plan results in a total of eight choice scenarios. The main effects plan that served as the basis for the first five variables in the updating design is presented in Table 1. Given their importance to the design, some discussion of how the initial levels for each of the attributes were determined is warranted.

Bird lists from birding sites in Michigan and nearby Pt. Pelee, Ontario, were used to set the bird-related attribute levels. Most birders are familiar with bird checklists, which are available for many popular birding sites. These checklists present the names of all the species, often with abundance categories, that have been sighted at the birding location. In order to maintain some of the complexity of information contained in a checklist without making the experimental design too complicated, warblers and rare or unusual species were considered separate attributes from the general attribute of "the number of bird species." This specification was based on the finding from the qualitative research that most respondents have a particular preference for warblers, and for species that are rare or unusual for a specific area in general.

The bird lists were analyzed in order to set the range of species for warblers, rare or unusual species, and the number of other species. An experienced birder provided information to determine which species would be considered rare or unusual in the study area in Michigan (Johnson). The range for the number of warbler species was set at 5 – 25, the range for rare or unusual species at 5 – 30, and the range for number of other species at 75 – 201. These ranges represent the numbers that would reasonably be the minimum and maximum that birders might see at a site, without compromising the realism of the hypothetical sites. Since the abundance categories "rare", "uncommon", and "common" were available or could be constructed for all sites, the boundary values for "abundance category" were set at "rare" and "common" for the choice setting[4]. Habitat was designated as "forest with edge" habitat for the low, homogeneous habitat level and as "forest, wetlands, open water with sandy-gravel shoreline" for the high, diverse habitat level. The homogeneous habitat was selected as forest with edge because warbler species are specifically included in the scenarios and they require forest habitat.

This led to the values for the main effects plan for each of the variables except the entrance fee (see Table 1). The entrance fee also served as the balancing variable in the study. While public birding sites usually do not have an entrance fee, some public sites and most private sites that birders visit have entrance fees. Pre-tests were conducted to determine how the fees should initially be set. Two types of information were considered for setting the fees: respondent experience with fees, and responses to some open-ended willingness-to-pay questions.

[3] For complete details on how the attribute levels were determined see Steffens (1999).

[4] Because "rare" was also used to designate species not typically found in the area, some confusion between the two concepts was expected and respondents were alerted to the two different meanings of "rare". A change in terminology was contemplated but rejected because this term is commonly used for both concepts and birders are familiar with it.

Birders in the pre-test indicated that most sites they visit for birding do not charge an entrance fee. The birders who had paid entrance fees for birding sites stated that they consider the fees nominal. Most fees reported by birders do not exceed $5 per day, though some birders had paid more than $25. For this reason, the fee for the site that the pre-tests indicated was the less desirable site was set at $1. In addition, open-ended willingness-to-pay questions for the sites were administered in the pre-tests. Only two pre-test respondents indicated a willingness-to-pay of more than $25 for the birding site that had high levels for all of the non-fee attributes. Based on this information, as well as the respondents experience with fees, it was determined that an entrance fee of $30 would serve as an upper limit on entrance fees to ensure that the scenarios remained realistic.

Having established some limits on the entrance fee, a fair amount of researcher judgement was used to set the fee differences for each of the eight scenarios. The pre-test selections helped in setting the fees, as did the desired response probabilities across the scenarios. If a site was clearly preferred by pre-test respondents based on non-fee attributes and had a high number of variables set at the high level, the fee was set at a high level. The highest initial level chosen was $25 for scenario 8 site A. This site had all of its non-fee attributes set at the high level and a targeted choice probability of 67% of the respondents. The initial fees for each of the eight scenarios are shown in the first row of table two. Note that the last column of Table 1 shows the fee pattern that would be used in a 2^6 main effects plan. While the main effects plan is not actually used to set the levels of the fee attributes, it is used to determine the direction of the D-optimal response probabilities (Kanninen 2000).

Finally, recall that we wanted to compare the design efficiency of the updating model to the efficiency of a traditional approach based on preset attribute levels. Thus, prior to data collection, two entrance fees, $1 and $11, were selected as fees that would have been used had a traditional approach been taken. The selection was based on pre-test information that elicited open-ended responses on birders' maximum willingness-to-pay for visiting the alternative birding sites, as well as pre-test data on actual experiences with entrance fees for birding sites.

5. Results

Updating

Perhaps the most immediate result was that the updating was feasible and was manageable for the personal interviews we conducted. Table 2 lists the starting fees for each of the eight scenarios and also lists the sequence of fees that was used for each scenario. For convenience, the actual and D-optimal shares are presented in the final two rows of Table 2. For each choice scenario in Table 2, the first row in the column shows the starting fees, and the last row in the column shows the ending fees. The number of different pairs of fees that were used across the 60 interviews ranged from a low of three for scenarios one and eight, to a high of eight for scenario five. In all, there were 39 different sets of fees used across the eight scenarios. Note that fees did not always change at the same time for the different scenarios so that the times that fees were adjusted do not correspond to the rows of Table 2.[5]

The last rows of Table 2 give the desired and actual response probabilities. With six attributes in the study, the desired response probabilities were 67% and 33% respectively. These probabilities were not exactly achieved for any of the scenarios. Scenario 3 was the closest

[5] Table 2 simplifies the data considerably – the full sequence of fees for each person and for each scenario is given in Steffens 1999.

while the actual shares for scenario 2 were essentially the opposite of the target. It turned out that at some point during the updating, most of the fees reached the preset $30 upper bound on the fees thereby preventing further fee adjustments to achieve the D-optimal response probabilities. For seven of the eight scenarios, the fee for one of the alternatives in the scenario reached the predetermined upper bound of 30 dollars. The fee for the third scenario was quite close to 30 by the end of the interviews. Some scenarios reached the maximum fee quickly. For example, in scenario 7 the maximum fee was reached by the 14^{th} interview, and in scenario 1 it was reached by the 26^{th} interview. Alternatively, the six other scenarios did not reach their final fees until 75% or more of the interviews were conducted.

One possible downside to the updating approach is that the researcher has to use some judgment to set the initial entrance fees. However, because the responses are continually monitored, and the fees adjusted accordingly, the approach is particularly forgiving of poor priors. In our case, the sign of our priors was generally on track. In only one of the scenarios was a higher fee set for the site alternative that ended up with a lower fee at the end of data collection (see scenario 5 in Table 2). In all other scenarios, the site alternative that started with a higher entrance fee also had the higher fee after the interviews were concluded. For the single scenario where the fees moved in the opposite direction from what was anticipated, birders had not shown a clear preference for one or the other sites in the pre-tests. This illustrates that the pre-tests were a good indicator of site preference. Even though the initial fees for scenario 5 were set in the wrong direction, this was easily determined during the survey and the fees were updated. Also note that most of the fee adjustments generally moved in one direction, though not in all cases (e.g., scenario 3). In one case, the fees were inadvertently updated in the wrong direction for a few interviews. Again, with the constant monitoring and the updating, it was easy to identify and correct misdirection's (see row 2, scenario 2, in Table 2).

Estimated Model Results

The random-utility model forms the utility-theoretic underpinning for the research application. In the context of recreational site choice, the model is particularly suitable when individuals choose between sites with different attribute levels (Bockstael et al. 1991). The method makes it is possible to model resource users' site choice as a function of the differences in site attribute levels. The random-utility model of birder's site preferences was estimated as a binomial logit model (equation 1). The estimated coefficients, $\hat{\beta}$, for the differences in the site attributes are given in Table 3. All of the estimated coefficients were significant (95% confidence) and had the expected sign (Table 3). The probability of choosing a site increases with the number of warblers, rare or unusual species, other species, higher abundance of warblers (as indicated by abundance categories), higher levels of habit diversity, and decreases as the entrance fee to the site is increased. The estimation results are presented here for completeness – a full discussion is provided in Steffens 1999.

Design Comparison

Kanninen (2000) developed the optimal design for binary-choice experiments analytically. The theoretical level of design efficiency cannot be reached with the empirical model because the β's are not known *a priori*. However, using the updating approach, the efficiency of the empirical model can potentially approach the theoretical model efficiency. In this section we discuss how the efficiency of a traditional binary-choice experiment and the efficiency of the updating approach was compared with that of the D-optimal design. Model efficiency depends on the unknown parameters, i.e., the β's. Since the best and only estimates we have for the β's are the logit model estimates, $\hat{\beta}$ is used to compute the D-optimal design. Table 4 shows the fee difference required for the D-optimal design given $\hat{\beta}$. These fee differences were calculated using $\hat{\beta}$ in Equation 1 and solving for the fee differences that yield the desired 67/37 splits for each scenario. In one of the scenarios in Table 4, one of the sites was so desirable that the entrance fee would have had to be set extremely high (-\$72) to achieve the desired response probabilities – well beyond any respondent's experience with entrance fees. It is likely that many respondents would have rejected a scenario with entrance fees at levels beyond respondents' experience. While the entrance fee differences that would have been required to obtain the desired choice probabilities in the other cases were lower, they ranged from \$24 to about \$59 (Table 4).

Table 4 also presents for comparison the average and final fee differences for the updating approach and the fee differences for the traditional design. Notice that the sign for the fee differences for the D-optimal design is often different than it is for the traditional orthogonal design. Also, notice that the average fee differences for the updating approach have the same sign as the D-optimal fee differences.

There are three designs represented by the fees shown in Table 4: the D-optimal design, the design for the updating approach, and the traditional design based on fixed fees. To compare the three designs, the determinant of the Fisher information matrix, I, was evaluated using $\hat{\beta}$ and each of the three design matrices. By definition, the design matrix with the D-optimal fees for $\hat{\beta}$ has the largest value for $|I|$. In addition, we expect that the updating model will yield a higher value for $|I|$ than will the traditional approach using the fixed fees of \$1 and \$11. To further compare the designs, two measures of design efficiency were calculated.

$$\text{“D-optimality ratio”} = |I(X;\hat{\beta})| \,/\, |I(X^D;\hat{\beta})|$$

$$\text{“D-efficiency ratio”} = |I(X;\hat{\beta})|^{(1/6)} \,/\, |I(X^D;\hat{\beta})|^{(1/6)}$$

where X represents the design matrix for the updating or the traditional approach, and X^D represents the D-optimal design for $\hat{\beta}$, i.e., the main effects plan with all variables but the fee set at their boundaries, and the fees set as in Table 4. The first measure is one we developed for comparing the models. The second is based on the ratio of the "D-efficiency" measure sometimes found in the literature (Kuhfeld et al. 1994). The two measures differ in that the D-efficiency measures raise the value of $|I|$ by $1/m$. The numerator of the D-efficiency ratio is often used to compare the efficiency of designs that have different numbers of attributes, i.e., different m. It is important to note that these measures are suitable for relative comparisons of efficiency, but absent comparison to another model, the value of any measure is not meaningful (Kuhfeld et al 1994).

The D-optimality results are presented in the last rows of Table 5. As expected the updating approach performs better relative to the D-optimal model than does the traditional design with fixed fees of \$1 and \$11. Since the ratio is not equal to one, the updating model does not achieve the D-optimal design efficiency. Also presented in Table 5 are the estimated standard errors for the six attributes, relative to the standard errors for the D-optimal design (all evaluated at $\hat{\beta}$). D-optimality and D-efficiency are concepts that apply to overall efficiency of the model design. This does not imply that the model with the highest level of model efficiency also has the lowest variance for each and every one of the individual coefficient estimates (Table 5). While the relative standard errors are fairly similar for most of the non-fee attributes, the standard error for the fee for the updating approach is much smaller than it is for the traditional design. The relative variance for the entrance fee has implications for the precision of the welfare measures.

The D-optimality ratio and D-efficiency ratio for the traditional model are functions of the pre-selected entrance fee difference. If a particularly "bad" entrance fee differential were selected for the traditional model, it would look worse in comparison to the updated model. To address this possibility, D-optimality ratios and D-efficiency ratios for several alternative entrance fee differences were computed. The results are presented in Table 6. The highest D-optimality ratio was achieved for a $20 fee difference but the relative efficiency was still lower than that of the updated model. D-efficiency ratios present a similar picture (thought the absolute values for this measure are much closer to the D-optimal values). One explanation for the relative efficiency of the updating approach is that under the traditional approach, pre-selected fees are assigned across all scenarios according to the orthogonal design plan, whereas the updated model allows fees to be adjusted independently for each scenario (see Table 4).

6. Conclusions

The results of the study show that the updating approach works. Updating during the data collection process is feasible and efficiency gains are possible. Efficiency gains that can be achieved will depend on how quickly, and if, the updating converges to the D-optimal choice probabilities. Even the limited updating in our study led to efficiency gains and showed that some updating is better than none. The approach has several caveats, however. The model is based on a linear utility function that precludes examination of any interaction effects, yet linearity may not be appropriate for any given the application. If the present design is used, then it is not possible to test for any non-linear or interaction effects. The experimental design is based on the existence of boundary values for the attributes. However, if boundary values cannot be identified, the model can still be used and it is likely that there will be gains relative to the typical orthogonal main effects plan. A dilemma of the approach is that the more extreme the boundary levels, the greater the efficiency gains. However, such extreme attribute levels may also results in unrealistic scenarios. In reality respondents may not be faced with choices between the extreme site attributes that are generated by the optimal experimental design. Moreover, some studies have shown that more complex choice scenarios could yield noisier estimates for $\hat{\beta}$ (Mazzatto and Opaluch 1995).

Despite these caveats, the D-optimality ratios and D-efficiency ratios for the alternative design matrices suggest the usefulness of the updating approach, particularly in cases where little information is available about the unknown parameters and where time and/or budget constraints exist and small samples must be used. In the end, the researcher must decide whether efficiency gains through more extensive pre-testing in conjunction with a traditional approach is worth the time, effort, and money relative to the 'costs' involved in using the sequential updating approach used in this study.

No matter what one concludes about the relative performance of the updating approach in this study, it would be hard to discount the wisdom of some monitoring of response probabilities, with adjustments being considered for scenarios where the response probabilities appear to drift substantially from the D-optimal shares. In addition, the empirical results illustrate several principals of experimental designs for discrete choice data. First, orthogonal designs are not necessarily the most efficient designs. Second, unlike the designs obtained by completely relying on a main effects plan, it may be desirable to have fees that differ across the scenarios (i.e., fees that violate attribute balance). Finally, within the class of orthogonal main effects designs, plans that set attribute levels as a part of the design can yield more efficient designs than the more common approaches in which attribute levels are not a part of the design. This later fact is illustrated by comparing the D-efficiency ratios of the orthogonal main effects designs with the $10 and $20 fee differences.

The study also underscored the trade-off between efficiency gains and realism in the choice scenarios. The model is based on the assumption of a linear utility function. This led to the design requirement of setting attribute levels at their extreme boundaries. As a result the optimal choice probabilities may require values for the balancing variable that respondents consider unrealistic. A constraining factor in the bird-watching application was the upper threshold of $30 that was placed on the entrance fees. Any higher amount was felt to be too unrealistic for a daily entrance fee to go birding for one day. Again, the research application shows that despite the fact that several scenarios were far from the optimal entrance fees, the updating approach led to design efficiency that was superior to a traditional orthogonal design for choice experiments. While the research application was conducted with a small number personal interviews, other survey methods, telephone, mail surveys or a combination of both, may prove feasible, as may administering a survey through the internet.[6]

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[6] While it may not be feasible to continuously update the design of a mail survey, the survey could be broken into manageable waves across which the updating occurs. For example, Rollins (1997) has implemented a contingent valuation study through the mail in which results from early survey waves were used to update the bid design in later waves of the mail survey.

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Table 1. Main effects plan for the traditional design with fixed fee levels.

Choice Scenario	Alternative	Number of Warblers	Warblers Abundance	# Other Species	# Rare Species	Habitat Diversity	Entrance Fee
1	A	5	Rare	75	30	High	High
	B	25	Common	201	5	Low	Low
2	A	25	Rare	75	5	Low	High
	B	5	Common	201	30	High	Low
3	A	5	Common	75	5	High	Low
	B	25	Rare	201	30	Low	High
4	A	25	Common	75	30	Low	Low
	B	5	Rare	201	5	High	High
5	A	5	Rare	201	30	Low	Low
	B	25	Common	75	5	High	High
6	A	25	Rare	201	5	High	Low
	B	5	Common	75	30	Low	High
7	A	5	Common	201	5	Low	High
	B	25	Rare	75	30	High	Low
8	A	25	Common	201	30	High	High
	B	5	Rare	75	5	Low	Low

Table 2. Fees resulting from the sequential updating design for each of the eight choice scenarios.*

	Choice scenario 1		Choice scenario 2		Choice scenario 3		Choice scenario 4		Choice scenario 5		Choice scenario 6		Choice scenario 7		Choice scenario 8	
	A	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
Starting fees	1	21	1	16	1	21	11	1	1	5	11	1	1	11	25	1
2nd set of fees	1	28	2	12	2	17	20	1	3	5	18	2	1	16	28	1
3rd set of fees	1	30	2	20	2	20	30	3	10	5	25	2	1	20	30	1
4th set of fees			2	25	2	24	30	1	16	3	28	2	1	30		
5th set of fees			2	27	1	28			20	3	29	1				
6th set of fees			1	30					28	3	30	1				
7th set of fees									28	1						
8th set of fees									30	1						
Shares**																
D-optimal	67	33	67	33	33	67	33	67	33	67	33	67	67	33	67	33
Actual	52	48	33	67	24	76	51	49	41	59	54	46	53	47	83	17

* The fees served as the balancing variable that was updated during the survey to approach the D-optimal response shares for each choice scenario. For each choice scenario, the first row in the column shows the starting fees. Subsequent rows show each round of updated fees for that scenario, and the last row in the column shows the ending fees.

** The desired D-optimal response probabilities, or shares, are shown for each of the eight scenarios. These shares depend only on the number of attributes which in our case is 6. The actual shares are the average response probabilities for each scenarios across the 60 individuals.

Table 3: Logit Estimation Results

Variable	Estimated Coefficient (Standard Error)
No. of warblers	0.033 (0.007)
Abundance of warblers	0.27 (0.10)
No. of rare species	0.027 (0.005)
No. of other species	0.0057 (0.001)
Habitat	0.23 (0.10)
Entrance fee	-0.029 (0.0074)
-Log Likelihood Fct.	293.15
% Correctly Predicted	64%

Table 4: Fees and response probabilities for the various designs.

Choice Scenario	Altern-ative	D-optimal Design (given $\hat{\beta}$) Desired Response Shares	D-optimal Design (given $\hat{\beta}$) Fee Spread	Updating Design Actual Response Shares	Updating Design Avg. Fee Spread	Updating Design Final Fee Spread	Traditional Design Fixed Fee Spread
1	A B	0.67 0.33	-55	0.52 0.48	-27	-29	10
2	A B	0.67 0.33	-72	0.33 0.67	-23	-29	10
3	A B	0.33 0.67	-24	0.24 0.76	-17	-27	-10
4	A B	0.33 0.67	51	0.51 0.49	24	29	-10
5	A B	0.33 0.67	37	0.41 0.59	18	29	-10
6	A B	0.33 0.67	53	0.54 0.46	21	29	-10
7	A B	0.67 0.33	-49	0.53 0.47	-26	-29	10
8	A B	0.67 0.33	59	0.83 0.17	26	29	10

Table 5: Ratio of standard errors for each design relative to D-optimal, all evaluated at estimated B.

	Updating Model	Traditional Model
Entrance fee	4.51	10.32
Warblers	1.25	0.75
Abundance	0.92	1.12
Rare species	1.08	0.77
Other species	1.00	0.73
Habitat	0.92	1.15
D-Optimality ratios*	0.91	0.25
D-Efficiency ratios**	0.98	0.79

* This is the ratio of the determinant of the information matrix using the given design to determinant of the information matrix using the D-optimal design, both evaluated at the estimated parameter vector.

"D-optimality ratio" $= |\, I\,(X; \hat{\beta}\,)\,| \,/\, |\, I\,(X^D; \hat{\beta}\,)\,|$

** Same as the D-optimality ratio, but raised to the power 1/6. D-efficiency is common in the literature and aids in comparing models where the number of parameters differs.

"D-efficiency ratio" $= |\, I\,(X; \hat{\beta}\,)\,|^{(1/6)} \,/\, |\, I\,(X^D; \hat{\beta}\,)\,|^{(1/6)}$

Note: Both of these measures are only suitable for relative comparisons, not absolute comparisons (Kuhfeld et al. 1994). Thus, in interpreting the numbers in either column, we can conclude that a model with a higher ratios has a more efficient design.

Table 6. Relative design efficiencies under other fixed fees.

	"D-ratio"*	D-efficiency ratio**
Updating approach	0.91	0.98
Fee difference (fixed)		
10	0.25	0.79
15	0.51	0.89
20	0.82	0.96
25	0.72	0.94
40	0.46	0.87
50	0.31	0.82
60	0.20	0.76

* This is the ratio of the determinant of the information matrix using the given design to determinant of the information matrix using the D-optimal design, both evaluated at the estimated parameter vector.

"D-optimality ratio" = $| I(X; \hat{\beta}) | / | I(X^D; \hat{\beta}) |$

** Same as the D-optimality ratio, but raised to the power 1/6. D-efficiency is common in the literature and aids in comparing models where the number of parameters differs.

"D-efficiency ratio" = $| I(X; \hat{\beta}) |^{(1/6)} / | I(X^D; \hat{\beta}) |^{(1/6)}$

Note: Both of these measures are only suitable for relative comparisons, not absolute comparisons (Kuhfeld et al. 1994). Thus, in interpreting the numbers in either column, we can conclude that a model with a higher ratios has a more efficient design.

Testing Transferability of Forest Recreation Demand in the Three Intermountain States with an Application to Forest Fire Effects

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Abstract

Surveys of visitors to National Forests in Colorado, Idaho, and Wyoming were conducted to determine whether non-motorized recreation visitation responded to different fire ages and fire intensities. Actual and intended behavior data was combined using a negative binomial count data travel cost model. The intended behavior trip questions involved changes with the presence of a high-intensity crown fire, prescribed fire, and a 20-year-old high-intensity fire at the area they were visiting. Using the estimated recreation demand function, fire age had a statistically significant effect on the demand of non-motorized recreation users, holding other site attributes such as forest type constant. The temporal pattern revealed an initial positive visitation response to recent fires, with decreasing visitation for the next 17 years, followed by an eight year rebounding in use. Statistical tests for transferability indicate significant differences in number of trips and price slopes between Wyoming and the other two states. Thus the Idaho and Colorado demand functions and benefit estimates ($127 and $108 per trip, respectively for Idaho and Colorado) suggest limited transferability with each other but not with Wyoming ($218 per trip).

INTRODUCTION

The growing societal awareness of maintaining a healthy environment and the rising costs of Federal and State fire fighting is forcing public agencies to incorporate the economic value of non-marketed resources into their fire management planning and decisions (González-Cabán 1993). However, estimating the impacts of fire on non-market resources and the resulting economic consequences is a difficult problem for fire managers because of a lack of information on the effects of fire on non-market uses such as recreation. However, recreation is one of the dominant multiple uses in the Intermountain west. Field users of the USDA Forest Service National Fire Management and Analysis System use the Resources Planning Act (RPA) values for recreation but do not have a solid empirical basis for determining how recreation use changes immediately after fire and over the recovery interval. Flowers et al. (1985) found that "The studies demonstrate that no clear consensus has been reached on the duration for which fire effects on recreation should be measured or valued. The duration effects ranges from 6 months to 7 years among the studies ....The choice of duration is subjective and somewhat arbitrary because research on the question is scant" (p.2).

Englin (1997) noted in his recent review of the literature on the effects of fire on recreation, "At present there are few studies quantifying the impacts of fire on the non-timber values produced by forests."(p.16.). The primary recreation demand studies that have been done on fire effects on recreation value focus on canoe trips in Nopiming Provincial Park in Manitoba, Canada (Englin, et al., 1996, Boxall, et al., 1996). These studies use a travel cost model framework that estimates a random utility model of canoe route choice in the face of a 10 year old fire versus old growth forest. The loss in trip value varied between $15 and $22 with a fire in this canoe area (Englin, 1997). Using the two studies Englin (1997) constructs a simple time profile of value per trip as a function of years since a fire. Value per trip increases up to 60 years after the fire and then levels off in the Jack pine forest.

A very recent master's thesis (Hilger 1998) applied a Poisson count data model to compare before and after recreation use levels with fire in the Alpine Lakes Wilderness Area in Washington State. Hilger found a substantial drop-off in recreation use during the year of the fire and up to 2 years after the fire. However, by the third year use had surpassed the pre-fire use levels. The value per day of recreation did not change with the fire, however.

This paper begins to fill the gap by reporting empirical estimates of how recreation use and benefits change with different ages from fire and whether the fire was a crown fire. In addition, we statistically test for differences in visitors' demand and benefits from Colorado, Idaho, and Wyoming National Forests to determine if these three demand curves are similar enough that they might be generalized to other Intermountain forests. This latter test is referred to as the transferability issue in the remainder of this paper.

Research Design

Demand Estimating Method

To estimate the effects of fire on recreation demand, this research combines data on actual number of trips taken by visitors to locations on National Forests unaffected and affected by fire with contingent visitation for alternative fire situations. The Travel Cost Method (TCM) is used to estimate the recreation demand function. The seasonal trips with actual fire conditions and the three fire scenarios are regressed on travel cost to the site, characteristics of the visitors, and attributes of the recreation area, including years since last fire and fire intensity level. The basic form of the travel cost method demand function is:

(1) Trips = function (TC, Demographics, Fire Characteristics, Trail characteristics)

where TC is full trip costs including time costs. Since Trips per person per year to the site is an integer, a count data regression model is appropriate (Creel and Loomis 1990, Englin and Shonkwiler 1995). If the mean of trips is not equal to the variance of trips, the overdispersion parameter (alpha) will be significant and a negative binomial form of the count data model is appropriate.

Equation (2) provides the empirical specification of the model estimated:

(2) Trips= exp(Bo+B1(ID)+B2(CO)+B3(TC)+B4(TC*ID)+B5(TC*CO)+B6INCi+

+B7(Age)+B8(Male) +B9(ElevGain)+B10(LodgePole)+B11(DougFir)+B12(DirtRd)+

B13(FireAge)+B14(FireAgeDY0)+B15(FireAgeDY2)+B16(FireAgeDY11-12)+

B17(FireAgeDY17-19)+B18(FireAgeDY25)+B19(CrownFire))

where:

Trips is the number of trips over the season

ID and **CO** are dummy variables if National Forest was in Idaho or Colorado, respectively. (National Forests in Wyoming were chosen as the omitted category).

TC is the individual's share of reported travel cost plus opportunity cost of travel time valued at 25% of the wage rate. This approach is consistent with labor-leisure trade-offs. The exact fraction of wage rate chosen will not affect the shape of the trip response to fire relationship nor the tests of transferability.

INC is the household income of the survey respondent

Age is the respondent's age

Male is a dummy variable for gender, where 1 is male, and female is 0.

ElevGain is the feet of elevation gain on the particular trail.

LodgePole is a dummy variable equal 1 if LodgePole pine was one of the dominant forest species.

DougFir is a dummy variable equal 1 if Douglas Fir was one of the dominant forest species.

DirtRd is a dummy variable equal 1 if the access road to the trail head was dirt.

FireAge is the negative of how old any fire was at the recreation area. Thus a one year old fire is coded -1 while a 20 year old fire is -20.

FireAgeDY0, FireAgeDY2,FireAgeDY11-12, FireAgeDY17-19, FireAgeDY25 are a series of dummy variables for whether the trail had a fire of age zero, two, 11-12 years old, 17-19 years old and 25 years old. These ages were picked as several of our sites had actual fires of these ages and we wished to test if visitation was affected by fires of these ages, without constraining the effect to have the same coefficient value as it would if we just used FireAge alone. Specifically, this series of dummy variables allow for a non-linear affect of fire without resorting to a high order polynomial series (these series are often highly correlated which can result in serious convergence problems in a negative binomial count data estimator).

CrownFire is a dummy variable for whether the fire intensity level was sufficiently high that it caused a fire to burn all the way to the top (i.e., crown) of the tree.

Calculation of Consumer Surplus per Day

Consumer surplus is found by integrating the demand function over the relevant price range, which yields seasonal consumer surplus. Given that the negative binomial count data model is equivalent to a semi-log demand function, in general the per trip consumer surplus is simply 1/B3 (Creel and Loomis, 1990). Since Wyoming is the default, CS_{WY}= 1/B3. If the state specific (ID and CO) travel cost slope interaction terms are statistically significant then CS_{ID}= 1/(B3+B4) and CS_{CO} = 1/(B3+B5).

Transferability Hypothesis Tests

To test whether the same demand function describes recreation visitation to National Forests in Wyoming, Idaho and Colorado, the statistical significance of the intercept shift and price slope interaction terms can be tested using the t-statistics on each variable. The null hypothesis is of equivalence involves:

(3) Ho: B1(ID)= B2(CO) = 0

(4) Ho: B4(TC*ID)= B5(TC*CO) = 0

From a benefit-cost standpoint we are also interested in testing whether the consumer surplus per day estimates are statistically different between the three states. Even if coefficient estimates are significantly different, the benefit measures may not be. Therefore we also test the null hypothesis:

(5) Ho: $CS_{WY} = CS_{ID} = CS_{CO}$.

This test is performed by determining if the confidence intervals of the respective state estimates overlap.

Fire Hypotheses Tests

The hypothesis that fire has no effect on recreation visitation can be tested as follows:

(6) Ho: B13(FireAge)= 0 vs Ha: B13(FireAge)$\neq$0

(7) Ho: B14(FireAgeDY0) = 0 vs Ha:B14(FireAgeDY0)$\neq$0

(8) Ho: B15(FireAgeDY2)=0 vs Ha: B15(FireAgeDY2)$\neq$0

(9) Ho:B16(FireAgeDY11-12) vs Ha: B16(FireAgeDY11-12)$\neq$0

(10) Ho: B17(FireAgeDY17-19) vs Ha: B17(FireAgeDY11-12)$\neq$0

(11) Ho: B18(FireAgeDY25) vs Ha: B18(FireAgeDY11-12)$\neq$0

(12) Ho:B19(CrownFire)=0 vs Ha: B19(CrownFire)$\neq$0

These null hypotheses can be tested using t-tests on the individual coefficients.

Overall Sample Design

The National Forests selected for the study will form the basis for the analysis. Trailhead locations form a "subject-specific" (SS) sample frame which is distinct from a population-averaged (PA) sample frame (Zeger and others 1988).

Sampling Strategy in Colorado

Only two sample strata were consistently available with data judged by the U.S. Forest Service as reliable: acres burned and year of fire. Thus, the main strata were fires of size D (100-

299 acres), E (300-999 acres), F (1,000-4,999 acres) and G (5,000+ acres). The years were grouped into fire ages with zero equal to the year of the survey (1998) and counting back from there (e.g., 1-2, 3-6, 7-10, 11-20 and 21-29). This puts the earliest dates at 1970. Equivalent unburned sites were sampled on each of the National Forests to provide a control and represent the seventh age category. There were 28 possible cells (four sizes times seven time periods). Our goal was to have at least one fire site in each cell of the matrix. Unfortunately, there were several empty cells with no fire data. Thus, three National Forests in Colorado were selected that provided coverage of most of the cells and were logistically functional (e.g., one Forest was on the way to another Forest or was proximate to Fort Collins). The Arapaho-Roosevelt, Gunnison-Uncompaghre and Pike-San Isabel National Forests were chosen in Colorado. This provides two-front range National Forests and one interior, National Forest.

In Colorado we can generalize to class D and larger fires and areas with a full range of low, moderate, and high recreation use. We believe we can generalize from the forest sites sampled within a cell to the other forests within that same cell. Specifically, the common cells between the Arapaho-Roosevelt, Pike and Gunnison National Forest areas sampled and other Rocky Mountain Region forests that were not sampled. For example, many of the Arapaho-Roosevelt fires were similar in size and date to fires on other National Forests.

Counting sampling days and travel days in between, there were about 35 sampling days during the main summer recreation season. Each site was sampled one weekday and one weekend day each month of July and August. A total of 10 sites over the three National Forests were sampled. This schedule generally allowed one sampling rotation of two days (one weekday and one weekend day) at nearly all of the Colorado sites.

Sampling in the Idaho and Wyoming Sites

The Bridger-Teton and Wind River National Forests were the focus of the sampling in Wyoming. Trailheads located in the Teton and Gros Ventre Wilderness areas were sampled. Specifically, 13 trailheads were sampled that gave hikers access to 25 distinct trails/destinations. The majority of these trails were in Wilderness areas. In Idaho, there were 11 trailheads providing access to 25 distinct trails/destinations. The majority of these were in the Sawtooth National Recreation Area. All surveying occurred in the months of July and August 1998.

Survey Protocol

The interviewers stopped individuals as they returned to their cars at the parking area. The interviewers introduced themselves, gave their university affiliation, and gave a statement of purpose. Then the interviewer gave a survey packet to all individuals in the group 16 years of age and older with the following statement: "We would like you to take a survey packet with you today as you are leaving. You do not need to fill it out now, although you can if you like. Rather take the survey packet with you and answer the questions on your way home or when you return home. All the instructions are included. The packet includes a postage paid return envelope. The survey asks a few questions about your visits to this area and how they may be affected by different fire management options. We think you will find the survey interesting. Your answers will be used by the U.S. Forest Service in deciding the level of fire prevention and response to fires."

In Colorado, we further stated "I do need you to fill out your name/address on this card, so we can send you a reminder if we don't get the survey back in the next couple of weeks.

However, your name/address will not be associated with your responses. Your responses are completely confidential and you will not be put on any mailing lists as a result of this survey."

Surveys were also handed out by University of Nevada-Reno students at sites in Wyoming and Idaho. In addition, at sites in Wyoming, surveys were given to the Campground Host to hand out to visitors as well.

Survey Structure

Recreation users were first asked to check off their primary or main recreation activity. Then they were asked their travel time and travel distance to the site. This was followed by questions about their travel costs and a dichotomous choice contingent valuation question for participating in their current activity (e.g., hiking, camping) at the site where they were contacted at for the existing forest condition. Individuals were asked whether visiting the site was their primary purpose, one of many equally important reasons, or a minor stop. Then individuals were asked about past years trips, current number of trips so far this year and planned trips to the site during the rest of the year. In addition, we asked how these trips would change if their trip costs increased. By sampling at different hiking trails or sites, some of which had not been burned, some recently burned, and some burned in the past, we could determine whether there is a statistical relationship between site visitation and fire effects by using current observed behavior.

The next portion of the survey presented three contingent behavior scenarios:

- One-half of the trail experienced a recent high-intensity crown fire. This was depicted with a color photo of standing blackened trees that had no needles. The photo was taken from the Buffalo Creek fire that occurred 2 years earlier.

- One-half of the trail experienced a light (prescribed) burn. The photo used had the lower trunk and lower branches of the trees burned, there were reddish colored needles on these lower branches, but the tops of the trees were green and there were numerous other green trees present.
- One-half of the trail reflected an old (20 years) high-intensity fire. The photo used had standing dead trees with white tree trunks, downed trees, and younger newer, green trees.

For each scenario, visitors were asked how their trips to the site where they were intercepted would change if half the trail were as depicted in the photo. The questionnaire concluded with standard demographic questions.

The advantage of the fire effects in the stated preference portion of the survey is that a wide range of the impacts of fire on forest conditions could be conveyed to each visitor. These photos allowed us to determine the effect that high-intensity crown fires, prescribed fires, and older fires have on recreation use.

The increase in trip costs used as bid amounts were $3, 7, 9, 12, 15, 19, 25, 30, 35, 40 and 70. These were based on limited pretesting and previous recreation studies.

The surveys were pretested at two of the National Forests. Individuals were asked to fill out the survey and provide any comments or feedback. A few questions were clarified as a result of comments during the pretests. No focus groups were performed as the subjects of this survey were on-site users who were knowledgeable about the areas they were visiting and had first hand experience in trading their travel time and travel cost for access to the recreation sites studied.

Inclusion of Non-survey Site Characteristics

To isolate the effects that fire may have on recreation visitation, it is important to control for non-fire related site attributes. The candidate measures of site attributes chosen included those that have been significant in past forest recreation studies (Englin et al. 1996). Thus several site characteristics such as elevation gain of the trail, miles of dirt road, elevation of trail above sea level, etc., were chosen on this basis. Fire attributes included the fire age, acres burned, and fire intensity level. These data were obtained from the USDA Forest Service KFAS system and verified with the District Offices. By the sample design, there was a range of small to large fires and low-intensity prescribed fires to high-intensity fires. There was also a range of ages of fires, although most were fairly recent. There were also several unburned sites in each state. Data on dominant forest type was also used to test for any differences in response by forest type.

Results

Survey Returns

In Colorado, the interviewer took note of refusals. There were only 14 refusals out of 541 contacts made. A total of 527 surveys were handed out. Of these, 354 were returned after the reminder postcard and second mailing to non-respondents. Thus, the overall response rate was 67 percent. In Idaho and Wyoming, a total of 1,200 were handed out. Of these, 325 were returned. The response rate was 27 percent. This is lower because of the inability to send reminder postcards and second mailings to non-respondents.

Descriptive Statistics

Given the sampling at trailheads on the Colorado National Forests, it is not surprising that most of the visitors in Colorado were hiking (59 percent) or mountain biking (30 percent). The average visitor was on-site for 5 hours and had three persons in their group. About two-thirds of the trips were single-destination trips. The typical Colorado visitor drove 77 miles (one-way) and had gas costs of $12 (for a gas cost per round trip mile of 7.8 cents).

Of most interest to this study is the comparison of current trips taken with trips that would be taken with the three fire scenarios. A typical visitor had taken about two trips and planned two more during the remainder of the season. These four trips would decrease to 2.3 trips with a recent, high-intensity fire over 50 percent of the trail (Table 1). The four trips would decrease to 3.35 trips if 50 percent of the trail had been burned by a light fire or prescribed fire. If 50 percent of the trail visited would have shown the effects of an old (20 years) high-intensity fire, they would take 2.96 trips instead of 4 trips. Pairwise t-tests of each fire scenario against the baseline trips all indicate a statistically significant reduction in trips at the 0.01 level. This pattern is consistent with the number of visitors that would change their trip visitation rate if there were a high-intensity fire (55 percent would change), low-intensity (23 percent), and old high-intensity (33 percent). Both the trip reduction and visitor reduction is similar to Flowers et al. (1985).

The demographics of the Colorado sample included 56 percent male respondents with an average age of 36.5 years and education of 16.3 years (Table 1). More than 90 percent of the sample worked outside the home and visited the recreation site on weekends, holidays, or paid vacation. The average household size was 2.54 people. The typical household earned $67,232.

The visitors to the Idaho and Wyoming National Forests were slightly older (42.4 years) than the Colorado visitors but had nearly identical education levels (college graduate). A lower proportion of the visitors returning surveys handed out in the Idaho and Wyoming National Forests were males (44 percent) as compared to Colorado National Forest visitors. However, in terms of timing of visits, nearly identical proportions visited on weekends, holidays, or vacations (75 percent) as did Colorado visitors. However, distance traveled of Idaho and Wyoming forest visitors was much greater at 613 miles.

The reaction of Idaho and Wyoming National Forest visitors to fire was similar to Colorado visitors in terms of the response pattern of trips. Specifically, total trips dropped the most from current condition to the High-Intensity Fire Scenario, dropping from 2.84 trips per year currently to 1.742 trips per year if 50 percent of the trail had been burned by a two year old high-intensity fire. A recent low-intensity or prescribed fire only results in a slight decrease in visitation from current levels, a reduction from 2.84 trips to 2.45 trips per year. Like Colorado, the drop in visitation with a older (20 years) high-intensity fire is in between these other two scenarios, a reduction from 2.84 trips to 2.02 trips with the older, high-intensity fire.

Multivariate Statistical Analysis

There are several empirical issues that need to be clarified before presenting the statistical results. First is that the sample is endogenously stratified and truncated. This is true because the respondents were intercepted on-site. The more often someone visits the site the more likely they are to be interviewed. While considerable progress has been made in the statistical correction of endogenous stratification and truncation with revealed preference data, no work has examined the role of these sampling issues when stated preference data is obtained with the revealed data. As a result, we are unable to deal with this issue in this analysis. The primary effect of this is that statements about the general population are problematic. Since the focus of this analysis is on users and transferability among users in the three different states, not the general population, this limitation is unimportant.

A second important point is that there is considerable evidence that some people who had travelled long distances misunderstood the primary purpose recreation survey question. A small number of visitors indicated they had come several thousand miles specifically for a hike on trails where they were intercepted. Inclusion of these observations could cause multi-destination trip bias in the estimated travel cost coefficient and hence overstate consumer surplus. Therefore our regression sample is limited to individuals who travel less that 1,100 miles in round trip distance. These omitted visitors may have been on longer trips from home and misinterpreted the question as asking about their travel that day or they belong to some other behavioral model that our pooled count demand function is not well equipped to capture.

Table 2 reports descriptive statistics for the sample used to estimate the model. Table 3 reports the econometric results. The models focus on three aspects of the analysis. First, the models we examine trace out the inter-temporal path of benefits that follows a fire event. Second, the models examine the transferability of the results between the three study areas. Finally, the robustness of the results to reduced specifications is examined. Each of these analyses will be discussed in order. Note that since the overdispersion parameter, alpha is always significant the negative binomial count data model is more appropriate than a Poisson count data model.

Table 3 shows the primary econometric results of the analysis. The model includes own price coefficients and intercepts for each of the three study areas, Wyoming, Colorado and Idaho. Wyoming is the base case and Colorado and Idaho are captured with shift variables. The model captures the independent demands in each area by adding together the base case coefficients and the other state specific shift variables. For Wyoming the base demand intercept is 0.32 and the own price slope is -0.0045. Idaho's demand curve is found by aggregating the base case parameter and the Idaho shift variable. The Idaho demand curve slope is -0.0077 (-0.0045 - 0.0032). Similarly Colorado's demand curve is -0.0091 (-0.0045 - 0.0046). Note that the Idaho demand curve is shifted down from the Wyoming curve and Colorado's curve is shifted down more yet. To standardize the comparisons we calculated the price elasticity of each demand curve at the mean of their observed prices (Ped= B1*Price). Idaho is the least inelastic demand curve (-.71), while Colorado being the most inelastic (-.22), while Wyoming was in the middle (-.43).

Results of Transferability Hypotheses Tests

For the full regression model in the left hand column of Table 3, the individual Idaho and Colorado intercept shifters are statistically different from zero at the 10% level for Idaho (t=-1.76 for B1) and at the 1% level for Colorado (t=-10.21 on B2). Thus we reject the null hypothesis of equivalent number of trips. The Idaho (B4) and Colorado (B5) price slope interaction terms are also statistically different from zero. Specifically, $P<.05$ for B4 and $P<.01$ for B5 in the full regression model. Thus we reject the null hypothesis of equality of Wyoming, Idaho and Colorado's demand curves. Note, however, that we cannot show that the Idaho and Colorado demand curves have significantly different slopes. The t-statistic testing this hypothesis is 0.97: ((-0.00325)-(-0.00461))/0.0014) which is insignificant at conventional levels.

Using the count data equivalence to a semi-log demand curve, we find that the trip consumer surplus estimates for Wyoming, Idaho and Colorado are, respectively, \$218, \$127 and \$108.

There are two ways to test whether these WTP values are significantly different. In one sense, since the t-statistics on the Colorado and Idaho travel cost interaction terms are significantly different from zero, one could infer that the Idaho and Colorado per trip consumer surpluses are statistically different from Wyoming's. An alternative approach is to construct confidence intervals around the respective mean WTP's, using the standard error of each coefficient and the covariance between the coefficients. Performing such calculations yields, 90% confidence intervals for Wyoming of $177-289, $89-227 for Idaho and $79-176 for Colorado. Based on the non-overlap of the tails of the 90% confidence interval between Colorado and Wyoming, these would be significantly different consumer surplus estimates.

These benefit measures make intuitive sense. The sampling area in Wyoming is in and around the Grand Teton and outside Yellowstone National Parks - an area famous for its beauty. The Idaho sampling area is in a well known area outside of Ketchum, Idaho but it is not as well regarded as Wyoming's nor does it draw from as wide an area as Wyoming. Finally, the majority of the Colorado sampling frame focuses on trails along the Front Range (e.g., Colorado Springs, Denver and Fort Collins) and primarily draws its visitors from Denver and Front Range cities (Colorado Springs to Fort Collins).

Results of Fire Effects Hypotheses

The effects of fire damage is captured using a combination of a continuous variable, years since fire, and dummy variables for five discrete times since the fire. These are immediately after the fire, two years after the fire, eleven or twelve years after the fire, seventeen to nineteen years after the fire, twenty five years after the fire and whether or not the fire was a crown fire. The discrete years since the fire reflect the distribution of actual fires that are present in the data. This approach allows great flexibility in modeling the time path of benefits after a fire. The crown fire variable reflects both the actual observed crown fires and the crown fire shown in one of the contingent behavior fires.

All of the fire variables are highly significant except for the crown fire variable. Thus, in general, we reject the null hypothesis that fire has no effect on recreation use in these three National Forests. The crown fire variable is positive but only significant at the 15% level. Nevertheless, there is good reason to suspect that it will be important to the values that people hold for a forest and omitting it may bias other fire effects coefficients. Unlike the speculation of Englin, Boxall and Watson (1996), the damage function is not a concave function growing over time. Rather, the function is S shaped. It jumps up above the old growth values during the first year, grows even higher by the second year, drops back to the level of the first year by years seventeen to twenty five. After this the value drops once more and then rises slowly to old growth values. The early part of this pattern is identical to the analysis of Hilger and Englin (1999) who performed an ex-post analysis of use and value following the Rat Creek/Hatchery Creek fire in Leavenworth, Washington in 1994. It is also consistent with Boxall and Englin's (1999) analysis of the damage function for canoeists in the Canadian boreal forest.

Thus while we reject the null hypothesis of no effect of fire on recreation use, the effect of fire is not unambiguously bad. The positive effect on recreation use is consistent with fires opening the forest canopy, enhancing flower growth in the near term and opening up distant views during the first decade after the fire.

CONCLUSIONS

Surveys of visitors to National Forests in Colorado, Idaho, and Wyoming were conducted to determine whether non-motorized recreation responded to different fire ages and fire intensities. Revealed and stated preference data were pooled when estimating a negative binomial Travel Cost Method demand curve. We found that fire age had a statistically significant effect on the demand of non-motorized recreation users, holding other site attributes such as forest type constant. The temporal pattern revealed an initial positive visitation response to recent fires, with decreasing visitation for the next 17 years, followed by a eight year rebounding in use. The tests for Transferability of demand and benefits estimates across the three states indicated significant differences in number of trips and price slopes between Wyoming and the other two states. The Idaho and Colorado demand functions and benefit estimates ($127 and $108 per trip, respectively for Idaho and Colorado) suggest limited transferability with each other but not with Wyoming ($218 per trip).

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Table 1.

Comparison of the descriptive statistics of the Colorado sample and Idaho/Wyoming samples.

Variable	Colorado	Idaho/Wyoming
Travel distance	77 miles	613
Previous season	2.06	1.42
Trips so far this year	2.19	1.77
Trips planned	1.77	1.06
Total trips this season	**3.96**	**2.83**
Trips if high-intensityfire	2.33	1.74
Trips if low-intensity fire	3.35	2.45
Trips if old high-intensity	2.96	2.02
Demographics of Visitors		
Percent males	56%	44%
Age	36.55	42.4
Education	16.3	16.1
Work	90%	80%
Visit on weekend, holiday vacation	78%	75%
Household income	$67,232	$70,179

Table 2. Descriptive Statistics of the Regression Sample

Variable	Mean	Std. Dev.	Minimum	Maximum
TRIPS	2.9246	8.3538	0.0000	109.0000
IDAHO	0.1834	0.3871	0.0000	1.0000
COLORADO	0.6095	0.4880	0.0000	1.0000
COST3	51.8143	63.4247	0.1940	444.5670
COLO*COST3	14.6869	30.1652	0.0000	322.1810
IDAHO*COST3	16.8165	42.7577	0.0000	254.0768
INCOME	64319.5266	40713.6689	5000.0000	175000.0000
AGE	37.8047	12.3636	12.0000	78.0000
MALE	0.5089	0.5000	0.0000	1.0000
ELEV. GAIN	1275.8432	842.1819	100.0000	3695.0000
LODGEPOLE	4438	0.4970	0.0000	1.0000
DOUG. FIR	0.3136	0.4641	0.0000	1.0000
DIRTROAD	0.3994	0.4899	0.0000	1.0000
FIREAGE	32.6006	20.3436	50.0000	0.0000
FIRE 0	0.1479	0.3551	0.0000	1.0000
FIRE 2	0.0178	0.1321	0.0000	1.0000
FIRE 1112	0.1391	0.3461	0.0000	1.0000
FIRE 1719	0.0621	0.2415	0.0000	1.0000
FIRE 25	0.0148	0.1208	0.0000	1.0000
CROWN FIRE	0.3964	0.4893	0.0000	1.0000

Table 3. Econometric Results for Three Models

Model Variable	Full Model Coefficient	Full Model Std Error	Fire Retricted Model Coefficient	Fire Retricted Model Std Error	State Restricted Coefficient	State Restricted Std Error
Constant	0.325152*	0.5281	2.07202*	0.20454	0.80830*	0.66695
IDAHO	-0.334781*	0.1896	-0.46808*	0.19026		
COLORADO	-1.547816*	0.1515	-1.45501*	0.12905		
TCOST	-0.004573*	0.0006	-0.00566*	0.00061	-0.00492*	0.00044
COLO*COST	-0.004617*	0.0015	-0.00448*	0.00150		
ID*COST	-0.003258*	0.0014	-0.00322*	0.00133		
INCOME	0.656E-06	0.761E-06	0.689E-06	0.757E-06	-0.141E-05	0.709E-06
AGE	0.018784*	0.0022	0.01926*	0.00223	0.02148*	0.00239
MALE	0.282668*	0.0680	0.33667*	0.06701	0.23214*	0.06311
ELEV. GAIN	-0.000297*	0.00006	-0.00023*	0.00004	-0.00021*	0.00006
LODGEPOLE	-0.678094*	0.1419	-0.55947*	0.12651	-0.14547*	0.12097
DOUG FIR	-0.222741	0.2228	0.07154	0.18143	-0.02790	0.22330
DIRTROAD	-0.412020*	0.1010	-0.73239*	0.07596	-0.04042	0.09664
FIREAGE	-0.038302*	0.0107	-0.00030	0.00215	0.00338	0.01308
FIRE 0	1.459751*	0.5080			-0.99542*	0.59774
FIRE 2	2.535639*	0.6749			-0.04945	0.80640
FIRE 1112	1.678467*	0.3626			0.24077	0.42427
FIRE 1719	1.155955*	0.3453			-0.53578	0.40085
FIRE 25	1.245977*	0.5122			0.07678	0.53484
CROWN FIRE	0.076520	0.0542			0.24844*	0.05747
alpha	1.406233*	0.0631	1.44926*	0.06306	1.56277*	0.06561
Log Likelihood	-4101.5		-4124.0		-4167.9	

* - significant at the 10% level or beyond

Combining Sources of Data in the Estimation of Consumer Preferences: Estimating Damages to Anglers from Environmental Injuries

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Abstract

To take advantage of the relative strengths of different types of data, stated preference data are combined with revealed preference data to estimate consumer preferences. Different decision protocols are specified for how individuals make actual choices and how individuals answer stated-choice questions. This paper is the first to combine stated preference *choice* data with stated preference *frequency* data. The unique combination of data not only allows for the estimation of how individuals trade off different characteristics of a commodity, but also how they substitute between commodities (i.e., change the quantities they consume) when characteristics change. Our method is especially useful when the commodity of interest is unique in its class. The application is to Green Bay recreational fishing, and compensating variations are derived for the elimination of fish consumption advisories.

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1. Introduction

One goal of consumer theory is to explain, estimate, and predict the demand for commodities as a function of their costs and characteristics. Often the intent is to estimate the demand for and benefits from a new commodity; that is, a commodity that currently does not exist in the marketplace. If some characteristics of the new commodity are not present in existing commodities, or there is not sufficient variation in the characteristics of existing commodities, estimation will not be possible using only market data. A solution is to use stated-preference (SP) data either by itself or combined with revealed preference (RP) data. Here we combine RP frequency data with choice *and* frequency SP data. This is the first study that combines these two types of SP data in an integrated model.[1]

SP and RP data provide different information about preferences, so combining them leads to better estimates of those preferences.[2] However, doing so raises interesting issues with respect to modeling and estimation. Opinions differ about whether SP data contain more or less information than RP data; the preference information in different data types takes different forms, and these need to be integrated into a utility-theoretic model.

The purpose of this research is to estimate the compensating variation associated with improving the quality of a unique commodity. Data were collected on how often the commodity

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1. A few environmental applications have used SP frequency data only, such as Adamowicz et al. (1994) and Englin and Cameron (1996), and a multitude of studies across disciplines have SP choice questions, which evolved from conjoint analysis. Cattin and Wittink (1982) and Wittink and Cattin (1989) survey the commercial use of conjoint analysis, which is widespread. For survey articles and reviews of conjoint, see Louviere (1988, 1992), Green and Srinivasan (1990), and Batsell and Louviere (1991). Transportation planners use choice questions to determine how commuters would respond to a new mode of transportation or a change in an existing mode. Hensher (1994) provides an overview of choice questions as they have been applied in transportation.

2. This practice is widely supported. See, for example, McFadden (1986), Ben-Akiva and Morikawa (1990), Morikawa et al. (1990), Cameron (1992), Louviere (1992), Hensher and Bradley (1993), Adamowicz et al. (1994, 1997), Ben-Akiva et al. (1994), Swait et al. (1994), Morikawa et al. (1991), Louviere (1996), Kling (1997), and Mathews et al. (1997).

is chosen under current conditions, but these RP data alone are not sufficient to estimate the demand for the commodity in its improved state. Therefore, we supplement the RP data with SP frequency data (how often the commodity would be chosen under alternative conditions) and SP choice data (which commodity would be preferred from a set of commodities with different characteristics).

We recognize that when individuals answer stated-choice and stated-frequency questions, they are providing information about their intentions. What they state they would do can be different than what they would actually do on some actual choice occasion, and that what they do on actual occasions might differ across occasions.[3] Specifically, we assume that when presented with hypothetical choices, the individual has some uncertainty as to what their preferences would be on any given day, and take this into account when they answer the questions.

In the application estimates are obtained for the parameters of two conditional indirect utility functions: one for a Green Bay fishing day, and one for fishing elsewhere. The motivation is to estimate the Green Bay anglers' compensating variation for the elimination of *fish consumption advisories* (FCAs) in Green Bay. Polychlorinated biphenyls (PCBs), which are a hazardous substance, were released into the Lower Fox River of Wisconsin, which feeds into Green Bay, by local paper companies primarily between the late 1950s and mid-1970s. Through the food chain, PCBs bioaccumulate in fish and wildlife. As a result of elevated PCB concentrations in fish, in 1976 the Wisconsin Department of Health and Human Services first issued FCAs for sport-caught fish in the Wisconsin waters of Green Bay, and the FCAs continue today.

3. See McFadden (1986) for a discussion of decision protocols and why different decision protocols for stated intentions and actual choices might be assumed.

The RP data consist of the total number of fishing days for each individual in the sample and the number of those days the angler fished Green Bay under current conditions. The SP data consist of the answers to choice questions. Each sampled individual indicated his or her choice between a pair of Green Bay alternatives (Green Bay under different conditions). Then, in a follow-up question to each pair, respondents indicated the number of times in *n* choice occasions (fishing days) the preferred Green Bay alternative would be chosen, in a choice set that includes it and all non-Green Bay fishing sites. For each sampled individual, these two questions were repeated eight times, where the characteristics of the Green Bay alternatives in the pairs are varied over the eight pairs. The use of SP data was deemed to be necessary because Green Bay is a unique fishing site in terms of size and species mix, and inland waters do not have FCAs for PCB contamination.

2. Brief review on combining RP and SP data

While most economists are comfortable with RP data, SP data have some advantages over RP data. Morikawa et al. (1990) states, "For example, since SP data are collected in a fully controlled "experimental" environment, such data has the following advantages in contrast with RP data that are generated in natural experiments: 1) they can elicit preferences for nonexisting alternatives; 2) the choice set is prespecified; 3) multicollinearity among attributes can be avoided; and 4) range of attribute values can be extended."[4] Further, because SP data allow the researcher to control more variables and because there are more unknowns influencing the

4. The same basic list of advantages can be found in Adamowicz et al. (1998).

decisions in RP data, the SP data often contain less noise and measurement error (Louviere, 1996).

Revealed preference (RP) data have a potential advantage in that these data reflect actual decisions made and the consequences of those decisions. If the consequences are significant, respondents have incentives to make choices consistent with their preferences (assuming they have adequate knowledge about the choices). With SP data, if the respondent does not feel his responses have meaningful consequences, the incentives to respond carefully and consistently with one's preference are reduced, which may result in data of reduced accuracy. To address this potential issue with SP data, we allow the error variances to differ across data types. To minimize the noise in the SP data, we designed the survey materials to communicate the importance of the respondents' answers for policy, and we implemented the assessment with anglers who are active in fishing the waters of Green Bay. These anglers are familiar with the site and issues at the site, and can be expected to understand and care that resource managers are evaluating options for the site.

Choice questions encourage respondents to concentrate on the trade-offs between characteristics. We asked whether the angler prefers to fish Green Bay under conditions "A" or "B." While such questions alone tell one nothing about how often an angler would fish Green Bay under different conditions, they can be used to determine how much an angler would be willing to pay per Green Bay fishing day to fish Green Bay without FCAs. This estimate multiplied by an estimate of the individual's current number of Green Bay fishing days is a lower-bound estimate of the compensating variation the angler would associate with the elimination of the FCAs. The choice questions alone also allow the estimation of how much other Green Bay characteristics (e.g. catch rates) would have to increase to compensate the angler for the FCAs. Adding the frequency data (RP and SP) allows the estimation of how much demand would change in the absence of the FCAs.

Combining SP choice and frequency data has wide applicability beyond recreation demand, particularly when the commodity is unique, although this method has not been used before. The SP frequency data can be used to determine how relative frequency will change when the characteristics of the commodity change, and the data on the actual frequencies under current conditions ground the model so that it predicts current demand under current conditions.

3. The Model

In this section, the data and model are described in general terms. Section 3.1 develops the choice probabilities for the two Green Bay alternatives using only the part of the SP data that indicates which Green Bay alternative is chosen. Section 3.2 uses all of the SP data and the RP data on the total number of fishing days under current conditions to any site to model how often the preferred Green Bay alternative would be chosen versus some other non-Green Bay site. Section 3.3 incorporates the RP data on the total number of fishing days to Green Bay under current conditions.

3.1 Choice probabilities for SP Green Bay pairs

Let utility for the Green Bay alternatives be given by:

$$U_{ij}^{k_{ij}} = \beta' x_{ij}^{k_{ij}} + \varepsilon_{ij}^{k_{ij}}, \; i = 1, \ldots, m; \; j = 1, \ldots, J; \; k_{ij} \in [1, 2], \tag{1}$$

where $U_{ij}^{k_{ij}}$ is the utility of the k-th alternative of pair j to individual i. That is, i indexes the m respondents, j indexes the eight pairs, and k_{ij} indicates which of the two alternatives within each pair is chosen. The $L \times 1$ vector $x_{ij}^{k_{ij}}$ contains the characteristics of the alternatives, and hence the elements of the unknown $L \times 1$ vector β can be interpreted as marginal utilities. The first element of $x_{ij}^{k_{ij}}$ is the difference between choice-occasion income for individual i and the cost of alternative k_{ij}, and the model is restricted to one with a constant marginal utility of money, which is the first element of β.

Assumption 1. $\varepsilon_{ij}^{k_{ij}}$ are independent (across i) and identically distributed mean zero normal random variables, uncorrelated with $x_{ij}^{k_{ij}}$, with constant unknown variance σ_{ε}^2.

For SP data, it is assumed that the individual does not know his stochastic component before actually deciding on the particular alternative. That is, $\varepsilon_{ij}^{k_{ij}}$ is assumed to be the sum of factors unknown to *both* the individual and the investigator, although its distribution is assumed to be known.[5] That an individual does not know his preferences completely results from the fact that preferences have a component that varies randomly over time. When the individual answers stated-choice questions he does not know exactly what his preferences would be if he were presented with these alternatives as an actual choice at some point in the future. We assume the

5. For RP data, the usual discrete-choice model specification is that the disturbances are known to the individual, and the behavioral assumption is utility maximization. We adopt this assumption for our RP data. The assumption is also sometimes made for SP data, although the rationale is less clear. However, even under the assumption that each unique pair of disturbances for each choice occasion is known to the individual a priori (and that the individual would evaluate utility for the two scenarios under the assumption of utility maximization), the identical likelihood function would be produced.

survey questions are answered probabilistically and reflect what he is likely to do if he were repeatedly presented with the actual choice. In contrast, we assume actual choices are made with preference certainty, and that those choices would maximize utility.

Specifically, let $K_{ij} \in [1,2]$ be the Bernoulli random variable that is the choice for individual i on occasion j. The individual is assumed to choose alternative k_{ij} with the probability:[6]

$$P(K_{ij} = k_{ij}) = P_{ij}^{k_{ij}} = P(U_{ij}^{k_{ij}} > U_{ij}^{3-k_{ij}}), \tag{2}$$

where k_{ij} is the observed value of K_{ij}. That is, we may think of the individual's choice as a drawing from a Bernoulli distribution with the probability given by Equation 2. Note that this is an alternative to the assumption that the individual's answers to stated-choice questions are generated by expected utility maximizing behavior.[7]

From Equations 1 and 2, the probability of choosing alternative k_{ij} is:

$$\begin{aligned} P_{ij}^{k_{ij}} &= P(\beta' x_{ij}^{k_{ij}} + \varepsilon_{ij}^{k_{ij}} > \beta' x_{ij}^{3-k_{ij}} + \varepsilon_{ij}^{3-k_{ij}}) \\ &= P\left[\varepsilon_{ij}^{3-k_{ij}} - \varepsilon_{ij}^{k_{ij}} < -\beta'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}})\right] \\ &= \Phi\left[-\beta'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}}) / \sqrt{2}\sigma_{\varepsilon}\right] \end{aligned} \tag{3}$$

where $\sqrt{2}\sigma_{\varepsilon}$ is the standard deviation of $\varepsilon_{ij}^{3-k_{ij}} - \varepsilon_{ij}^{k_{ij}}$ under assumption 2 and $\Phi(\cdot)$ is the univariate standard normal cumulative distribution function. Note that Equation 3 would be the probability in the usual probit model for dichotomous choice under the assumption the individual knows the

6. In this notation, if the individual chooses alternative $K_{ij} = 1$ [or 2], then the alternative that was not chosen is $3 - K_{ij} = 2$ [or 1].

7. We find the assumption of expected utility maximizing behavior less plausible than our assumption that individuals answer probabilistically . Expected utility maximizing behavior implies that if presented with the same hypothetical question a number of times, an individual would always answer the same, and this is not what we would expect or what our experience indicates (see also page 9 and footnote 6).

random component and maximizes utility. This probability will enter into the likelihood function in Section 3.4. The parameter vector β is identified only up to the scale factor $\sqrt{2}\sigma_{\varepsilon}$, and σ_{ε} is not identified, since only the sign and not the scale of the dependent variable (the utility difference) is observed. Nevertheless, we have chosen to list the parameters of the likelihood function $(\beta, \sigma_{\varepsilon})$ separately.

3.2 Frequency of selecting the preferred Green Bay alternative versus another site

Now suppose in addition to the data on k_{ij}, the individual answers a question giving the number of times Green Bay alternative k_{ij} would be chosen compared to some other (non-Green Bay) alternative, in their next n_i choice occasions (fishing days). Utility for the "other" alternative, U_{ij}^{0} (fishing elsewhere), is given by Equation 4:

$$U_{ij}^{0} = \beta' x_{ij}^{0} + \varepsilon_{ij}^{0}, \tag{4}$$

where ε_{ij}^{0} are disturbances and x_{ij}^{0} are the characteristics of the other site.

Assumption 2: The ε_{ij}^{0} are independent (across i) and identically distributed normal random variables, with zero expectation and variance σ_0^2, and $E\left(\varepsilon_{ij}^{0}\varepsilon_{ij}^{k_{ij}}\right) = \sigma_{\varepsilon 0}$.

In this model, the value of a random variable N_{ij} is known, where N_{ij} is the number of times Green Bay site k_{ij} is chosen over the non-Green Bay site in the next n_i occasions.[8] The nonstochastic parts of the utilities for the two alternatives in this choice set are $\beta' x_{ij}^{k_{ij}}$ and $\beta' x_{ij}^{0}$. The individual knows these terms, but does not know the random component associated with either alternative at the time of the choice. If $\beta' x_{ij}^{0} < \beta' x_{ij}^{k_{ij}}$, for example, he knows, on average, he would be better off choosing Green Bay site k_{ij} over fishing elsewhere, but he cannot be

8. The parameter n_i is the number of days individual i fished in 1998, and n_{ij}, the observed value of N_{ij}, is between zero and n_i.

certain. For some trips, ε_{ij}^{0} may be sufficiently larger than $\varepsilon_{ij}^{k_{ij}}$ so that $U_{ij}^{0} > U_{ij}^{k_{ij}}$. Over a future set of choice occasions, then, it is assumed that he calculates his answer to the number question probabilistically. That is, he calculates the conditional probability that he will prefer alternative k_{ij} over fishing elsewhere (see Equation 6 below) and then reports the closest integer to n_i times that probability.[9] This is the expected number of trips under the assumption made below that the N_{ij} are distributed binomially, and this average number of trips is elicited in the survey.

Since the N_{ij} are counts ranging from zero to n_i, given the behavioral assumption discussed above a plausible stochastic model for the N_{ij} is that they are distributed binomially, $N_{ij} \sim B(n_i, p_{ij}^{0})$, with probability mass function (conditional on the choice of k_{ij}):

$$P(N_{ij} = n_{ij} | K_{ij} = k_{ij}) = \binom{n_i}{n_{ij}} (p_{ij}^{0})^{n_{ij}} (1 - p_{ij}^{0})^{n_i - n_{ij}}, \tag{5}$$

where n_{ij} are the observed values of N_{ij}.[10]

The parameter p_{ij}^{0} in Equation 5 is the probability of choosing Green Bay alternative k_{ij} over the "other" site, conditional on choosing alternative k_{ij} over alternative 3 - k_{ij}:

$$\begin{aligned} p_{ij}^{0} &= P(U_{ij}^{k_{ij}} > U_{ij}^{0} | U_{ij}^{k_{ij}} > U_{ij}^{3-k_{ij}}) \\ &= P[\varepsilon_{ij}^{0} - \varepsilon_{ij}^{k_{ij}} < -\beta'(x_{ij}^{0} - x_{ij}^{k_{ij}}) | \varepsilon_{ij}^{3-k_{ij}} - \varepsilon_{ij}^{k_{ij}} < -\beta'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}})] \\ &= \frac{\Phi_2[-\beta'(x_{ij}^{0} - x_{ij}^{k_{ij}}) / \sigma_{0-\varepsilon}, \ -\beta'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}}) / \sqrt{2}\,\sigma_{\varepsilon}; \rho]}{\Phi[-\beta'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}}) / \sqrt{2}\,\sigma_{\varepsilon}]} \end{aligned} \tag{6}$$

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9. This is in contrast to assuming the individual repeatedly applies a maximum expected utility decision rule, which would imply a corner solution at either zero or n_i. When we consider revealed preference choices below, we assume that the individual knows his stochastic component and maximizes utility.

10. We are effectively assuming: $P(N_{i1} = n_{i1}, \ldots, N_{iJ}) = \prod_{j=1}^{J} P(N_{ij} = n_{ij})$. A model that explicitly recognizes the fact that the same individual makes all n_{ij} choices exists (it is called the multivariate binomial distribution; see Johnson et al., 1997). It appears to be unwieldy, except possibly for the case J = 2. For most if not all formulations of this multivariate distribution the marginals are univariate binomial, so the method of estimating the p_{ij}^{0}'s suggested here is justified. There has been some interest in testing the equality of the p_{ij}^{0} across j (see Westfall and Young, 1989), but that is not the main focus here.

where $\sigma^2_{0-\varepsilon}$ = Var $(\varepsilon^0_{ij} - \varepsilon^{k_{ij}}_{ij}) = \sigma^2_0 + \sigma^2_\varepsilon - 2\sigma_{\varepsilon 0}$ and where ρ is the correlation between

$\varepsilon^0_{ij} - \varepsilon^{k_{ij}}_{ij}$ and $\varepsilon^{3-k_{ij}}_{ij} - \varepsilon^{k_{ij}}_{ij}$,

$$\rho = \frac{\sigma^2_\varepsilon}{\sqrt{2\sigma^2_\varepsilon \sigma^2_{0-\varepsilon}}} \tag{7}$$

and Φ and Φ_2 are the standard univariate and bivariate normal distribution functions, respectively.[11] (For details of the derivation of Equation 6, see the appendix.).

3.3 Incorporating the RP Data on Actual Green Bay Fishing Days

In addition to the SP data and the n_i, we have for each i the number of fishing days to Green Bay, n^G_i (taken, of course, under current conditions). This RP data may be used with the other data in the estimation of the model parameters. Utility for the d-th actual Green Bay fishing day is given by:

$$U^G_{id} = \beta' x^G_i + \varepsilon^G_{id} \tag{8}$$

where x^G_i is a vector of characteristics of Green Bay under actual conditions.

Assumption 3: The ε^G_{id} are independent (across i) and identically distributed normal random variables, with zero expectation and variance σ^2_G, and $E\left(\varepsilon^G_{id}\varepsilon^{k_{ij}}_{ij}\right) = \sigma_{\varepsilon G}$.

In deciding how many days to fish Green Bay, the individual compares utility at Green Bay to utility at other sites, given by Equation 4. For RP data we assume the individual knows

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11. Note that in Equation 6, β appears twice. On one occasion it is normalized by $\sqrt{2}\sigma_\varepsilon$, and on the other by $\sigma_{0-\varepsilon}$. Also note that under the alternative assumption that disturbances are known to the individual a priori, he would perform the conceptual experiment of generating n_i pairs of disturbances, evaluating utility under the two scenarios, and counting the number of Green Bay trips under the assumption of utility maximization. This process would also imply Equations 5-7.

his random component at the time each fishing day's choice is made (the standard random utility assumption), so that the probability of going to Green Bay on day d is:

$$\begin{aligned} P_i^G &= P(U_{id}^G > U_{ij}^0) \\ &= P(\beta' x_i^G + \varepsilon_{id}^G > \beta' x_{ij}^0 + \varepsilon_{ij}^0) \\ &= P(\varepsilon_{ij}^0 - \varepsilon_{id}^G < \beta' x_i^G - \beta' x_{ij}^0) \\ &= \Phi[(\beta' x_i^G - \beta' x_{ij}^0) / \sigma_{0-G}] \end{aligned} \tag{9}$$

where:

$$\sigma_{0-G}^2 = \mathrm{Var}\,(\varepsilon_{ij}^0 - \varepsilon_{ij}^G) = \sigma_0^2 + \sigma_G^2 - 2\sigma_{G0} \tag{10}$$

Since P_i^G is a function of β, the information contained in n_i^G is useful in estimation, and is incorporated into the likelihood. The likelihood function is:

$$\begin{aligned} &L(n_{ij}, k_{ij}, n_i^G, i = 1, \ldots, m, j = 1, \ldots, J | x_{ij}^1, x_{ij}^2, n_i; \beta, \sigma_0, \sigma_\varepsilon, \sigma_G) = \\ &\prod_{i=1}^{m} \left[\binom{n_i}{n_i^G} (P_i^G)^{n_i^G} (1 - P_i^G)^{n_i - n_i^G} \prod_{j=1}^{J} P(N_{ij} = n_{ij} | K_{ij} = k_{ij}) P(K_{ij} = k_{ij}) \right] \end{aligned} \tag{11}$$

Note that in this likelihood β appears in several expressions: in P_i^G normalized by σ_{0-G}, in $P(N_{ij} = n_{ij} | K_{ij} = k_{ij})$ normalized by $\sigma_{0-\varepsilon}$, and in P_i and $P(K_{ij} = k_{ij})$ normalized by $\sqrt{2}\sigma_\varepsilon$. The ratios of any two of these three parameters are identified in estimation.[12] The maximum likelihood parameter estimates are consistent. They are also asymptotically efficient under the additional assumption that ε_{ij}^0 and $\varepsilon_{ij}^{k_{ij}}$ are uncorrelated across j.

4. Green Bay recreational angling data

A three-step procedure was used in 1998 to collect data from a sample of anglers in the target population: anglers who purchased licenses in eight counties near Green Bay and who fished

12. Although all parameters are listed separately, it is evident that normalizations are necessary.

Green Bay in 1998. First, a random sample of anglers was drawn from 1997 license holders in the county courthouses in the eight targeted counties. Second, using the license holder list, a telephone survey was conducted to identify and recruit Green Bay anglers for a followup mail survey and to collect data from a cross-section of anglers. The telephone survey collected some attitudinal data and data on the number of fishing days at Green Bay and elsewhere. The overall response rate to the telephone survey was 69.4%. Third, a mail survey with the SP questions was conducted with current Green Bay anglers The overall response rate to the mail survey was 78.9%, yielding a data set of 647 individual anglers used in the model.

5. Implementation and Estimation

The empirical model for equation 1 is assumed to be:

$$U_{ij}^{k_{ij}} = \sum_{l=p,s,w,b} \beta_l c_l^{k_{ij}} + \sum_{q=2}^{9} \beta_{FCAq} FCA_q^{k_{ij}} + \beta_y (y_i - TC_i - fee^{k_{ij}}) + \varepsilon_{ij}^{k_{ij}}, \tag{12}$$

for $i = 1,..., m; j = 1,..., 8$, $k_{ij} = 1$ or 2, and where y_i and TC_i are choice occasion income and travel cost for individual i, and average catch times by species (c_l, l = *perch, salmon/trout, walleye, bass*) are measured as the time (in hours) it takes on average to catch one fish of a particular species (perch, salmon/trout, walleye, bass). For example, the perch catch time is approximately 0.75 hours. Therefore, it is expected that the coefficients of the catch times will be negative. The nine FCA levels are represented by a set of eight dummy variables, each representing a certain configuration of fish consumption advisories for the four target species. The FCA levels corresponding to the dummy variables generally increase in severity, so that $FCA_3 = 1$ means more (and/or more severe) restrictions than $FCA_2 = 1$, for example.[13] A value of zero for all of

13. The exception is in moving from FCA_4 to FCA_5 and from FCA_5 to FCA_6 with the consumption of some species becoming more restricted and others less restricted.

the dummy variables (FCA_2 through FCA_9) means essentially no restrictions (eat as many of all species as desired), and $FCA_9 = 1$ is a warning not to eat more than one perch meal per month or *any* of the remaining three species at all. Since y_i and TC_i do not vary by k_{ij}, these variables disappear from the utility difference relevant for estimation.

Since there are no data on the characteristics of the alternative fishing sites for the respondents, utility for the non-Green Bay alternative site (Equation 4) is assumed to be constant across individuals and choice occasions, with an additive random disturbance:

$$U_{ij}^{0} = \gamma_O + \varepsilon_{ij}^{0}. \tag{13}$$

This means that variables such as catch time, travel cost, and any fish advisories at other sites (but not income, as it will drop out) are grouped into the error term. Although a component of travel cost such as distance to the site cannot contribute to a utility difference when the site is Green Bay for both choices, as it is in the binary choice SP data, it could affect the utility differences between other sites and Green Bay. We assume here that the variation in distance to anglers' other sites is not great across anglers. We further assume that any variation is likely to be randomly distributed across anglers (anglers living close to and far from Green Bay have alternative sites both near and far), so that the lack of these data adds noise (in the form of increased variance of the disturbance term in Equation 13), but does not bias parameter estimates.

Utility for going to Green Bay under current conditions (equation 8) is given by:

$$U_{id}^{G} = \sum_{l=p,s,w,b} \beta_l c_l + \sum_{q=2}^{9} \beta_{FCAq} FCA_q + \beta_y (y_i - TC_i - fee) + \varepsilon_{id}^{G}, i \quad = 1,\ldots,m, \tag{14}$$

where the values for explanatory variables are the current conditions.

Convergence was achieved for a variety of starting values, and always at the same point. Table 1 provides the estimated values of the parameters and their estimated asymptotic t-statistics. All parameters have the expected signs and all are statistically significant by conventional standards. The perch catch time has by far the largest parameter of the four species catch times. The pattern of estimated coefficients on the FCA variables is somewhat striking: as the FCA level increases they increase (in absolute value) nearly uniformly, and where they do not, it is as expected (see footnote 13). The same is true for their precision, as measured by their asymptotic t-statistics.

The parameters $\sigma_{0-\varepsilon}$ and σ_{0-G} are the standard deviations of the error differences $\varepsilon_{ij}^{0} - \varepsilon_{ij}^{k_{ij}}$ and $\varepsilon_{ij}^{0} - \varepsilon_{ij}^{G}$, respectively. Since we have allowed for nonzero covariances between the errors ($\sigma_{\varepsilon 0}$ and σ_{G0}; see Sections 3.2 and 3.3), identification of individual components of $\sigma_{0-\varepsilon}$ and σ_{0-G}, in particular σ_{ε}^{2} and σ_{G}^{2} is not possible. Thus we are not able to answer the question of which data, RP or SP, contain more information. This question is sometimes addressed in studies that use both RP and SP data by assuming that the disturbances are uncorrelated (see, for example, Ben-Akiva and Morikawa, 1990; Bradley and Daly, 1991; Hensher and Bradley, 1993; Louviere, 1996; Swait and Louviere, 1993; and Swait et al., 1991).[14] For our data and model, this restrictive assumption is easily rejected.

14. Kling (1997) simulates nonzero covariances, but restricts the variances to be constant across the two types of data.

Table 1 Parameter Estimates		
Parameter	Estimate	Asy. t-ratio
β_y	0.0535	20.57
β_p	- 0.5307	- 14.99
β_t	- 0.0212	- 7.58
β_w	- 0.0287	- 11.95
β_b	- 0.0231	- 11.44
β_{FCA2}	- 0.0972	- 3.07
β_{FCA3}	- 0.2599	- 7.65
β_{FCA4}	- 0.5215	- 12.92
β_{FCA5}	- 0.6017	- 15.80
β_{FCA6}	- 0.5303	- 13.08
β_{FCA7}	- 0.7660	- 18.91
β_{FCA8}	- 1.0581	- 23.40
β_{FCA9}	- 1.1616	- 24.79
γ_0	- 1.1420	- 34.40
$\sigma_{0-\varepsilon}$	5.5540	33.15[a]
σ_{0-G}	3.5257	17.32[a]
a. t-statistics apply to the logged parameter estimates.		

The model predicts choices correctly 73% of the 5,038 choice occasions (647 individuals × 8 experiments = 5,176 - 138 missing = 5,038). The pseudo-R^2 is 0.453. The mean predicted probability of the preferred alternative from the stated preference experiment is 0.63, with a standard deviation of 0.22.

An alternative is infrequently chosen when its probability of being chosen is small, and frequently chosen when its probability is high. For example, when the predicted probability of selecting alternative A is less than 0.1, A is chosen in only 5% of the pairs; but when the predicted probability is greater than 0.9, A is chosen in almost all of the pairs, 96%.

The parameter estimates from the model can be used to predict the conditional probability of choosing Green Bay under the hypothetical conditions over the individual's other (real) choices. This is Equation 6. Multiplying this probability by the actual number of open-water days for the respondent produces an estimate of the number of Green Bay days under hypothetical conditions. The means (standard deviations) of both the indicated number of Green Bay days (truncated to be no larger than the total days at all sites for each angler) and the estimated number of days are 12.0927 (14.8531) and 12.0917 (12.2885), respectively. While the means are very close, there is substantial variation. Finally, the estimated mean number of expected days to the chosen Green Bay alternatives (12.09) is larger than the reported number of days under current conditions (9.95). Conditions are, in general, inferior to the average conditions of the chosen alternatives.

6. Estimated responses to and compensating variations for the elimination of FCAs

The model can be used to estimate how the probability of fishing Green Bay will change (and hence how the number of days fishing Green Bay will change, holding constant total fishing days) from either a change in catch times or FCA levels. For example, holding constant other site characteristics, the probability of going to Green Bay would increase from 0.40 to 0.46 if FCAs were eliminated. At an existing FCA Level of four, doubling the catch rate for perch would only cause an increase from 0.40 to 0.42.

Denote individual i's expected compensating variation for a season for a change in the characteristics of Green Bay, $E(CV_i)$. We do not estimate this; rather we report a lower-bound estimate. Denote individual i's expected compensating variation for a fishing day for a change in the characteristics of Green Bay, $\mathrm{E}(CV_i^F)$, and denote individual i's compensating variation for a Green Bay fishing day for a change in the characteristics of Green Bay, CV_i^G. The estimated CV_i^G and $\mathrm{E}(CV_i^F)$, along with estimates of the current number of fishing days and Green Bay fishing days are used to obtain two lower-bound estimates of WTP for the elimination of FCAs for this target population.

For an improvement in Green Bay, CV_i is how much the angler would pay per season (year) for the improvement, whereas CV_i^G is how much the angler would pay per Green Bay fishing day for the improvement, and CV_i^F is how much the angler would pay per fishing day. Note that for an improvement in Green Bay, $0 \leq CV_i^F \leq CV_i^G$, and for a deterioration in Green Bay, $CV_i^G \leq CV_i^F \leq 0$. An angler will pay no more per fishing day to have the FCAs at Green Bay reduced than he would pay per Green Bay fishing day because all fishing days are not necessarily to Green Bay.

For an improvement in Green Bay conditions, $CV_i^G \times D_i^{G^0} \leq CV_i^F \times D_i^{F^0} \leq CV_i$, where $D_i^{G^0}$ is the number of days in a season individual i fishes Green Bay under current (injured) conditions, and $D_i^{F^0}$ is the number of days individual i fishes (all sites) under current conditions (Morey, 1994).[15]

$(CV_i^G \times D_i^{G^0})$ would be individual i's seasonal compensating variation if he were constrained to fish Green Bay the same number of days with the improvement as he did in the injured state. $CV_i^G \times D_i^{G^0} \leq CV_i$ because he has the ability to take greater advantage of the improvement by increasing the number of days he fishes Green Bay. $(CV_i^F \times D_i^{F^0})$ would be individual i's compensating variation if he were constrained to fish the same total number of

15. Given the model, CV^F and CV^G are constants independent of the individual's number of fishing days and Green Bay fishing days. This follows from the assumption that the utility from a fishing day (Green Bay fishing day) is not a function of the number of fishing days (Green Bay fishing days). In this case, any quality increase can be represented by an equivalent price decrease, and the inequality holds if the marginal utility of money is positive, which it is. That is, the inequality holds because the angler will not decrease fishing days if Green Bay improves in quality.

days with the improvement as he did in the injured state. $CV_i^F \times D_i^{F^0} \leq CV_i$ because he has the ability to take advantage of the improvement by increasing the number of days he fishes.

$CV_i^G \times D_i^{G^0} \leq CV_i^F \times D_i^{F^0}$ because an individual who is constrained to fish Green Bay the same number of days both before and after Green Bay is improved is more constrained in his ability to take advantage of the improvement than an individual constrained to fish the same number of total days both before and after Green Bay is improved. The latter constraint allows the individual to increase his days to Green Bay by reducing the days to other sites if this makes him better off, whereas the former constraint does not.

Since CV_i^G is per Green Bay fishing day and since the only alternative is Green Bay, CV_i^G is not a random variable and can be estimated. The random component(s) cancel out of the CV formula when the individual chooses the same alternative in each state. In discrete choice models without income effects, the compensating variation can be written as the difference between the maximum utility in the two states multiplied by the inverse of the constant marginal utility of money:

$$CV_i^G = \frac{1}{\beta_y}\left(U_i^{G^1} - U_i^{G^0}\right) = \frac{1}{\beta_y}\left(\beta' x_i^{G^1} - \beta' x_i^{G^1}\right) \qquad (16)$$

where $U_i^{G^1}$ is the utility from a Green Bay fishing day in the improved state, and $U_i^{G^0}$ is the utility in the current state; that is, G^1 denotes Green Bay under improved conditions and G^0 denotes Green Bay under current conditions.

In addition, $x_i^G = x^G \; \forall \; i$, so $CV_i^G = CV^G \; \forall \; i$. $C\hat{V}^G$ (the estimated value of CV^G) for reducing FCAs from FCA Level 4 to FCA Level 1 (no FCAs) is \$9.75; that is, \$9.75 for every Green Bay fishing day. For comparison, \$9.75 is 13% of the average reported cost of a Green Bay fishing day. The 95% confidence interval on the \$9.75 estimate is \$8.06 to \$11.73.

FCA Level 4 represents FCAs by species that are equal to or less stringent than current levels. \$9.75 is 13% of the average of current expenditures per Green Bay fishing day (\$74.32). $C\hat{V}^{G}$ for reducing FCAs from Level 3 to Level 1 (no FCAs) is \$4.86. For reducing FCAs from FCA Level 2 to no FCAs, it is \$1.81. For comparison, $C\hat{V}^{G}$ for doubling the perch catch rate is \$3.72, for quadrupling it is \$5.58, for a ten-fold increase it is \$6.97, and for doubling the catch rate of all species it is \$12.78.

The current damages from the FCAs could be offset with improved catch rather than money. The model estimates indicate that to do this, catch rates for all four species would have to increase by 61%. Note that increasing all catch rates by 61% would not compensate for past damages.

$CV^{G} \times D^{G^{0}} \leq N \times CV$, where N is the number of individuals in the target population and $D^{G^{0}}$ is the number of Green Bay fishing days by the target population under current conditions, so $(CV^{G} \times D^{G^{0}})$ is a lower-bound estimate of the recreational fishing damages to the target population. We estimate 255,160 Green Bay fishing days in 1998. Multiplying this by \$9.75 results in a lower-bound CV estimate of \$2.49 million, with a confidence interval of \$1.93 million to \$3.05 million. \$2.48 million is a lower-bound estimate because it does not account for the prospect that anglers might wish to fish Green Bay more if it did not have FCAs.

Since CV_{i}^{F} is per fishing day and on each fishing day the angler has the choice of two sites: Green Bay or elsewhere, CV_{i}^{F} is a function of unobservable stochastic components, and so cannot be estimated. Instead we estimate its expectation:

$$\mathrm{E}\left(CV_{i}^{F}\right)=\frac{1}{\beta_{y}}\left[\mathrm{E}(\max(U_{i}^{G^{1}},U_{i}^{O}))-\mathrm{E}(\max(U_{i}^{G^{0}},U_{i}^{O}))\right] \tag{17}$$

where U_{i}^{o} is the utility from fishing at another site. Given that U_{i}^{G} and U_{i}^{o} are bivariate normal:

$$E\left(\max(U_i^G, U_i^O)\right) = \gamma_0 + (\beta' x_i^G - \gamma_0)\Phi\left(\frac{\beta' x_i^G}{\sigma_{0-G}} - \frac{\gamma_0}{\sigma_{0-G}}\right) + \sigma_{0-G}\phi\left(\frac{\beta' x_i^G}{\sigma_{0-G}} - \frac{\gamma_0}{\sigma_{0-G}}\right) \tag{18}$$

where $\Phi(\cdot)$ is the univariate standard normal cumulative distribution function, $\phi(\cdot)$ is the standard normal density function (Maddala, 1983, p. 370), and

$\sigma_{0-G}^2 = \mathrm{Var}[\varepsilon_{ij}^0 - \varepsilon_{ij}^G] = \sigma_0^2 + \sigma_G^2 - 2\sigma_{G0}$ (see Section 3).

Substituting Equation 18 into 17, and simplifying it one obtains:

$$\begin{aligned} &E(CV_i^F) \\ &= \frac{1}{\beta_y}[(\beta' x_i^{G^1} - \gamma_0)\Phi\left(\frac{\beta' x_i^{G^1} - \gamma_0}{\sigma_{0-G}}\right) + \sigma_{0-G}\phi\left(\frac{\beta' x_i^{G^1} - \gamma_0}{\sigma_{0-G}}\right) \\ &-(\beta' x_i^{G^0} - \gamma_0)\Phi\left(\frac{\beta' x_i^{G^0} - \gamma_0}{\sigma_{0-G}}\right) - \sigma_{0-G}\phi\left(\frac{\beta' x_i^{G^0} - \gamma_0}{\sigma_{0-G}}\right)] \end{aligned} \tag{19}$$

Since, in this model, $x_i^G = x^G \;\forall\; i$, $E\left(CV_i^F\right) = E(CV^F) \;\forall\; i$. $C\hat{V}^F$ for reducing FCAs from Level 4 to Level 1 (no FCAs) is \$4.17; that is, \$4.17 for every fishing day. Remember that \$4.17 applies to all fishing days, not just Green Bay fishing days, so it is less than $C\hat{V}^G$, which is \$9.75.[16] The 95% confidence interval on the \$4.17 estimate is \$3.41 to \$5.00. $C\hat{V}^F$ for reducing FCAs from FCA Level 3 to no FCAs is \$2.15, and for reducing FCAs from FCA Level 2 to no FCAs is \$0.82. For comparison, $C\hat{V}^F$ for doubling the perch catch rate is \$1.52, for quadrupling it is \$2.32, for a ten-fold increase it is \$2.80, and for doubling the catch of all species it is \$5.58.

Consider again the inequality $CV_i^F \times D_i^{F^0} \le CV_i$. Taking the expectation of both sides and noting that $D_i^{F^0}$ is exogenous: $E(CV_i^F) \times D_i^{F^0} \le E(CV_i)$. Since

16. Both \$9.75 and \$4.17 fall within the range of values in the literature. See, for example, Herriges et al. 1999, Chen and Cosslett 1998, Jakus 1998, and Parsons et al. 1999.

$E(CV_i^F) = E(CV^F)\ \forall\ i$,this simplifies to $\mathrm{E}(CV^F) \times D_i^{F^0} \leq \mathrm{E}(CV_i)$. Summing over individuals, one obtains:

$$\mathrm{E}(CV^F) \times D^{F^0} \leq \sum_{i=1}^{N} \mathrm{E}(CV_i)\ , \tag{20}$$

where D^{F^0} is the number of Green Bay fishing days by the target population under current conditions, so $\left[\mathrm{E}(CV^F) \times D^{F^0}\right]$ is a second lower-bound estimate of the recreational fishing damages to the target population. It is less constrained than the first estimate, so it is expected to be larger than the first lower-bound damage estimate. Anglers value improvements in Green Bay more highly when they can fish it more. We estimate that in 1998 current Green Bay anglers fished 641,060 days at all sites. Multiplying this by \$4.17 results in a second lower-bound estimate of damages of \$2.67 million. The confidence interval is \$2.13 million to \$3.22 million. \$2.67 million is a lower-bound estimate because it does not account for the prospect that anglers might increase their total open-water fishing day if there were no FCAs in Green Bay. It is larger than the other lower-bound estimate because it accounts for the possibility that anglers might spend a larger proportion of their fishing days at Green Bay if it were not injured.

7. Conclusions

To take advantage of the relative strengths of different types of data, SP data are combined with RP data to estimate preferences. This paper is the first to combine SP choice data with SP frequency data. It assumes that individuals answer probabilistically when answering SP questions, because when an individual answers an SP question he has some uncertainty as to what preferences would be if he were actually presented with this choice at some point in the future.

The unique combination of data not only allows for the estimation of how individuals would trade off different characteristics of a commodity that is unique, but also how they would be expected to change the relative quantities they consume when characteristics change. Our method would have wide applicability in various markets for new products with characteristic levels that do not currently exist. Estimation is general because it allows for nonzero covariance between the various stochastic components associated with the different types of data, a new approach.

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Appendix: Derivation of the conditional probability

Consider the probability of choosing Green Bay site k_{ij} over a non-Green Bay site, conditional on the choice of Green Bay site k_{ij} over Green Bay site 3 - k_{ij}. To ease the notation, suppose alternative 1 is chosen rather than alternative 2, and the individual and choice occasion subscripts are ignored. Under assumptions 2 and 3, the random vector $(\varepsilon^1,\ \varepsilon^2,\ \varepsilon^0)$ has a multinormal distribution with zero mean vector and covariance matrix:

$$\begin{pmatrix} \sigma_\varepsilon^2 & 0 & \sigma_{\varepsilon o} \\ 0 & \sigma_\varepsilon^2 & \sigma_{\varepsilon o} \\ \sigma_{\varepsilon o} & \sigma_{\varepsilon o} & \sigma_0^2 \end{pmatrix} \tag{A1}$$

This implies:

$$\omega = \begin{pmatrix} \omega_1 \\ \omega_2 \end{pmatrix} \underset{=\!=}{\text{def}} \begin{pmatrix} \varepsilon^0 - \varepsilon^1 \\ \varepsilon^2 - \varepsilon^1 \end{pmatrix} \sim N(0,\Omega) \tag{A2}$$

where:

$$\Omega = \begin{pmatrix} \sigma_{0-\varepsilon}^2 & \sigma_\varepsilon^2 \\ \sigma_\varepsilon^2 & 2\sigma_\varepsilon^2 \end{pmatrix} \tag{A3}$$

The probability in Equation 6 is a conditional probability of a bivariate normal random variable, where the conditioning event does not have zero probability (which is the more usual case).[17] Let $a_1 = -\beta'(x_{ij}^0 - x_{ij}^{k_{ij}})$ and $a_2 = -\beta'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}})$. From Amemiya (1994, pp. 35-36), denoting the joint, marginal, and conditional density functions of ω and its elements as f, we have:

$$f(\omega_1|\omega_2 < a_2) = \frac{\int_{-\infty}^{a_2} f(\omega_1,\omega_2)d\omega_2}{P(\omega_2 < a_2)} \tag{A4}$$

so that:

$$P(\omega_1 < a_1|\omega_2 < a_2) = \int_{-\infty}^{a_1} f(\omega_1|\omega_2 < a_2)d\omega_1 = \frac{\int_{-\infty}^{a_1}\int_{-\infty}^{a_2} f(\omega_1,\omega_2)d\omega_2 d\omega_1}{\int_{-\infty}^{\infty}\int_{-\infty}^{a_2} f(\omega_1,\omega_2)d\omega_2 d\omega_1} \tag{A5}$$

17. It *is* a conditional probability, rather than a conditional expectation, so the Mill's ratio results from the selection literature (e.g., Maddala, 1983, p. 367) cannot be used.

This is the ratio of a bivariate normal cumulative distribution function evaluated at α_1 and α_2 to a univariate normal cumulative distribution function evaluated at α_2 :

$$P(\omega_1 < a_1 | \omega_2 < a_2) = \frac{\Phi_2\left(a_1 / \sigma_{0-\varepsilon}, a_2 / \sqrt{2}\sigma_\varepsilon; \rho\right)}{\Phi\left(a_2 / \sqrt{2}\sigma_\varepsilon\right)}, \tag{A6}$$

which is Equation 6.

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Alternative Methodologies for Incorporating the Opportunity Cost of Time in Recreation Demand Models

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When modeling recreation demand, it is important to carefully consider the role of the opportunity cost of time. For goods that are very time-intensive, as is the case with outdoor recreation, the valuation of travel time is likely to be very important. Bishop and Heberlein (1979) found that valuing travel time at half the wage rate, as opposed to not including it, resulted in a fourfold difference in consumer surplus estimates.

However, no consensus has emerged as to the appropriate method of dealing with travel time. Several options have been explored (Smith et al. 1983, McConnell and Strand 1981, Bockstael et al. 1987, Feather and Shaw 1999), but the most common approach is to value the respondent's travel time as a fixed fraction of their full wage rate.

In this paper we examine several modeling options for including the opportunity cost of travel time. Further, each modeling option will be examined using three different methodologies for valuation. These methodologies can be thought of as three different "laboratories" in which we can investigate the consequences of alternative treatments of time costs. The first "laboratory" will be an examination of the opportunity cost of travel time using revealed preference (RP) data, the second will be an examination using stated preference (SP) data, and the third will be an examination using a model that links both RP and SP data.

The next section will be used to describe the methods of incorporating time into the recreation demand model. The three laboratories will then be discussed as well as the forms of data used to estimate each model. Parameter estimates will be presented and the implications of the results will be explored.

Methods of Incorporating Time into the Recreation Demand Model

This paper will examine four methods of incorporating time into the recreation demand model: picking a fixed fraction of the wage rate, estimating the fraction of the wage rate without accounting for the employment status of the respondent, estimating the fraction of the wage rate while explicitly accounting for the employment status of the respondent, and a more general approach developed by Bockstael et al. (1987).

We do not explore hedonic wage models (Smith et al. 1983, Feather and Shaw 1999) in this paper. However, these models represent another approach to modeling time in the recreation demand model, and will be a part of this research in the future.

The first method to be examined is the use of a fixed fraction of the wage rate. The majority of past authors have chosen to model the opportunity cost of travel time as some fixed fraction of the full wage rate. Cesario (1976), in a survey of empirical evidence concerning urban commuters, concluded that the opportunity cost of travel time was between one-fourth and one-half of the wage rate. Based on this evidence he concluded that it would be reasonable to value travel time at one-third the wage rate. Although clearly ad hoc, this method has the advantage of simplicity.

The second method we will examine is direct estimation of the marginal opportunity cost of travel time. McConnell and Strand (1981) develop a model that explicitly estimates the fraction of the full wage rate at which time is valued by adding that fraction as a parameter to be estimated. This approach is more appealing than the assertion of a fixed fraction of the wage rate, but has not enjoyed common usage due to difficulties with collinearity. Although we did not find these difficulties in our applications, we briefly discuss this issue later.

The third method is akin to the McConnell and Strand (1981) approach, but estimates a separate fraction of the wage rate for respondents who can alter their work hours at the margin and for respondents who must work a fixed number of hours. This allows more flexibility for the data to yield information on the opportunity cost of time.

The final method we will consider was developed in Bockstael, Strand, and Hanemann (1987). Bockstael et al. develop a model that is similar to the McConnell and Strand (1981) model, except they take a closer look at the structure of the time constraint. They point out that the nature of an individual's labor supply decision determines whether their wage rate yields information about the marginal value of their time. It may not be possible for a respondent to optimally adjust the number of hours worked. If this is the case, they will be found at a corner solution where they choose either to not work, or to work a job with a fixed number of hours. The respondent may choose to work a part-time job with a flexible number of hours in addition to their job with fixed hours, or they may choose not to work at all.

In general, these models progress from ad hoc to more rigorous treatments of the opportunity cost of travel time. Whether the more rigorous treatments yield vastly different empirical results than the simpler methods is the focus of this paper.

Empirical Models

Three separate laboratories will be used to estimate the models. Each model will be estimated using revealed preference data alone, stated preference data alone, and both revealed and stated preference data in a linked model. In this section we will describe the RP model, the SP model, and the model that links both RP and SP data.

Laboratory 1: Revealed Preference Data

The demand model describing the RP data assumes an individual allocates income between a composite commodity (z) and a recreation good (q). The ordinary demand (Marshallian) associated with the recreation good can be written simply as

$$q_i^R = f^R\left(p_i^R, y_i; \beta^R\right) + \varepsilon_i^R, \tag{1}$$

where q_i^R is the quantity consumed by individual i, p_i^R denotes the associated price, y_i is the individual's income, and β^R is a vector of unknown parameters. The additive stochastic term is assumed to follow a normal distribution, with $\varepsilon_i^R \sim N\left(0, \sigma_R^2\right)$. Since LHS censoring is present in our data (as in many recreation demand applications), standard econometric estimators are used to obtain consistent estimates of the parameters of this function accounting for censoring. Specifically, the likelihood function is written

$$LL^R = \sum_{i=1}^{n} \left(D_i^R \ln\left\{ \sigma_R^{-1} \phi\left[\frac{q_i^R - f^R\left(p_i^R, y_i; \beta^R\right)}{\sigma_R} \right] \right\} + \left(1 - D_i^R\right) \ln\left\{ \Phi\left[\frac{-f^R\left(p_i^R, y_i; \beta^R\right)}{\sigma_R} \right] \right\} \right) \tag{2}$$

where Φ and ϕ are the standard normal cdf and pdf, respectively, and $D_i^R = 1$ if $q_i^R > 0$; $= 0$ otherwise.

Laboratory 2: Stated Preference Data

Now suppose that in the process of gathering RP data, the survey respondents are asked: "How many recreation trips would you have taken to this site if the cost per trip increased by \$B?" The response to this question represents a form of SP data. We will have both quantity (q_i^S) and price (p_i^S) information for each individual. If, as in the case of the RP data, we assume that the survey responses are driven by an underlying set of preferences, the stated demands flow from demand equations of the form

$q_i^S = f^S\left(p_i^S, y_i; \beta^S\right) + \varepsilon_i^S$, where $p_i^S = p_i^R + B_i$.

Having constructed the log-likelihood function for the RP data, it is quite straightforward to construct it for the SP data since they are of identical form. Thus, the log-likelihood function in Equation (2) will also describe the SP data, requiring only that R be replaced with S everywhere.

Laboratory 3: Linking Revealed and Stated Preference Data

The past several years have seen a change in the research agenda of environmental valuation. Rather than treating RP and SP as competing valuation techniques, analysts have begun to view them as complimentary, where the strengths of each approach can be used to provide more precise and possibly more accurate benefit estimates. The impetus for this change was a paper by Cameron (1992) where she combined information on the number of fishing trips in Southern Texas with responses to an SP question regarding the angler's willingness-to-pay for annual angling. She notes that the same set of preferences that generate the RP data ought also to generate the SP data. Thus, both sources of data yield information on a common set of parameters. There are now numerous examples of authors using both RP and SP data to jointly estimate the parameters of a preference function (McConnell, et al. 1999, Adamowicz et al. 1994, Larson 1990).

If the RP and SP data are to be linked in joint estimation of preferences, efficiency would dictate that we take into account the likely correlation between the RP and SP responses. The log likelihood function is given by[1]

$$\begin{aligned} LL = \sum_{i=1}^{n} \Bigg\{ & D_i^R \left[\ln \phi\left(\frac{q_i^R - f_i^R}{\sigma_R} \right) - \ln(\sigma_R) \right] + D_i^R D_i^S \left[\ln \phi\left(\frac{(q_i^S - f_i^S) - \theta^S (q_i^R - f_i^R)}{\sigma_S \sqrt{1-\rho^2}} \right) - \ln\left(\sigma_S \sqrt{1-\rho^2}\right) \right] \\ & + D_i^R (1 - D_i^S) \left[\ln \Phi\left(\frac{-f_i^S - \theta^S (q_i^R - f_i^R)}{\sigma_S \sqrt{1-\rho^2}} \right) \right] + (1 - D_i^R)(1 - D_i^S) \ln \int_{-\infty}^{\frac{-f_i^R}{\sigma_R}} \int_{-\infty}^{\frac{-f_i^S}{\sigma_S}} \phi_2(\eta_1, \eta_2; \rho) d\eta_1 d\eta_2 \Bigg\} \end{aligned} \tag{3}$$

where, $\rho \equiv Corr(\varepsilon_i^R, \varepsilon_i^S)$, $\theta \equiv \rho \sigma_S / \sigma_R$, $f_i^k = f^k(p_i^k, y_i^k; \beta^k)(k = R, S)$, and $\phi_2(\cdot, \cdot; \rho)$ denotes the standard normal bivariate pdf. This model can be used to test a variety of hypotheses concerning the consistency of the RP and SP data. All of the coefficients entering the SP portion of the likelihood can be constrained to be the same as those in the RP portion, they can all be allowed to differ, or some subset can be constrained to be equal

[1] The derivation of this log-likelihood function is available from the authors upon request.

across the data sources. The parameter estimates reported in this paper will be for a linking model that restricts all RP and SP parameters to be equal.

Parametric Specifications of Time

The four models we are considering differ according to the specification of the variables related to the time cost in the demand function.

Model 1: Fixed Marginal Opportunity Cost of Time

In the first case, a fixed marginal opportunity cost of time is used. The trip demand function takes the form

$$q_i^j = \alpha^j + \beta_p^j p_i^j + \beta_y^j y_i + \varepsilon_i^j, \tag{4}$$

where $\varepsilon_i^R \sim N(0, \sigma_R^2)$ and $j = R, S$. The price term takes the form $p_i^j = C_i + (1/3) w_i T_i$, where C_i denotes out-of-pocket travel expense, w_i denotes the wage rate, and T_i is round-trip travel time. The marginal opportunity cost of time is assumed to be one-third of the wage rate for all recreators, regardless of their employment status or ability to work additional hours.

Model 2: Estimating a Single Marginal Opportunity Cost of Time

The second model allows the marginal opportunity cost of travel time to be estimated as a parameter in the model. In this case the price specification takes the form

$$p_i^j = C_i + \lambda^j w_i T_i, \tag{5}$$

where λ^j is the proportion of the wage at which travel time is valued. A single λ^j is estimated for all respondents, again imposing that the rate is fixed across all recreators.

Model 3: Accounting for Employment Status, First Approach

The third model estimates a different λ^j for respondents who can optimally adjust their work hours at the margin than for respondents who must work at a job with a fixed number of hours. In this case the price specification takes the form

$$p_i^j = C_i + I_i \lambda_a^j w_i T_i + (1 - I_i) \lambda_f^j w_i T_i, \tag{6}$$

where I_i is an indicator variable that takes a value of unity if respondent i can optimally adjust their work hours and a value of zero if they must work a fixed number of hours, λ_a^j is the marginal opportunity cost of time for respondents who can adjust their work hours, while λ^j_f is the marginal opportunity cost of time for respondents who must work a fixed number of hours.

This approach allows for some flexibility, but is still a rather ad hoc method of accounting for the employment status of the respondent.

Model 4: Accounting for Employment Status, Bockstael et al. Model

The final model we will examine is Bockstael, Strand, and Hanemann (1987). The essence of the Bockstael et al. model is that respondents face both a time and income constraint. If the respondent can freely substitute time for money, the two constraints can be collapsed. However, if the respondent cannot freely substitute time for money the constraints cannot be collapsed. This implies that the structure of the demand function will be different for the two cases.

We will estimate the linear model developed in the Bockstael et al. paper. The trip demand function for respondents who can optimally adjust their work hours takes the form

$$q_i^j = \alpha^j + \gamma_1^j\left(y_i + w_i\overline{T}_i\right) + \beta'^j\gamma_2^j\left(C_i + w_iT_i\right) + \varepsilon_i^j, \tag{7}$$

where $\overline{T}_i$ represents discretionary time (time spent not working) and $\beta'^j = \beta^j / \left(\gamma_1^j + \gamma_2^j\right)$.

The trip demand function for respondents who cannot optimally adjust their work hours takes the form

$$q_i^j = \alpha^j + \gamma_1^j y_i + \gamma_2^j\overline{T}_i + \beta_i'^j\gamma_1^j C_i + \beta_i'^j\gamma_2^j T_i + \varepsilon_i^j. \tag{8}$$

The important distinction between this model and the previous three is that the wage does not enter the demand function of respondents who cannot optimally adjust their work hours.

The Data: An Application to Wetlands in Iowa

These models will be applied using data from a 1997 survey of Iowa residents concerning their use of Iowa wetlands. Of the 6,000 surveys sent, 594 were returned by the post office as undeliverable. There was a 59 percent response rate (with 3,143 surveys returned). The survey instrument elicited travel cost information, contingent behavior information in both continuous and discrete form, as well as socioeconomic information (e.g., gender, age, and income). A complete discussion of the wetland data set can be found in Azevedo (2000).

The state of Iowa was divided into fifteen zones, shown in Figure 1. These zones each contained between 3 and 12 counties, and were designed to encompass similar types of wetlands. For analysis, the zones were further grouped into "megazones" with each megazone containing three zones. Zones 1, 2, and 3 comprise the 1,2,3 megazone, zones 4, 5, and 8 comprise the 4,5,8 megazone, zones 6, 7, and 12 comprise the 6,7,12 megazone, zones 9, 10, and 11 comprise the 9,10,11 megazone, and zones 13, 14, and 15 comprise the 13,14,15 megazone. For this analysis only the data from zones 4, 5, and 8 (4,5,8 megazone) were used.

One section of the survey asked respondents to indicate the number of trips they had taken to each of the fifteen zones over the past year. This provided the RP data for our analysis. The respondents were then asked to consider a $B increase in the total cost per trip of each of the trips they had taken in 1997, and asked the following SP question concerning the trips they made to zones near their residence (X, Y, and Z for illustration): "With this additional cost of $B per trip of visiting zones X, Y, and Z, would this affect the number of trips you made to any of the 15 zones?" They were then asked to elaborate on how many fewer trips they would have taken to each of zones X, Y, and Z. The bid values ($B) were varied randomly across the sample, ranging from $5 to $50. This provided the data for the SP model.

The surveys provided direct information on the trip quantities. The next step was to calculate the out-of-pocket cost of travel as well as the travel time associated with visiting each zone. We used the software package PC Miler, designed for use in the transportation and logistics industry, to establish both travel distance $\left(d_i^z\right)$ and time $\left(T_i^z\right)$ for each household from their residence to the center of each wetland zone. The price of visiting a given wetland zone z was then constructed as $C_i^z = 0.22d_i^z$.

Summary statistics for the data used in this analysis are provided in Table 1. The average out-of-pocket travel cost, C_i, was $22.57. Average round trip travel time, T_i, was 1.31 hours, with an average number of trips take within the 4,5,8 megazone of 8.28. After the price increase, the average out-of-pocket travel cost was $47.76, with an average quantity of trips at the new price of 2.72.

Parameter Estimates

Table 2 shows parameter estimates for each of the four models. The most striking aspect of these results is the difference in the estimates of λ between the RP and SP data. Model 2 estimates a revealed preference λ of –0.06 (not significantly different from zero), while the stated preference λ is 0.43. Model 3 also estimates revealed preference λ's very near zero with stated preference λ's significantly larger. This implies that the practice of using a fixed λ, often chosen at one-third, would likely be more problematic with the RP data.

Another interesting result is that the estimates of λ_f and λ_a (Model 3) are very similar. In the RP laboratory, the estimate for λ_f is 0.002 while the estimate for λ_a is 0.00. In both the SP and RP-SP laboratories the estimates for λ_f and λ_a are slightly different (0.48 vs. 0.41 in the SP case and 0.48 vs. 0.42 in the RP-SP case) but still very close. This indicates that with respect to the marginal opportunity cost of time, for this demand specification, there does not appear to be much difference between respondents who can adjust their work hours and those who cannot.

All models exhibit a high degree of correlation between the RP and SP data sets, as shown by the estimates of ρ in Laboratory 3. Parameter estimates are 0.70 for Model 1, 0.72 for Model 2, 0.72 for Model 3, and 0.64 for Model 4.

Implications: Welfare Measures and RP-SP Consistency

Table 2 also shows that the choice of model can have a significant effect on the consumer surplus measure. Within the RP Laboratory, fixing the marginal opportunity cost of time at one-third resulted in a consumer surplus of 185.12, significantly larger than the consumer surplus measures of the other three models (82.80 for Model 2, 93.11 for Model 3, and Model 4 estimates of 148.17 for respondents with flexible work hours and 118.50 for respondents with fixed work hours).

Within Laboratory 2, consumer surplus ranges from a low of 202.29 (Model 4, CS: fixed) to 242.68 (Model 3). Within Laboratory 3, there is very little difference between the consumer surplus estimates of Models 1 through 3 (188.03, 197.39, and 199.66 respectively). However, Model 4 estimates are slightly lower (171.24 and 136.95). In general, RP data alone (Laboratory 1) produces lower consumer surplus estimates than SP data alone (Laboratory 2), with RP-SP (Laboratory 3) falling between the two.

The modeling choice can also have a significant effect on the hypothesis test of consistency between RP and SP data. The linked RP-SP model can be used to test the hypothesis of parameter equality between the RP and SP data sets.[2] With Models 2 and 3, the null hypothesis of parameter equality between the revealed and stated preference data sets was rejected. However, with Models 1 and 4, the null hypothesis of parameter equality was not rejected.

To further investigate the effect of choosing a fixed λ, a search procedure was conducted that tested consistency between revealed and stated preference data using a different value of λ for each test. Figure 2 shows the result of this search procedure for each megazone as well as for the overall data set.

For each group of data there exists a range of values of λ that will result in a failure to reject the null hypothesis of consistency between the revealed and stated preference data. The "fail to reject" region for the 4,5,8 data (the data used in this analysis) includes values of λ between 0.12 and 1.10. Four out of the five megazones (1,2,3 megazone, 4,5,8 megazone, 6,7,12 megazone, and the 13,14,15 megazone) include the value of one-third in the consistency region. The only megazone for which a value of λ equal to one-third results in a rejection of consistency is the 9,10,11 megazone.

This is a very important result. Testing for consistency between revealed and stated preference data is often a primary goal of papers that link both forms of data. As these results show, the choice of model can have a significant impact on the outcome of hypothesis tests of consistency between revealed and stated preference data. When estimating the model with a fixed λ, the consistency results depend on whether the value of λ chosen falls into the range of "consistent λ's" for that data set. However, if the opportunity cost of travel time is added as a parameter to be estimated, all tests result in a rejection of the null hypothesis of consistency. Consistency tests for Model 4 resulted in a failure to reject the hypothesis of consistency.

[2] Restricted (RP and SP parameters equal) and unrestricted models were estimated, and a likelihood ratio statistic was used to test the null hypothesis of parameter equality between the RP and SP data sets.

Final Comments

In this paper we have examined the modeling of travel time in the recreation demand model. Four separate models were each considered in one of three laboratories. It was shown that the way the opportunity cost of time is modeled in the recreation demand model can have a significant impact both on the estimates of consumer surplus and the hypothesis tests of consistency between revealed and stated preference data.

Table 1: Iowa wetlands data set, summary statistics for 4,5,8 megazone

Number of respondents	274
Average out-of-pocket travel cost	\$22.57
Average round trip travel time	1.31 hours
Average quantity of trips taken to this megazone	8.28
Average out-of-pocket travel cost with price increase	\$47.76
Average quantity of trips after price increase	2.72
Median income	\$37,4995

Table 2: Parameter Estimates (t-statistic in parenthesis)

	Laboratory 1 RP	Laboratory 2 SP	Laboratory 3 RP-SP
Model 1: Fixed $\lambda = 1/3$:			
α	15.69 (7.20)**	10.57 (2.66)**	14.79 (7.64)**
β	-0.52 (-7.68)**	-0.45 (-5.99)**	-0.50 (-15.40)**
γ	0.18 (4.81)**	0.18 (3.20)**	0.18 (5.01)**
σ	13.79 (18.09)**	15.26 (10.97)**	14.12 (18.97)**
ρ	--	--	0.70 (16.33)**
CS	185.12	216.53	188.03
RP-SP consistency			Fail to reject
Model 2: Estimating λ			
α	27.11 (8.77)**	9.77 (2.31)*	14.52 (7.48)**
β	-1.15 (-8.37)**	-0.42 (-4.64)**	-0.47 (-11.34)**
λ	-0.06 (-1.59)	0.43 (2.39)*	0.44 (3.93)**
γ	-0.02 (-0.32)	0.20 (2.92)**	0.21 (4.29)**
σ	13.26 (18.30)**	15.31 (11.25)**	14.34 (18.40)**
ρ	--	--	0.72 (16.28)**
CS	82.80	239.85	197.39
RP-SP consistency			Reject
Model 3: Different λ's			
α	25.04 (8.90)**	9.77 (2.41)*	14.33 (7.03)**
β	-1.03 (-8.61)**	-0.41 (-4.70)**	-0.47 (-11.69)**
λ_f	0.002 (--)[1]	0.48 (--)[1]	0.48 (--)[1]
λ_a	0.000 (0.08)	0.41 (2.36)	0.42 (3.57)**
γ	0.04 (1.10)	0.20 (3.10)	0.22 (3.93)**
σ	13.33 (18.30)	15.27 (10.46)	14.31 (17.74)**
ρ	--	--	0.72 (15.25)**
CS	93.11	242.68	199.66
RP-SP consistency			Reject
Model 4: Bockstael et al.			
α	11.89 (5.76)**	8.95 (133.91)**	10.82 (4.82)**
γ_1	0.07 (4.46)**	0.04 (11.71)**	0.06 (4.50)**
γ_2	0.32 (0.96)	1.90 (25.10)**	0.57 (2.48)*
β'	-7.18(-6.11)**	-6.82 (-101.21)**	-7.17 (-4.86)**
σ	12.60 (15.24)**	10.65 (157.04)**	12.56 (16.01)**
ρ	--	--	0.64 (10.31)**
CS: flexible	148.17	252.95	171.24
CS: fixed	118.50	202.29	136.95
RP-SP consistency			Fail to reject

** Denotes significance at the 99% confidence level
* Denotes significance at the 95% confidence level
[1] t-statistic not available at the present time

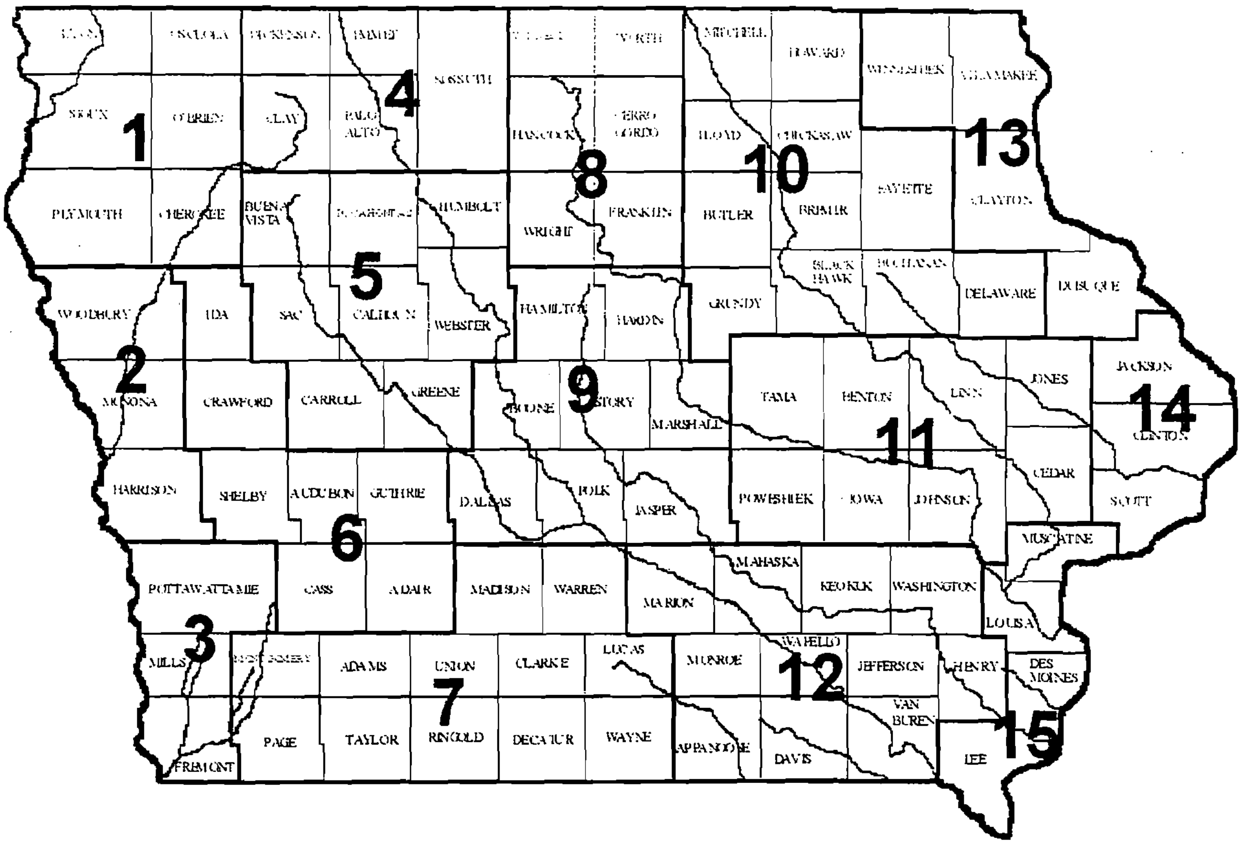

Figure 1: Iowa wetland zones

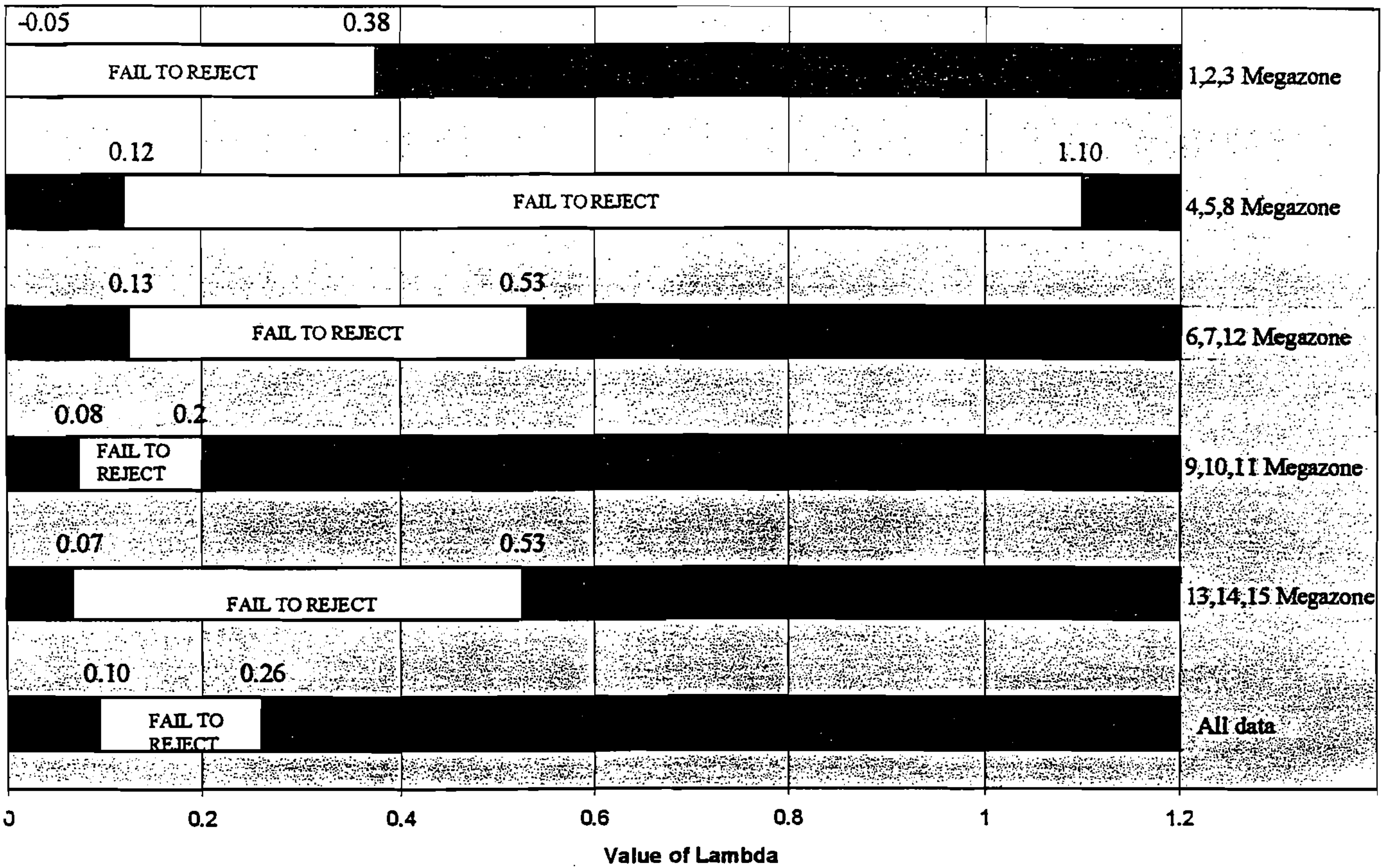

Figure 2: Testing general consistency with fixed lambda

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A New Approach to Random Utility Modeling
with Application to Evaluating Rock Climbing in Scotland

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A New Approach to Random Utility Modeling with Application to Evaluating Rock Climbing in Scotland

ABSTRACT

We introduce a new econometric approach to the analysis of site choice data, the Dirichlet multinomial model, which has a number of advantages over the standard conditional multinomial logit model. We use this model to estimate the impacts on per-trip consumers surplus of alternative management strategies for popular rock climbing sites in Scotland. The management alternatives are increasing access time to the crags and charging a car parking fee. Results show that the Dirichlet approach gives more precise coefficient and welfare estimates in this case. We also compare classical welfare measures with their posterior equivalents.

INTRODUCTION AND POLICY CONTEXT

A. Rock-climbing in Scotland

This paper is concerned with the estimation of the impacts on per-trip consumers surplus of management alternatives for a recreational resource. We use the example of popular rock-climbing areas in Scotland and model the impacts of a range of increases in both the time necessary to access crags on foot from parking areas and the direct money cost of access. In order to produce welfare estimates, we introduce a new way of modeling site choice data, the Dirichlet multinomial model, which turns out to have some advantages over the standard approach found in the literature. We do not attempt to represent changes in participation following the introduction of time or direct money charges; for a paper which attempts to do this using a conventional repeated nested logit model, see Hanley, Alvarez-Farizo and Shaw [7].

Rock climbing is one of the fastest-growing leisure activities in the United Kingdom, and shows a rising trend for Scotland over the period 1945-95 according to a variety of indicators (Wightman, [21]). Around 767,000 mountaineers from the UK visited the Highlands and Islands of Scotland for hillwalking (hiking on hills >2500 ft), technical climbing, ski mountaineering or high level cross-country skiing in 1995, the most recent year for which data is available (Highlands and Islands Enterprise [8]). This gave an estimated total number of rock climbers of between 82,836 - 153,400, spending a predicted total of 1,159,704 - 2,147,600 total climbing days in the area. Although almost all rock-climbing areas are located on private land, access is free in the sense that no monetary access fee is charged. A strong cultural resistance to charging for access to the hills has developed since mountaineering became established in Scotland at the end of the 19th century. However, the growth in participation in mountaineering of all types has led to an increasing number of problems in popular areas, including footpath erosion, the disruption of wildlife, and congestion. This has led a number of bodies, such as the National Trust for Scotland (which owns several mountain areas) and private landowners, to look at alternative means of restricting access. In the Cairngorms (the most visited mountain area in our survey), a "long walk in" policy has been introduced at some sites, whereby car and bicycle access to crags has been banned, thus increasing the time it takes to walk to the crags from parking areas. In other areas, parking charges have been proposed as a feasible and effective means of restricting access (most climbing sites have very few access points where cars may be left).

In the random utility travel cost model, recreationists make probabilistic choices over where to visit from amongst a set of choice alternatives, based on the attributes of these alternatives. Travel cost has always been viewed as a very important attribute, as it provides the key to obtaining consumer surplus estimates for changes in recreation site quality and/or availability. Many researchers include travel time along with petrol costs as one element of travel costs. This follows from a household production view of demand which recognizes that recreational time has a positive opportunity cost. More recently, Shaw and Feather [18] have argued that time should be included separately to travel costs. Whichever view is correct, travel time is a potentially relevant attribute in terms of demand. For rock climbers, travel time is composed of two elements: the time taken to drive to the nearest point of access to their target crag from their home; but also the time it takes to walk to the foot of the crag. This can be anything up to four hours for some popular crags in Scotland. We anticipate that, other things being equal, climbers will prefer sites with lower access times. Since income possesses a positive marginal utility in the random utility model, we also anticipate that charging a car parking fee where none currently exists will lower utility.

B. Literature review

An interesting paper by Louwenstein [13] sets out reasons why the actual behaviour of climbers may lie outside the explanatory power of utility theory. Despite this allegation, several papers have applied random utility demand models to climbing. Shaw and Jakus [19] estimate demand models based on a survey of members of the Mohonk Preserve in New York State in 1993. A site choice model based on choices between four sites (Mohonk, Ragged Mountain, the Adirondacks and the White Mountains) was estimated, using two site attributes: (i) travel costs (from respondent's home); and (ii) the number of routes within each area which the respondent was technically able to climb. This was estimated jointly with a double-hurdle count model which controlled for the participation decision (whether to go climbing at all), in addition to the decision as to how many trips to make to Mohonk, given a decision to climb. Estimates from these models were then used to produce consumer surplus figures for changes in climbing opportunities at Mohonk. Hanley et al [6] use a standard multinomial logit model of rock-climbers in Scotland combined with a count model, to look at the determinants of both site choice and participation. Hanley, Alvarez-Farizo and Shaw [7] use a similar data set to estimate a repeated nested logit model of site choice and participation.

In the US, Cavlovic et al [2] report results from a national repeated nested random utility model of climbers, which estimates the welfare losses associated with closing access to certain sites on Forest Service lands. Principal attributes governing site choice were the number of rock climbing areas in a region and climate. Results showed that proposed changes had welfare losses in excess of $100million per annum. In a similar context, Cavlovic and Berrens [1] carried out a climbing participation study of 1,084 members of the general public. They found that gender, education and membership in environmental organizations were all significantly related to participation in 1998, although income was not. Finally, in a somewhat different vein, Jakus and Shaw [9] analyzed the response of climbers to hazard warnings relating to the degree of protection on routes. They found that more skillful climbers were more likely to undertake hazardous climbs than less-skillful climbers, but that they "mitigate the likelihood of a hazardous outcome by reducing the technical difficulty of the hazardous route chosen" (page 581). Their empirical results add to the support for an underlying economic rationale behind climber decision-making.

This paper contributes to this literature by using a new econometric approach to estimate changes in per-trip welfare for a range of management alternatives at popular climbing sites in Scotland. In what follows, section 2 outlines the econometric approach taken and the reasons for choosing it. Section 3 describes the sample collection procedures and sample characteristics. Results are presented in section 4 and then some conclusions close the paper.

ECONOMETRIC APPROACH

A. Background

A conventional recreation site choice model is the random utility model (RUM) of McFadden [16]. This model possesses useful properties for analyzing the site allocation problem because visitation data are discrete and the model can be used to estimate exact per-trip welfare measures for site quality changes. Here we consider that the i^{th} ($i=1, 2, \ldots, N$) individual's indirect utility for the j^{th} ($j=1, 2, \ldots, J$) site takes the linear form

$$U_{ij} = v_{ij} + \varepsilon_{ij} \tag{1}$$

where v_{ij} is parameterized to depend upon observed conditioning variables and ε_{ij} is an idiosyncratic term unknown to the observer. When the ε_{ij} are assumed independently and identically distributed as generalized extreme value variates, the probability of selecting site j is generated as

$$\pi_{ij} = \exp(v_{ij}) / \sum_{k=1}^{J} \exp(v_{ik}) . \tag{2}$$

Further, expected maximum utility, $E\{\max[v_{i1} + \varepsilon_{i1}, v_{i2} + \varepsilon_{i2}, \ldots, v_{iJ} + \varepsilon_{iJ}]\}$, has a simple closed form expression which may be evaluated if the v_{ij} terms are known or estimated.

The multinomial or, perhaps more precisely, the conditional logit model (see Greene [4] for the somewhat arbitrary distinction) is customarily used to estimate the parameters of v_{ij}. Specifically let y_{nj} denote the number of trips for the i^{th} (i=1, 2, ..., N) individual to the j^{th} unique site. Let $Y_i = \sum_{j=1}^{J} y_{ij}$ denote aggregate trips for the i^{th} individual to all the sites of interest. Now suppressing the i^{th} individual's index, if the $y_1, y_2, \ldots, y_J$ are independently distributed as Poisson, i.e. $y_j \sim Po(\mu_j)$, then these results follow:

i) Y is distributed $Po(\mu = \Sigma\mu_j)$

ii) $$P(Y_1 = y_1, Y_2 = y_2, \ldots, Y_J = y_J | Y) = \prod_{j=1}^{J} \mu_j^{y_j} e^{-\mu_j} (y_j!)^{-1} \Big/ \mu^{Y} e^{-\mu} (Y!)^{-1}$$

$$= \frac{Y!}{y_1! y_2! \ldots y_J!} \left(\frac{\mu_1}{\mu}\right)^{y_1} \left(\frac{\mu_2}{\mu}\right)^{y_2} \ldots \left(\frac{\mu_J}{\mu}\right)^{y_J}$$

$$Mn(y|\pi, Y) = \frac{Y!}{y_1! y_2! \ldots y_J!} \pi_1^{y_1} \pi_2^{y_2} \ldots \pi_J^{y_J}; \quad \text{where } \pi_j = \mu_j/\mu$$

iii) The independent, non-negative, integer valued variables $y_1, y_2, \ldots, y_J$ have Poisson distributions if and only if the conditional distribution of these variables for the fixed sum $\sum y_j = Y$ is a multinomial distribution (Johnson et al., [11]).

Result i) follows from the reproductive property of the Poisson distribution (Johnson et al., [10]). Result ii) explicitly links the multinomial distribution, denoted as Mn(.), to a conditional multivariate distribution of independent Poisson variates. Result iii) provides the converse of the result in ii), namely that a multinomial distribution implies Poisson distributions for the components of Y. Yet if the $P(Y_j)$ are not exactly distributed as $Po(\mu_j)$, then there can be no claim that the conditional distribution is indeed multinomial. In other words, the multinomial specification imposes stringent requirements on the underlying data. While travel cost modelers of recreation demand who attempt to model either the number of visits to a single site, y_j, or aggregate visits to closely related sites, Y, routinely consider alternatives to the Poisson distribution in the event of over-dispersion or excess zeros, random utility modelers rarely concern themselves with such possible distributional misspecifications.

Pearson's χ^2 statistic (McCullagh and Nelder, [15]) can be used to assess the presence of distributional misspecification. The test statistic has the form

$$X^2 = \sum_{ij} (y_{ij} - E(y_{ij}))^2 / V(y_{ij}) . \tag{3}$$

For the multinomial model the summation is over all individuals and all alternatives, where $E(y_{ij} \mid Y_i) = Y_i \hat{\pi}_{ij}$ and $V(y_{ij} \mid Y_i) = Y_i(\hat{\pi}_{ij} - \hat{\pi}_{ij}^2)$. Under the null hypothesis of proper specification, the test statistic is asymptotically distributed as χ^2 with $N(J-1)-K$ degrees of freedom. Here K represents the number of estimated parameters. Unfortunately, rejection of the null may leave the random utility modeler with no known alternatives to the multinomial model.

Fortunately the multinomial distribution is a member of the linear exponential family of probability density functions and as such can provide consistent estimators of the conditional means of the y_j even though the true distribution of the data is not multinomial (Gourieroux et al.,[3]). Under this misspecified maximum likelihood approach, termed pseudo- or quasi-maximum likelihood, standard errors of estimated parameters may be consistently estimated using the robust or sandwich method (White [20]; Gourieroux et al.[3]). So in lieu of having the estimated multinomial logit model pass a specification test, random utility modelers can be assured of conducting proper inference if robust standard errors are calculated for the estimated parameters. A drawback to this procedure is that the modeler sacrifices efficiency by not addressing the distributional misspecification. In general this will result in less precisely estimated parameters and may potentially affect the statistical significance of calculated welfare measures.

B. The Dirichlet Multinomial Distribution

Random utility modelers may be unaware that there are alternatives to the multinomial logit model which can accommodate distributional violations such as over-dispersion of the visitation data. Recall this may be a problem if the units of observation (individuals or zones of origin) display multiple trips to one or more sites since these trip counts are required to be Poisson distributed under the multinomial distribution. We consider the Dirichlet multinomial (Dm) model which was first derived by Mosimann [17], although in a somewhat restrictive form. More recently the distribution has been presented in an empirical Bayes framework (Leonard and Hsu [12] ; Lwin and Maritz [14]). Below we outline its derivation and comment on several of its interesting properties. In the subsequent development note that the observational index, i, has been suppressed.

Let $y_1, y_2, \ldots, y_J$ possess a multinomial distribution ($\Sigma y_j = Y$) with corresponding cell probabilities $\pi_1, \pi_2, \ldots, \pi_J$ and define the J-1 dimensional unit simplex $S_U = \{(\pi_1, \pi_2, \ldots, \pi_J): \pi_j > 0, \Sigma\pi_j = 1\}$. Now assume that the prior distribution of $\pi_1, \pi_2, \ldots, \pi_J$ is Dirichlet with parameters $\alpha\theta_1, \alpha\theta_2, \ldots, \alpha\theta_J$ ($\theta \in S_U, \alpha > 0$). This prior distribution is chosen since it is a conjugate prior for the multinomial distribution and is written as:

$$f(\pi|\alpha, \theta) = \frac{\Gamma(\alpha)}{\prod_{j=1}^{J}\Gamma(\alpha\theta_j)}\prod_{j=1}^{J}\pi_j^{\alpha\theta_j-1}.$$

Now the joint distribution of $y_1, y_2, \ldots, y_J$ is obtained by integrating out the π_j. That is we wish to evaluate

$$\int\int\ldots\int_{S_U}\frac{Y!}{\prod y_j!}\prod\pi_j^{y_j}\frac{\Gamma(\alpha)}{\prod_{j=1}^{J}\Gamma(\alpha\theta_j)}\prod_{j=1}^{J}\pi_j^{\alpha\theta_j-1}d\pi.$$

This results in the Dirichlet multinomial distribution which has probability mass function

$$p(y|\alpha, \theta, Y) = \frac{Y!\,\Gamma(\alpha)/\Gamma(Y+\alpha)}{\prod\{y_j!\Gamma(\alpha\theta_j)\}}\prod\Gamma(y_j+\alpha\theta_j); \quad \text{such that } \theta\in S_U, \alpha > 0. \qquad (4)$$

By specifying a Dirichlet prior for the multinomial probabilities an additional parameter, α, has been introduced. The θ_j, like the multinomial π_j, may be interpreted as probabilities. The relationship between the first two central moments of the two multivariate discrete distributions makes this evident.

Moment	Multinomial	Dirichlet Multinomial
$E(y_j\|Y)$	$Y\pi_j$	$Y\theta_j$
$Var(y_j\|Y)$	$Y(\pi_j - \pi_j^2)$	$\rho Y(\theta_j - \theta_j^2)$
$Cov(y_j y_k\|Y)$	$-Y\pi_j\pi_k$	$-\rho Y\theta_j\theta_k$

Here $\rho=(Y + \alpha)/(1 + \alpha)$ and, since it is strictly greater than zero, this factor provides for over dispersion of the conditional variances and covariances of the y_j. Thus the larger the value of ρ (or the smaller the value of α), the more diverse is the sample from what would be expected under multinomial sampling (Wilson, [22]). Note that as $\alpha \to \infty$, $\rho \to 1$ and consequently the moments converge in this case. In fact it can be shown that as $\alpha \to \infty$, then $p(y \mid \alpha, \theta, Y) \to \frac{Y!}{\prod y_j!} \prod \theta_j^{y_j}$, that is the Dm distribution converges to the multinomial distribution as the α parameter goes to positive infinity.

This result can be exploited to construct a test of the multinomial versus the Dm distribution. Simply define $\gamma = 1/\alpha$ and maximize the log likelihood over the N observation sample. For the ith individual the log likelihood is

$$\ell_i = \ln(Y_i!) + \ln\Gamma(\gamma^{-1}) - \ln\Gamma(Y_i + \gamma^{-1}) + \sum_{j=1}^{J} \{\ln\Gamma(y_{ij} + \gamma^{-1}\theta_{ij}) - \ln\Gamma(\gamma^{-1}\theta_{ij}) - \ln(y_{ij}!)\}. \quad (5)$$

Maximizing $\sum \ell_i$ should in principle be no more computationally demanding than estimating a negative binomial regression model. Upon convergence, a test of $\gamma = 0$ can then be conducted. Failure to reject this hypothesis would suggest that the underlying data generating mechanism was the multinomial distribution.

Finally the empirical Bayes derivation of the Dm distribution permits a posterior analysis. Given the prior density of π, $f(\pi|\alpha, \theta)$, and the Dirichlet-multinomial distribution of $\mathbf{y}$, $p(\mathbf{y}|\alpha, \theta, Y)$, which can be used to identify θ, then the posterior density of π is $Mn(\mathbf{y}|\pi, Y)f(\pi|\alpha, \theta)/p(\mathbf{y}|\alpha, \theta, Y)$ or specifically

$$f^*(\pi|\alpha, \theta, y) = \frac{\Gamma(\alpha + Y)}{\prod_{j=1}^{J} \Gamma(\alpha\theta_j + y_j)} \prod_{j=1}^{J} \pi_j^{\alpha\theta_j + y_j - 1}.$$

The posterior mean of π_j is $\pi_j^* = \frac{y_j + \alpha\theta_j}{Y + \alpha}$. (6)

This expression makes explicit how observed behavior and estimators determined by the data affect the magnitude of the posterior probabilities. Also note that as $\alpha \to \infty$ the posterior mean, π_j^*, converges to the probability θ_j, showing that the information incorporated in the prior distribution is uninformative. We now outline the procedure by which data were collected to estimate the Dirichlet multinomial model.

SAMPLE COLLECTION PROCEDURE AND SAMPLE CHARACTERISTICS

A. Sample collection procedure

The initial steps in the empirical part of this study were to identify the appropriate choice set for Scottish climbers and to check on relevant attributes to describe these choices. To accomplish this, focus groups were conducted with climbers from university mountaineering clubs in Edinburgh and Stirling. In terms of the choice set, eight principal climbing areas were identified. These were the Northern Highlands, Creag Meagaidh, Ben Nevis (including Glen Nevis), Glen Coe (including Glen Etive), the Isle of Arran, Arrochar, the Cullins of Skye and the Cairngorms. This meant we excluded some more minor climbing locations such as sea cliffs and lowland quarries and outcrops. The focus groups identified travelling costs and approach time to the crags from the road as relevant attributes in deciding where to visit on any given occasion.

The sampling frame was provided by the Mountaineering Council of Scotland through a list of climbing club members in Scotland. A random sample of addresses was selected and questionnaires mailed to these individuals, who were asked to complete and return the questionnaire. A donation of £2 was promised to the John Muir Trust (a charity which exists to conserve wilderness areas in Scotland) for every questionnaire returned as an incentive. To widen the sample in terms of representativeness, questionnaires were also administered at indoor climbing walls in Edinburgh, Glasgow and Falkirk (many climbers do not belong to official mountaineering clubs). One major problem which became apparent with the sampling frame was that we had no way of identifying which members of a given mountaineering club were actually rock climbers and which were just hill walkers. This resulted in a very large number of questionnaires being returned by hill-walkers. Since many of the questions did not apply to them, thus a number of additional mail-outs became necessary. Nevertheless, a sample of 267 useable responses from climbers was eventually acquired of which 245 surveys had sufficient detail to permit estimation.

Climbers were asked questions relating to their total trips in the last twelve months (both summer and winter) to each of the 8 climbing areas noted above; to evaluate each area in terms of the access time attribute; to provide us with their post code (zip code) so that distance from home to sites could be computed; to provide information on spending related to rock-climbing; to provide information on their climbing abilities and experience; and finally, to provide us with standard socio-economic information. Trip lengths to the sites were computed by the authors using Autoroute (travel distance from home). Travel distance was converted into travel costs using a per-mile cost of 10 pence, which reflects the marginal (petrol) cost of motoring. For the two sites that can only be accessed by ferry (Arran and the Cullins), round trip travel costs were augmented by the appropriate fares.

B. Descriptive statistics for the sample

Some 55% of all climbers questioned were in the 25-40 years age bracket, which exhibited twice as many climbers as in any other age group. 19% and 24% of climbers were in the age brackets under 25 years and 41-55 years respectively. Only 2% of climbers were aged over 55 years. The majority of those responding were male (79%). 55% of the sample were single, whilst 29% of those interviewed had children. The majority of climbers (71%) were university degree holders with a further 16% having completed a certificate or diploma. The mean household income before tax was £27,111, which is considerably in excess of the Scottish mean. Climbers in the sample were thus high income and highly-educated on average.

Over 58% of climbers had been climbing for 10 years or less, with another 28% stating that they had been climbing for between 10 and 20 years. In terms of participation, 36% of all respondents completed 25 climbs or less in a year, with the next largest group of 31% of respondents completing from 26 to 50 climbs. Overall the mean number of climbs completed per year (any given year) was 57, with the median at 40 and mode at 100 climbs. Since more than one route is typically climbed per trip, mean trips were much lower at 14.2 per year, with the average length of trip being just over one day in duration. Climbers claiming more than 99 trips per annum were dropped from the data set prior to estimation as there was concern that their activities were business related rather than recreational.

RESULTS

A. Estimation

Table I presents the estimation results for the conditional logit model fit to the data on eight sites and representing 245 individuals. Travel cost and access times both have the expected negative coefficients. Additionally site specific dummy variables were added to account for unobserved differences between the sites. Evidence of misspecification is manifested both by the substantial differences in the robust and conventional standard errors for the cost coefficient and by Pearson's specification test (p=.0000). As a consequence the Dm distribution was adopted and these estimation results appear in Table II.

Here we see that now conventional and robust standard errors correspond more closely and that the payoff to the more efficient estimator is smaller robust standard errors for the parameters of interest. Pearson's test does not reject the null of proper specification at standard levels of statistical significance (p=.2534). A robust Wald test of the null hypothesis that $1/\alpha=0$ (implicitly that $\alpha=\infty$) yields a test statistic of 73.6 (p=.0000). Further investigation of the precision of the robust standard errors in both models was performed by comparing them to those obtained by bootstrap methods. Results (available from the authors) indicated a very close correspondence. Thus we conclude that there is significant over-dispersion (relative to the multinomial) and that the Dm probability mass function is appropriate for these data.

B. Welfare Analysis

Following the approach of Hanemann [5], write the systematic component of indirect utility for site j when the individual specific index is suppressed as

$v_j = \beta p_j + h(\mathbf{q}_j)$

where p_j is travel cost and $\mathbf{q}_j$ is a vector of site-specific attributes. In this no income effects model consumers surplus is

$C = -1/\beta[V(\mathbf{p}^1, \mathbf{q}^1) - V(\mathbf{p}^0, \mathbf{q}^0)]$; where $V = E\{\max[v_1 + \varepsilon_1, v_2 + \varepsilon_2, \ldots, v_J + \varepsilon_J]\}$.

For the Dirichlet multinomial model when the θ_j are expressly parameterized as

$$\theta_j = \exp(v_j) / \sum_{k=1}^{J} \exp(v_k), \text{ then } V = \ln \sum_{k=1}^{J} \exp(v_k) + .577215665 .$$

Thus welfare analysis follows the same methodology as for the conditional logit model. Welfare measures for a number of changes in entry fees and approach times are presented in Table III. The welfare measures from the Dirichlet multinomial model are generally about five to fifteen percent larger than their conditional logit counterparts. Also the bootstrapped standard errors and confidence intervals almost uniformly show that the Dm based welfare measures are estimated as precisely or more precisely than those from the conditional logit approach.

The results in Table III stem from considering possible strategies for limiting access at three of the four most popular climbing sites in Scotland. Site 3 (Ben Nevis) accounts for 11% of the trips in our sample. Here parking/entry fees are being considered as a means for reducing visitation rates and providing improved parking facilities. We see that the introduction of £3 and £5 fees reduces per trip surplus by £0.37 and £0.59, respectively. This is about half the impact such fees generate at site 4 (Glencoe) due to the fact that it is a more popular destination accounting for about 22% of all trips. Also being considered at site 4 is the re-routing of paths to the crags in order to reduce erosion and wildlife disruption. An hour increase in approach time is revealed to be an important disamenity. A further increase of approach time to two hours at the most popular site,

site 8 (Cairngorms) with 25% of all trips, reveals a per trip reduction in consumer surplus of over £4. Such large reductions in welfare document rock climbers' aversion to long access routes and suggest a strategy for reducing congestion at popular areas.

An additional welfare measure is also available under the empirical Bayes derivation of the Dm model. That is, welfare analysis can be based on both the estimated parameters (using the behavior of all individuals) and each individual's observed behavior. This we term a posteriori welfare analysis, and its derivation obviously differs from the classical approach above since it is conditioned by individual-specific outcomes. Again following Hanemann's no income effects case, the surplus from a change in a single site, v_j, has the form

$$C^* = -1/\gamma \int_{v_j^0}^{v_j^1} \pi_j(v_1, \ldots, v_J)dv_j = -1/\gamma \int_{v_j^0}^{v_j^1} \int_{S_U} \ldots \int \pi_j f^*(\pi \mid \alpha, \theta, y) d\pi dv_j$$

In this case $C^* = \frac{1}{Y+\alpha}\left\{ -\beta^{-1} y_j v_j \right]_{v_j^0}^{v_j^1} + \alpha C \Big\}$; where $C = -1/\beta[V(\mathbf{p}^1, \mathbf{q}^1) - V(\mathbf{p}^0, \mathbf{q}^0)]$ as before. Notice that C^* explicitly depends on both the individual's trips to site j as well as total trips to all sites—this is a consequence of the posterior analysis. Additionally note that as $\alpha \to \infty$, then $C^* \to C$ as would be expected.

To illustrate the consequences of using the posterior distribution to perform welfare analysis, we consider the implications of (arbitrary) price changes at the least visited site (Arran) and the most visited site (Cairngorms). The first part of Table IV provides descriptive statistics for these two sites. Next, consumers' surplus measures are given for large price changes. Note that the classical welfare measures indicate that for large enough price changes visitation is forced to zero so that further price increases do not affect the subsequent welfare values: for example, for Cairngorms, the fact that visits fall to zero beyond an entry fee of £200 means that increasing it further has no welfare cost. On the other hand, since the posterior welfare measures take into account observed levels of visitation, welfare losses increase without bound. The feature that past behavior is invariant to amenity or price changes is not necessarily attractive or even defensible.

However, for traditional surplus measures the feature that relative modest price changes can drive visitation at a site to zero may not be very realistic, since many committed and wealthy climbers may continue to climb at good sites even if costs increase substantially.

CONCLUSIONS

This paper has applied a new method of analyzing site choice data within a random utility framework to rock-climbing in Scotland. We find that increasing approach times to the crags by re-routing paths to reduce erosion and wildlife disruption may provide the additional benefit of reducing visitation. Apparently rock climbers view longer approaches as a substantial disamenity. The introduction of modest parking/entry fees does not appear to impact welfare nearly to the same extent if the results from site 4 are at all representative. Here the welfare loss from increasing the approach time by an hour is more than twice the loss from imposing a £5 entry fee.

The Dirichlet multinomial (Dm) approach proved to be a superior approach to standard conditional logit modeling in this case, in terms of potential misspecification, in the precision of parameter estimates, and in (generally) tighter confidence intervals for mean consumers' surplus. While the current application of the Dm distribution suggests its relative superiority to the customary conditional logit model, other potential uses may also prove its value. Certainly the over-dispersion parameter, α, could be parameterized to depend on a set of conditioning variables—the only constraint being that it be greater than zero. This might be useful if sampling variability can be linked to individual-specific traits. Another possible extension is in pooling random utility models. In this case the dispersion parameter might vary across data sets. Or if pooling revealed and stated preference data, it might be of interest to investigate whether the dispersion parameter varies between observed and hypothetical behavior.

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Table I.
Maximum Likelihood Results for Conditional Logit Model (N=245)

Variable	Coefficient	StdErr(R)[a]	t-value(R)	StdErr(H)[b]
Cost	-0.0578	0.0062	-9.3133	0.0025
Access	-0.0093	0.0016	-5.9682	0.0011
Site1	0.5585	0.1686	3.3134	0.0612
Site2	-1.4984	0.1197	-12.5152	0.0960
Site6	-1.7092	0.1526	-11.2024	0.0808
Site7	0.8518	0.2039	4.1783	0.0971
Site8	0.4912	0.0920	5.3397	0.0430

Log likelihood value: -6120.59

Pearsons χ^2 statistic: 4249.2 (1708 degrees of freedom)

[a]Robust standard errors calculated as per White
[b]Conventional standard errors calculated from estimate of the Hessian matrix

Table II
Maximum Likelihood Estimates of the Dirichlet Multinomial Model (N=245)

Variable	Coefficient	StdErr(W)[a]	t-value(W)	StdErr(H)[b]
Cost	-0.0484	0.0041	-11.8816	0.0035
Access	-0.0094	0.0014	-6.6758	0.0018
Site1	0.2263	0.1156	1.9582	0.0990
Site2	-1.3707	0.1126	-12.1782	0.1319
Site6	-1.7078	0.1304	-13.0990	0.1254
Site7	0.6396	0.1485	4.3064	0.1357
Site8	0.3897	0.0765	5.0915	0.0698
$1/\alpha$	0.1051	0.0122	8.5782	0.0086

Log likelihood value: -5717.33

Pearson's χ^2 statistic: 1745.4 (1707 degrees of freedom)

[a]Robust standard errors calculated as per White
[b]Conventional standard errors calculated from estimate of the Hessian matrix

Table III
Welfare Measures in £. 200 Bootstrap Replications.

Site	Change	Conditional Logit Mean[a]	Conditional Logit 95% C.I.	Dirichlet Multinomial Logit Mean[a]	Dirichlet Multinomial Logit 95%C.I.
3	+3 Entry	-0.34 (0.02)	-0.39 -0.30	-0.37 (0.02)	-0.40 -0.33
3	+5 Entry	-0.54 (0.03)	-0.61 -0.48	-0.59 (0.03)	-0.65 -0.53
4	+3 Entry	-0.70 (0.03)	-0.77 -0.63	-0.72 (0.03)	-0.79 -0.66
4	+5 Entry	-1.11 (0.05)	-1.23 -1.01	-1.16 (0.05)	-1.27 -1.07
4	60' Approach	-2.00 (0.44)	-2.98 -1.24	-2.47 (0.46)	-3.37 -1.62
8	120' Approach	-3.70 (0.69)	-4.96 -2.47	-4.24 (0.61)	-5.52 -3.04
3&4 **4** **8**	+3 Entry 60' Approach 120' Approach	-7.25 (1.23)	-9.65 -5.04	-8.40 (1.17)	-11.06 -6.23
3&4 **4** **8**	+5 Entry 60' Approach 120' Approach	-7.90 (1.23)	-10.31 -5.68	-9.09 (1.16)	-11.74 -6.92

[a]Bootstrap standard errors in parentheses

Table IV
Closing Sites. Prices and Welfare Measures in £ .

Sample Values	Site 5 (Arran)	Site 8 (Cairngorms)
Average Trips	0.322	4.02
Average Price	60.41	23.83
Price Range	(44.06,105.62)	(2.54,86.02)

Consumers Surplus per Trip

	Site 5			Site 8		
ΔPrice	CL	DM	DMP	CL	DM	DMP
50	-0.39	-0.62	-0.96	-5.44	-5.88	-9.68
100	-0.41	-0.68	-1.60	-5.81	-6.50	-16.58
200	-0.41	-0.68	-2.83	-5.83	-6.57	-29.75
400	-0.41	-0.68	-5.29	-5.83	-6.57	-56.03

CL: Conditional logit
DM: Dirichlet multinomial logit
DMP: Dirichlet multinomial posterior

Valuing Time Onsite and in Travel in Recreation Demand Models

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Valuing Time Onsite and in Travel in Recreation Demand Models

Introduction

The separate roles of onsite time and travel time in determining recreation demand have been long recognized, as they represent two separate margins of quantity choice: a discrete margin associated with trips to gain access to recreation (travel time) and a continuous margin associated with consumption of recreation (time onsite). Early versions of the travel cost model (Clawson; Knetsch) distinguished the "site demand curve" from the first-stage participation demand curve, and noted the desirability of netting out the value of travel time from the value of the overall recreation experience, in order to isolate the value of the recreation site services, which are often the focus of policy questions. Yet there has been no generally satisfactory way of doing this in practice. Researchers commonly impose the assumption that the marginal utility of travel is zero in order to interpret the area under the demand for trips as the value of site services alone.

Such an assumption has often been required because studies focused only on one quantity margin of choice, trips taken.[1] As McConnell has noted, the spatial dependency of time onsite upon trips means that when zero trips are taken, zero days onsite necessarily result. (He termed this, together with its converse, "joint weak complementarity" of trips and days.) Thus raising the trips price to its choke level simultaneously reduces quantity consumed of both trips and time onsite to zero. As a result, the integral of the trips demand, from actual travel cost to the "choke" price for which trips are zero, necessarily calculates the value of the complete trip, which is a package consisting of both days onsite and travel to the site. Hence the need for an assumption about the marginal utility of travel in order to infer what the value of a site's services is.

Some recent papers have developed models of the choice of time onsite, either by itself (e.g., Bell and Leeworthy; Hof and King) or jointly with the choice of trips (e.g., McConnell; Larson). McConnell's joint choice model predicted the average time onsite per trip, like

Bell/Leeworthy and Hof/King, but also predicted the number of trips to the site. Larson's model instead predicts the total time per period (e.g., season) and trips, with the average time onsite determined implicitly as the ratio of the two.

Models that explain time onsite are attractive because, in principle, they can be integrated directly to obtain site value. However, the empirical papers which have attempted this approach are pessimistic about its prospects; for example, Hof and King note that limited variability in the dependent variable, among other factors, may make it difficult to estimate the onsite time demand equation with sufficient precision to generate reliable welfare measures.

This paper shows that earlier papers may have been overly pessimistic about the prospects for measuring recreation site values separately from travel time values, due to the form of the time onsite demand. Using a utility-theoretic model of recreationists' joint choices of trips and total days per season, we estimate statistically-significant trips and days demand for pink salmon fishing. The model generates separate estimates of the value of travel to the site (which is allowed to be positive or negative, depending on whether travel is viewed as a "good" or a "bad") and the value of time onsite (which is by definition a good), thereby avoiding the need for a tenuous assumption about the marginal value of travel time.

A second contribution of the paper is to characterize the demands for days onsite and for trips in a utility-theoretic, inverse demand system framework. The inverse demands approach is dual to the direct demands approach, and is just as appropriate for demand estimation as is the direct demand (quantity-dependent) approach, because it is consistent with the basic "story" of consumer choice of quantities in response to fixed and parametric prices. The distance function underlying the inverse demand approach proves especially convenient for evaluating the "provision-or-removal" welfare questions that are prevalent in the environmental economics literature. Because quantities are exogenous, the change in quantities can be evaluated directly in the distance function to obtain the compensating variation for provision or removal (or any other policy-induced quantity change). The distance function and associated implicit price relationships are developed using a generalized Leontief functional form, which accommodates corner solutions for quantities easily.

The Joint Trips-Days Recreation Choice Model

Consider an individual who allocates scarce time and money income in choosing consumption of goods which have both a marginal cost of consumption and a fixed cost of access. Recreation goods fit this description particularly well because of the spatial element: consumption typically takes place away from home. Other goods also have this characteristic, though the fixed cost component of consumption may be trivially small. The consumer must choose not only how much to consume of each good, but how many times to gain access to it, thereby also choosing the average duration of consumption.

With this in mind, let the consumer's utility function be $u(\mathbf{x},\mathbf{r},\mathrm{a},\mathbf{c})$, where $\mathbf{x}$ is a vector of recreation goods with corresponding prices $\mathbf{p}_x$, a is a numeraire good with unit price, and $\mathbf{c}$ is a vector of consumer characteristics. A related decision is how many times $\mathbf{r}$ to gain access to consumption, at access prices $\mathbf{p}_r$ which are travel costs in the recreation demand setting. Both price vectors $\mathbf{p}_x$ and $\mathbf{p}_r$ are, for our purposes, full prices with the time required for travel and onsite valued at the wage rate. While trips are assumed to be strictly an economic "good," with positive marginal utility, trips may be a good or a bad (i.e., a source of either utility or disutility), due to the spatial linkage with consumption on site. For some, travel might be a bad experience yielding disutility, but still would be undertaken because of the highly-enjoyable consumption of time onsite which it permits. For others, travel might be a good and valued in its own right.

It is useful to briefly describe the primal optimization problem, as it generates familiar expressions for interpreting marginal values in the model. This problem is

$$\max_{x,r} u(\mathbf{x},\mathbf{r},\mathrm{a},\mathbf{c}) + \lambda[\mathrm{M} - \mathbf{p}_x\mathbf{x} - \mathbf{p}_r\mathbf{r}] + \phi[\mathbf{r}^0 - \mathbf{r}] \tag{1}$$

where M is money income. It is assumed that interior solutions can be achieved for the choice of days onsite ($\mathbf{x}$), which is the set of goods primarily motivating the analysis. To allow for negative marginal utility of travel, we recognize that the choice of trips may not be at a first-best interior solution, due to the spatial dependency of valued days onsite upon trips taken, and therefore, the marginal value of the incremental trip may not equal its marginal cost. This is represented by a constraint on trips to specific sites, given by $\mathbf{r}^0$, and the corresponding vector of shadow values $\boldsymbol{\phi}$, which can have either sign depending on whether $\mathbf{r}^0$ is a lower or upper bound. The first order conditions for this problem are

$$u_{x_i} - \lambda \mathrm{p}_{x_i} = 0 \tag{2}$$

and

$$u_{r_i} - \lambda \mathrm{p}_{r_i} - \phi_i = 0 \tag{3}$$

and (2) and (3) can also be rearranged as equalities relating marginal value to marginal cost:

$$\frac{u_{x_i}}{\lambda} = \mathrm{p}_{x_i} \tag{4}$$

and

$$\frac{u_{r_i}}{\lambda} = \mathrm{p}_{r_i} + \phi_i/\lambda \tag{5}$$

The left sides of (4) and (5) are the consumer's marginal money valuations of days onsite (u_{x_i}/λ) and of trips (u_{r_i}/λ), while the right sides are the marginal costs of each. The marginal utility of money, λ, is assumed strictly positive, while ϕ may have either sign. Equation (4) just says that days onsite per period (e.g., season or year) will be chosen so that its marginal value equals the marginal (money plus time) cost. In equation (5), ϕ_i is a "wedge" between marginal value and marginal cost if trips to site i are not chosen freely of their own right. If $\phi_i > 0$, r_i^0 is an upper constraint on trips chosen and the marginal utility of travel exceeds its marginal cost.

If, on the other hand, $\phi_i < 0$, r_i^0 is a lower constraint and the marginal trip is valued at less than its marginal (money plus time) costs. We would expect this case to be more likely based on the supposition that the marginal value of travel is less than its cost, but is undertaken nevertheless to make the consumption of days onsite possible.

The choice of both total quantity of consumption x_i and the number of trips r_i implicitly defines the average duration of consumption, or average length of a trip d_i/r_i to site i. A change in number of trips, *ceteris paribus*, potentially affects utility in two ways: through its effect on total time spent traveling, which is a source of (dis)utility directly, and through its effect on trip length, changing the utility derived from a given number of total days onsite.

Using Inverse Demands to Characterize Quantity Choice with Fixed Prices

The basic paradigm of consumers choosing quantities in response to fixed prices can be used to motivate either a direct or inverse demands approach to estimation. To motivate the inverse demands approach, note that changes in quantity consumed affect a consumer's marginal valuation of each good, which is its implicit price. Thus associated with every consumption vector is a corresponding vector of implicit prices (implicit price functions, really). When the consumer is confronted with a set of actual market prices, s/he chooses the optimal quantity vector which maximize the net value or consumer surplus that is attainable at those prices. If choice is unconstrained, the best quantity vector will be the one for which the implicit prices just equal the actual prices.

The inverse demand approach identifies the determinants of the implicit price functions that are used in the consumer's quantity choice. Quantities are chosen in response to fixed prices, by comparing the implicit prices associated with each quantity vector to the actual market prices. The causality is the same as with estimating demands, but the mechanism for quantity choice is simply articulated as a comparison of virtual to actual prices.

The reason for characterizing the consumer's demands in inverse form is that the underlying distance function is convenient when working with empirical models that seek provision-or-removal welfare measures, which involve setting consumption to zero. In the usual, direct demand approach, where prices and budget are exogenous, this requires calculating a "choke price" that implicitly drives quantity consumed to zero. Several problems can arise, including the fact that choke prices may not be analytic, and they may be very imprecise because they are forecasts out of sample. With inverse demand approaches, quantities are independent so that zero quantities can be evaluated directly.

The Conceptual Model

With these considerations in mind, let D(**x**,**r**,a,**c**,u) be the consumer's distance function, defined as

$$D(\mathbf{x},\mathbf{r},a,\mathbf{c},u) \equiv \max_t \{t > 0 : u(\mathbf{x}/t,\mathbf{r}/t,a/t,\mathbf{c}) > u\}, \tag{6}$$

which is increasing, homogeneous of degree 1, and concave in **x** and a, and decreasing in u (Deaton and Muellbauer; Deaton; Kim).[2] The solution to (6) defines the normalized implicit prices $p^*_{x_i}(\mathbf{x},\mathbf{r},a,\mathbf{c},u) = p_{x_i}(\mathbf{x},\mathbf{r},a,\mathbf{c},u)/M$ and $p^*_{r_i}(\mathbf{x},\mathbf{r},a,\mathbf{c},u) = p_{r_i}(\mathbf{x},\mathbf{r},a,\mathbf{c},u)/M$, i=1,...,n, of all goods, where $p_j(x,r,a,\mathbf{c},u)$ is the implicit price of good j and M is the consumer's income. By the envelope theorem, the logarithmic quantity derivatives of the distance function are

$$\begin{aligned}\partial D(\mathbf{x},\mathbf{r},a,\mathbf{c},u)/\partial \ln(x_i) &= x_i \cdot p^*_{x_i}(\mathbf{x},\mathbf{r},a,\mathbf{c},u), \quad i = 1,\ldots,n\\ &= s^*_{x_i}\end{aligned}$$

$$\begin{aligned}\partial D(\mathbf{x},\mathbf{r},a,\mathbf{c},u)/\partial \ln(r_i) &= r_i \cdot p^*_{r_i}(\mathbf{x},\mathbf{r},a,\mathbf{c},u) \quad i = 1,\ldots,n\\ &= s^*_{r_i}\end{aligned}$$

and

$$\partial D(\mathbf{x},\mathbf{r},a,\mathbf{c},u)/\partial \ln(a) = a \cdot p_a^*(\mathbf{x},\mathbf{r},a,\mathbf{c},u)$$
$$= s_a^*$$

where $s_{x_i}^*$, $s_{r_i}^*$, and s_a^* are the implicit normalized budget shares of x_i, r_i, and a. Net value of consumption is maximized for the consumer by choosing consumption quantities for **x** and a such that implicit prices for all goods equal the actual (normalized) prices faced, or equivalently, implicit budget shares equal actual budget shares.[3] For trips **r**, the possibility of disequilibrium leads to a first-order condition equating the marginal value of trips to a fraction of the marginal cost determined by the magnitude of the shadow value.[4] Thus, appending an additive error to reflect errors in measurement and observation of the relevant influences on implicit prices, and substituting in the direct utility function to remove the unobservable utility term, a set of budget share estimating equations are

$$s_{x_i} = x_i \cdot p_{x_i}^*(\mathbf{x},\mathbf{r},a,\mathbf{c},u(\mathbf{x},\mathbf{r},a,\mathbf{c})) + \epsilon_{x_i}, \qquad i = 1,\ldots,n \tag{7}$$

$$s_{r_i}(1-\phi_i) = r_i \cdot p_{r_i}^*(\mathbf{x},\mathbf{r},a,\mathbf{c},u(\mathbf{x},\mathbf{r},a,\mathbf{c})) + \epsilon_{r_i}, i = 1,\ldots,n \tag{8}$$

and

$$s_a = a \cdot p_a^*(\mathbf{x},\mathbf{r},a,\mathbf{c},u(\mathbf{x},\mathbf{r},a,\mathbf{c})) + \epsilon_a, \tag{9}$$

where $s_{x_i} = x_i \cdot p_{x_i}/M$, $s_{r_i} = r_i \cdot p_{r_i}/M$, and $s_a = a \cdot 1/M$ are the actual budget shares of each consumption good. This defines a 2n+1-good system of budget shares for days onsite and trips to n sites, and the numeraire good.

An Empirical Model

In implementing the distance function model empirically, we focus on the interaction between trips and days for recreation at a single recreation site. Since n = 1 in equations (2)-

(4) above, this defines a three good inverse demand system. Using a generalized Leontief form, the distance function in this case is

$$D(x,r,a,\mathbf{c},u) = \Big\{\gamma_x \cdot x + \gamma_r \cdot r + \gamma_a \cdot a + \gamma_{rx} \cdot (r \cdot x)^{0.5} + \gamma_{ar} \cdot (a \cdot r)^{0.5}$$

$$+ \gamma_{ax} \cdot (a \cdot x)^{0.5} + \sum_j (\gamma_{jx} \cdot x + \gamma_{jr} \cdot r) \cdot c_j\Big\} \cdot u^{-1}. \tag{10}$$

The systematic parts of the associated Hicksian implicit budget shares are

$$s_x^*(x,r,a,\mathbf{c},u) = \partial D(x,r,a,\mathbf{c},u)/\partial \ln(x)$$

$$= \Big\{\gamma_x \cdot x + 0.5 \cdot \gamma_{rx} \cdot (r \cdot x)^{0.5} + 0.5 \cdot \gamma_{ax} \cdot (a \cdot x)^{0.5} + \sum_j \gamma_{jx} \cdot x \cdot c_j\Big\} \cdot u^{-1} \tag{11}$$

$$s_r^*(x,r,a,\mathbf{c},u) = \partial D(x,r,a,\mathbf{c},u)/\partial \ln(r)$$

$$= \Big\{\gamma_r \cdot r + 0.5 \cdot \gamma_{rx} \cdot (r \cdot x)^{0.5} + 0.5 \cdot \gamma_{ar} \cdot (a \cdot r)^{0.5} + \sum_j \gamma_{jr} \cdot r \cdot c_j\Big\} \cdot u^{-1} \tag{12}$$

and

$$s_a^*(x,r,a,\mathbf{c},u) = \partial D(x,r,a,\mathbf{c},u)/\partial \ln(a)$$

$$= \Big\{\gamma_a \cdot a + 0.5 \cdot \gamma_{ar} \cdot (a \cdot r)^{0.5} + 0.5 \cdot \gamma_{ax} \cdot (a \cdot x)^{0.5}\Big\} \cdot u^{-1}. \tag{13}$$

The utility index is identified from the condition that $D(x,r,a,\mathbf{c},u(x,r,a,\mathbf{c})) = 1$ in (10); that is, that the distance function equals 1 when the utility index chosen is that given by the direct utility function evaluated at a given set of quantities. Thus,

$$u(\text{x,r,a,}\mathbf{c}) = \gamma_x \cdot \text{x} + \gamma_r \cdot \text{r} + \gamma_a \cdot \text{a} + \gamma_{rx} \cdot (\text{r} \cdot \text{x})^{0.5} + \gamma_{ar} \cdot (\text{a} \cdot \text{r})^{0.5}$$

$$+ \gamma_{ax} \cdot (\text{a} \cdot \text{x})^{0.5} + \sum_j (\gamma_{jx} \cdot \text{x} + \gamma_{jr} \cdot \text{r}) \cdot \text{c}_j, \qquad (14)$$

which can be substituted for the utility terms in (7)-(9) and (11)-(13). If the numerator terms in these equations (i.e., all the non-utility terms) are denoted N_x, N_r, and N_a, respectively, then $u = \text{N}_x + \text{N}_r + \text{N}_a$, and the Marshallian implicit share system is

$$s_x^* = \text{N}_x/(\text{N}_x + \text{N}_r + \text{N}_a)$$

$$s_r^* = \text{N}_r/(\text{N}_x + \text{N}_r + \text{N}_a)$$

and $$s_a^* = \text{N}_a/(\text{N}_x + \text{N}_r + \text{N}_a),$$

which exhibits a convenient symmetry.

The (Hicksian) implicit price functions are also of use in interpreting the coefficients of the econometric model. They are obtained by dividing each budget share in (11)-(13) by the corresponding own-quantity, so that

$$p_x^*(\text{x,r,a,c,u}) = \left\{\gamma_x + 0.5 \cdot \gamma_{rx} \cdot (\text{r/x})^{0.5} + 0.5 \cdot \gamma_{ax} \cdot (\text{a/x})^{0.5} + \sum_j \gamma_{jx} \cdot \text{c}_j\right\} \cdot \text{u}^{-1} \qquad (15)$$

$$p_r^*(\text{x,r,a,c,u}) = \left\{\gamma_r + 0.5 \cdot \gamma_{rx} \cdot (\text{x/r})^{0.5} + 0.5 \cdot \gamma_{ar} \cdot (\text{a/r})^{0.5} + \sum_j \gamma_{jr} \cdot \text{c}_j\right\} \cdot \text{u}^{-1} \qquad (16)$$

and

$$p_a^*(\text{x,r,a,c,u}) = \left\{\gamma_a + 0.5 \cdot \gamma_{ar} \cdot (\text{r/a})^{0.5} + 0.5 \cdot \gamma_{ax} \cdot (\text{x/a})^{0.5}\right\} \cdot \text{u}^{-1}. \qquad (17)$$

The coefficients γ_x, γ_r, and γ_a are intercepts of the implicit prices of days, trips, and the numeraire, respectively, while the characteristics terms γ_{jx} and γ_{jr} are intercept shifters, and the cross-product terms γ_{rx}, γ_{ar}, and γ_{ax} are cross-quantity parameters that act as own-quantity slope shifters. The own-quantity slopes are not identified as a single parameter; instead, they are functions of the cross-quantity parameters; for example, for $p_x^*(\mathrm{x,r,a,c,u})$, the own-quantity slope is $\partial p_x^*(\mathrm{x,r,a,c,u})/\partial \mathrm{x} = -0.5 \cdot [\gamma_{rx} \cdot \mathrm{r}^{0.5} + \gamma_{ax} \cdot \mathrm{a}^{0.5}] \cdot \mathrm{x}^{-1.5}\mathrm{u}^{-1}$. As a parameter change leads to an increase in the implicit price function, an increase in own quantity is implied to maintain the equality of implicit price to actual price.

Data

The data used to illustrate the model are from a salmon fishery at Willow Creek, Alaska, and are described in some detail elsewhere (Larson, 1993). This fishery occurs during the summer months, and draws anglers seeking principally red, king, and pink salmon. Because Willow Creek is on the road system, it draws heavy use from the two major population centers in Southcentral and Central Alaska, Anchorage and Fairbanks. One feature of this fishery which is useful for present purposes is the fairly wide range of times spent on site. Generally, regulations governing camping permit stays of up to 14 days consecutively in a given site, and a small fraction of anglers visiting Willow Creek stay up to that length of time or even longer (which is possible by changing campsites). The mode of the distribution of length of stay on site is 1-2 days, however, reflecting substantial weekend and other shorter-period use. The variation in length of stay onsite means that the decisions about how many *days* of recreation at Willow Creek to consume and how many *trips* to take to the site are two distinct margins for consumer choice. Thus this fishery provides a useful case study for implementing the model of joint quantity choice empirically.

Data were available on the money and time cost of travel to Willow Creek, along with the money cost while onsite at Willow Creek and the total days of recreation taken at Willow

Creek during the year. Information was also available on the number of trips taken to the site, and a variety of consumer demographics, including income, household size, average hours worked per week, and the discretionary time budget, which is hours remaining after work. Anglers also provided estimates of their catch rates, in fish per day.

Descriptive statistics on the variables used in this analysis are given in Table 1. The prices and budgets used to construct normalized prices were full prices and full budgets, with time valued at the wage rate. The principal consumer characteristics **s** used were individual catch rates (both catch rate and catch rate squared were included) and household size. We would expect higher catch rates to increase the demand for time onsite, though its effect on the number of trips is unclear. Household size might well have an impact on demand for days and trips, in part because it helps explain differences in behavior of households with the same money income, though it could have any sign.

Results

The model in equations (7)-(9), with implicit budget shares and utility given by (11)-(13) and (14), was estimated via nonlinear least squares using GAUSS Version 3.2.25, and the results are reported in Table 2. From (11)-(14) and (15)-(17) and it can be seen that the implicit prices and budget shares are overparameterized, so the normalization that $\gamma_a = 1$ is used.

All but two of the own-and cross-quantity terms were significant at the 1% level, and these were significant at the 10% level. The shadow value ϕ was significant at the 1% level, with a coefficient of .34, indicating that trips choice was in disequilibrium with the implicit price (marginal value) of an additional trip equalling 66% of the actual price of trips. This provides empirical evidence in support of the hypothesis of a number of earlier writers that the marginal value of travel may be negative on balance.

The own-quantity terms are intercepts of the implicit price functions and all are positive and highly significant. The interaction terms between trips and the numeraire, days and the numeraire, and trips and days were all significant. Inclusion of the numeraire in the implicit budget system helps to account for differences in consumption of non-recreational fishing goods, as they influence the inverse demands for both days and trips. A higher level of other-goods consumption increases the implicit price of days and decreases the implicit price of trips, implying that individuals with higher other-goods consumption (and higher income) took more days and less trips (therefore longer trips).

Catch rates entered the model in a quadratic form, and they were also highly significant and showed opposite effects on the implicit prices of days and trips. The implicit price, or marginal value, of days onsite was increasing and convex in catch rate, while the implicit price of trips was decreasing and concave in catch rate. Thus higher catch rates cause people to take more days but fewer trips, with a longer average trip.

Overall, the model predicted actual budget shares fairly closely. The mean implicit share of days onsite, taken across all observations, was .0149 with a range of .0020-.2033, compared with a mean actual share of .0133 and a range from .0014 to .1816. The mean implicit share of trips was .0064, with a range of -.0002 to .1264; this is .66 of the actual mean share of .0097, consistent with the estimate of .34 for the shadow value in the trips equation. The negative predicted shares for a few individuals are a consequence of those individuals having negative marginal willingness to pay (or implicit prices) for travel. These individuals undertook travel anyway because of the positive marginal value of a trip overall, as was discussed above.

Measuring the Separate Values of Time Onsite and in Travel

In the distance function formulation, it is straightforward to evaluate the effects of provision or removal of goods from the consumer's choice set, because the appropriate quantities can be set directly to zero.[5] Given the empirical inverse demand system, the total value lost by the consumer associated with elimination of all of the recreation, including both days onsite and travel, is

$$\text{Total Value(Trips and Days)} = M \cdot \{D(0,0,u) - D(x_1^0,r_1^0,u)\} \tag{18}$$

which is the double integral of the inverse demand system over trips and days. From this must be subtracted the cost savings from not consuming recreation (i.e., the expenditures on trips and days not made), to obtain the net economic value, or compensating variation measure:

$$\text{CV(trips and days)} = M \cdot \{D(0,0,u) - D(x_1^0,r_1^0,u)\} - p_{r_1} r_1^0 - p_{x_1} x_1^0 \tag{19}$$

This welfare measure corresponds to what would typically be calculated in a direct demand system when trips are integrated from initial price to choke price. Because of the spatial linkage of days and trips, setting trips to zero also sets days to zero of necessity, so the welfare measure captures the value of both.

It is technically feasible to set days to zero without setting trips to zero, however; this would correspond to trips that consist only of travel and no time at any particular site along the route. In this case, the welfare measure evaluates the willingness to pay for time onsite at the current level of trips, for which the net economic value measure is

$$\text{CV(days)} = M \cdot \{D(0,r_1^0,u) - D(x_1^0,r_1^0,u)\} - p_{x_1} x_1^0 \tag{20}$$

and subtracting (14) from (13) identifies the value of travel separately from the value of time onsite:

$$\text{CV(trips)} = \text{CV(total)} - \text{CV(days)}$$

$$= \left[M \cdot \left\{D(0,0,u) - D(x_1^0,r_1^0,u)\right\} - p_{r_1} r_1^0 - p_{x_1} x_1^0\right] - \left[M \cdot \left\{D(0,r_1^0,u)\right.\right.$$

$$\left.\left. - D(x_1^0,r_1^0,u)\right\} - p_{x_1} x_1^0\right]$$

$$= M \cdot \left\{D(0,0,u) - D(0,r_1^0,u)\right\} - p_{r_1} r_1. \tag{21}$$

The welfare measures in (19) – (21) are a natural decomposition of the total value of recreation into the net value of current days and the net value of current trips. This decomposition is unique in the sense that the other path of integration to set current levels of days and trips to zero (trips first, then days) is technically infeasible. Corresponding to the three compensating variation or net economic value measures in (19)-(21), there are also three total value measures, for days, trips, and the sum of the two, shown in equation (18).

Table 3 provides estimates of these welfare measures. Interestingly, the total value of travel time was negative for 37 of the 201 individuals in the sample, consistent with the notion that travel time has negative marginal utility for some individuals and is therefore an economic "bad." For most in the sample, travel was an economic good, and overall the mean total value of travel time (trips) was $133 and the median was $93. This corresponds to total value calculated as the area under the inverse demand curve for trips. To obtain the consumer's surplus (compensating variation), the cost of the trips must be deducted.

For a large majority (171 of 201 individuals), the net value of travel time after deducting costs of travel (out-of-pocket expenses plus the opportunity cost of time) was negative. The mean net value of travel was -$143 with a median value of -$105. Since on average 3.8 trips were taken per year, and travel time per trip was roughly 3.1 hours, the mean figure represents a net cost of roughly -$12/hour of travel. Thus while travel had a positive total value for most in the sample, this positive value did not match the opportunity costs of the trip.

Days onsite had a positive total value (mean of \$848, median of \$719) and, after subtracting the total cost of days onsite, also had a positive net value or compensating variation (mean \$309, median \$361). The fact that higher net value of days onsite illustrates the motivation to undertake travel which itself has negative net value. Given the mean number of days onsite per year was roughly 6, the mean net value onsite was approximately \$52/day.

Considering both travel and time onsite together as the package that makes up recreation trips, the total value for trips as a whole had a mean of \$981 and a median of \$858 per year. After netting out the costs of travel and onsite, the net value of trips as a whole had a mean of \$166 and a median of \$240 per year. The mean represents per-unit values of roughly $\$166/3.8 \approx \$44$ per trip, or approximately $\$166/6 \approx \$28$ per day onsite.

The variety of ways in which it is possible to value the travel and onsite components of recreation trips raises some interesting issues for policy evaluation. Writers such as Clawson and Knetsch focused on the value of a site's services as distinguished from the utility or disutility of travel. When it is possible to value both time onsite and travel separately, one might argue that the mean net value of \$52/day onsite is the correct value to place on the intrinsic worth of the recreational services provided at the site. However, the spatial character of recreation consumption means that transactions costs to gain access must be paid in order to enjoy the site's services. Therefore, the lower value of \$28/day onsite, which includes the net travel costs, also has a justification rooted in the realities of gaining access to consumption, as it presumably more closely reflects individuals' net economic values after the trip as a whole.

Conclusion

This paper has empirically implemented a model of the joint choices of days and trips for a popular salmon fishing destination, Willow Creek, in Alaska. An inverse demand formulation is used because of the ease with which provision and removal of multiple goods from the consumer's choice set can be evaluated. The model of joint recreation choices is utility-theoretic, so is capable of generating Hicksian surplus measures for both days of recreation onsite and travel time. The empirical model, which is based on the Generalized Leontief model, shows highly significant interactions of the numbers of trips, days, and the numeraire good on implicit prices (marginal willingness to pay), and highly significant effects of both household size and catch rates on days and trips consumed.

Notably, the common assumption that the marginal utility of travel time is zero is relaxed within this model. Accounting for the choice of number of trips taken, separately from the choice of days onsite, leads to estimates of the total value of, and compensating variation from, travel. While travel was a "good" for most individuals and had a positive total value, the net value of travel after deducting out-of-pocket and opportunity costs was negative. If travel to a site were the only purpose of a recreation trip, individuals would have to be compensated to undertake those trips. But of course the purpose of travel is to gain access to valuable consumption of recreation services at the site, and we find that the net value of the site's services exceeds the net travel costs that must be incurred to gain access.

The compensating variation measures of net economic value for travel and time onsite, associated with the existing level of days onsite and trips taken, were evaluated using the distance function underlying the empirical model. The mean net value of travel time was roughly -\$143 per year or -\$12/hour of travel time. The mean net value of days onsite per year was roughly \$166 per year, which comes to roughly \$28 per day onsite or \$44 per trip. These estimates should be considered preliminary. Given the possibility of identifying the value of a recreation site's services apart from the benefit or cost of travel to access it, an interesting question for policy evaluation is whether to use the site value alone or adjust this value in light of the costs of access required to gain access to it.

In contrast to previous authors who have estimated daily onsite values, we found that the onsite days equation was highly significant. We suspect that much of this is due to the use of a utility-theoretic framework which allows for joint estimation of demand for days onsite consistently with trips demand. The inverse demand approach deserves further attention for the convenience it offers in assessing total values of recreation goods and, potentially, their distribution among the component activities that make up a recreation trip.

Footnotes

1. A few empirical studies (e.g., Bell and Leeworthy; Hof and King) have instead focused on explaining variations in days onsite rather than in trips.
2. Because trips to site i (r_i) may be either a good or a bad, and is not chosen solely for its own marginal value but also to enable consumption of days onsite, we do not assume these properties for **r**.
3. Since net economic value to the consumer is maximized when $p_j/M = p_j^*(\mathbf{x},\mathbf{r},a,s,u)$ for all j, it is also maximized when $q_j \cdot p_j/M = q_j \cdot p_j^*(\mathbf{x},\mathbf{r},a,s,u)$, where q_j is the quantity of good j (x, r, or a).
4. The shadow value ϕ enters equation (8) multiplicatively as it seemed more reasonable to allow the difference between implicit and actual price of trips to be a constant fraction of the implicit price rather than a fixed amount. This equation is more general than (7) or (9) in that unconstrained choice case, where the marginal value of trips equal their marginal cost, emerges when $\phi = 0$; it is just not required *a priori*.
5. In contrast, with the direct demand approach, choke prices that hold quantities to zero must be calculated, which can be complicated when more than one good is held at zero. Choke prices, being functions of all parameters of the problem, must be adjusted as any parameter changes.

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Table 1. Characteristics of the Recreational Fishing Sample

Variable	Units	Mean	Std Dev	Minimum	Maximum
Trips	number/yr.	3.82	2.75	1	15
Days Onsite	days/yr.	6.03	6.65	1	45
Money Cost of Travel	$/trip	50.06	57.07	1.80	723.00
Travel Time	hrs/trip	3.11	2.05	0	14
Money Cost Onsite	$/trip	10.68	15.97	0	140
Full Income	$/yr.	48671	35560	30756	246309
Leisure Time	hrs/yr.	1487	108.1	996	1764
Wage	$/hr.	10.8305	7.8093	0.4996	50.3597
Full Budget Shares:					
Days Onsite		0.0133	0.0183	0.0014	0.1816
Trips		0.0097	0.0180	0.0097	0.0180
Numeraire		0.9770	0.0332	0.6148	0.9980
Catch Rate	fish/day	4.45	3.90	0	30
Household Size	number	3.63	1.55	1	8
Hours Worked Per Week	number	44.1	9.0	21	85

Table 2. Parameter Estimates for the Joint Days-Trips Model

Parameter	Estimate	Std. err.	Est./s.e.
γ_r	83.9880	13.6846	6.137
γ_{rx}	-22.4458	12.1924	-1.841
γ_a	1.0000		
γ_x	23.0479	4.0046	5.755
γ_{ax}	1.8126	0.1449	12.513
γ_{ar}	-0.3337	0.1895	-1.761
$\gamma_{hh,r}$	-1.5618	1.9023	-0.821
$\gamma_{cr,r}$	-3.0452	1.5063	-2.022
$\gamma_{cr^2,r}$	0.0820	0.0473	1.733
$\gamma_{hh,x}$	-1.1546	1.1365	-1.016
$\gamma_{cr,x}$	2.3232	1.0241	2.268
$\gamma_{cr^2,x}$	-0.1052	0.0370	-2.843
ϕ	0.3415	0.0537	6.356

Mean log-likelihood -4.01878
Number of cases 201

Table 3. Budget Shares and Values of Travel and Time Onsite

Variable	Units	Mean	Std Dev	Minimum	Maximum
Predicted Implicit Budget Shares:					
Days		0.0149	0.0177	0.0020	0.2033
Trips		0.0064	0.0125	-0.0002	0.1264
Numeraire		0.9817	0.0317	0.6225	0.9991
Actual Budget Shares:					
Days Onsite		0.0133	0.0183	0.0014	0.1816
Trips		0.0097	0.0180	0.0097	0.0180
Numeraire		0.9787	0.0290	0.6703	0.9981
Predicted Total Values of					
Travel Time	($/yr.)	132.7064	155.4500	-93.9750	713.0115
Days Onsite	($/yr.)	848.4241	558.8483	113.8710	4213.5921
Total Trips	($/yr.)	981.1305	611.6652	165.3817	4365.6668
Predicted Net Values of					
Travel Time	($/yr.)	-143.2925	184.4827	-1242.5013	353.6364
Days Onsite	($/yr.)	309.3414	245.4293	-1664.2497	786.4813
Total Trips	($/yr.)	166.0490	329.0604	-1934.4483	644.2701
Median Gross Values of:					
Travel Time	($/yr.)	93.21			
Days Onsite	($/yr.)	719.47			
Total Trip	($/yr.)	858.22			
Median Net Values of:					
Travel Time	($/yr.)	-105.12			
Days Onsite	($/yr.)	361.52			
Total Trip	($/yr.)	240.09			

An Investigation into Travel Cost Measurement

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An Investigation into Travel Cost Measurement

Abstract

This study uses the travel cost method for the Chena River State Recreation Area to examine two issues. The first issue being the differences in soliciting travel cost by asking a respondent about their personal expenses vs. their group's expenses. The second is to compare the sensitivity of trip changes to park user fees for the travel cost method in comparison to a contingent decrease visitation treatment when most visitors are local and travel costs are relatively low. It is found that the estimated per-capita travel costs are significantly higher for respondents who answered the question about their own personal expenses versus the group's expenses. Two reasons account for this. The first is a driver selection bias for on-site sampling which bias upwards the costs when personal costs are solicited. The second is a downward bias that occurs for respondents who answer the group question underestimating their fellow travelers' expenses. Finally, in either case, it is found that the travel cost method yields substantially lower elasticities of trips to user fees than does a contingent decrease in visitation question. This may be due in part to payment vehicle bias.

Key words: Travel Cost Method, Contingent Behavior, Recreation

Introduction

Benefit estimation can often be challenging when dealing with quasi-public goods such as outdoor recreation sites. Managers of these sites may wish to maximize the benefits received by the site visitors but lacking market data makes beneficial public policy decisions difficult. Recreational sites that have no user fees are among the most difficult sites to value. Ideally, a manager would like to obtain the counterpart to an established Willingness To Pay (WTP) curve for private commodities. In the case of recreation trips it is useful to use economic theory that postulates that an individual will continue to visit a recreation site until individual marginal benefits no longer exceed marginal costs. The use of deriving WTP values is a federally accepted measure for benefit-cost analysis (U.S. Water Resources Council, 1983, U.S. Department of Interior, 1986). Two common WTP estimation techniques are the Travel Cost Method (TCM), which was first introduced by Hotelling (1949) and then popularized by Clawson and Knetsch (1966) and the Continent Valuation Method, which was first applied by Davis (1963) and further refined by Bishop and Heberlein (1979) among many others.

This study uses the travel cost method to estimate the WTP curve for visitation to the Chena River State Recreation Area, outside of Fairbanks, Alaska. The study was motivated because state budget cuts have led to the consideration of user fees in the park. This paper focuses on the solicitation of travel cost expenses, the most basic component of the TCM method when surveys are administered on the recreational site. Because it is common for visitors to come to recreation areas in groups of two or more, the issue of travel cost metrics is examined. The current literature gives little indication of how to pose on-site travel cost expense questions. Should researchers solicit information from an individual about that individual's personal expense or about the group's expense?

Difficulties with the measurement of trip price are well documented in travel cost literature. Ward and Loomis (1986), in one of the first and most complete comprehensive literature reviews of the TCM method, state that there are two problems with defining price in TCM models. The first is one of which monetary expenditures to include in a recreational trip and the second is how one measures of the value of time. Randall (1994), in his rigorous critique of TCM method, states that many of the difficulties with the travel cost method arise because "travel cost is inherently unobservable (p. 88)." Randall focuses on the problems concerning the measurement of cost focusing on four areas including the allocation of joint costs involving joint production (multiple activities, sites, and the problem with heterogeneous trips), the treatment of substitute costs, the problem with multi-stage budgeting, and the opportunity cost of time. The problem with the opportunity cost of time has included the question of not only how travel time should be valued but whether on-site time should be valued at all (McConnel 1992). Boxall et al. (1996) suggests that the travel cost method may not be consistent with rational choice theory. The incorrect specification of trip price is a leading candidate for this violation.

Theoretically, there are reasons that questions about personal expenses versus group expenses may lead to different econometric results when modeling visitation rates by individual trips. Individual expenses should vary quite a bit more than group per-capita expenses and sometimes give misleading individual points on a demand curve. For instance, if a husband and wife travel together, the out-of-pocket family travel expense may be quite high however it may be that one person usually pays most of the expense. So, if the non-paying spouse is questioned it may seem like significant out-of-pocket expenses are actually quite low. This problem could be solved by asking about the group's expense. However, asking for a group's expense may be misleading if non-paying members of that group would not have taken the trip unless it involved little of out-of-pocket costs to them. Ideally, one would hope that these fluctuations would average out and that posing either type of question would lead to roughly the same WTP estimation for random draws and large sample sizes.

A more fundamental, and possibly disturbing, question is the accuracy of the travel cost recall associated with either type of question and whether there is any inherent bias associated with the cost question in on-site sampling itself. If recall is fairly accurate, in a true random sample, then whether the expense question is asked as to the personal expenses that the traveler made or of the per-capita group expense calculated from a group expense question, these reported expenses should be nearly identical in large sample sizes. It may be hypothesized that estimating a group's expense would be a bit harder for an individual than for his/her personal expense which may lead to some differences in reporting. However, one would expect that these estimates might be close, especially for trips where total expenses are fairly low, as in the case of the out-of-pocket costs to the Chena River State Recreational Area. Another possible problem that is associated with on-site sampling is that obtaining a true random sample may be very difficult when modeling individual visitation rates. This may bias the obtained travel cost estimates and it may be further exacerbated by the type of cost question posed. This paper examines both the consistencies in respondent cost estimation, and possible survey bias, in regard to the travel cost question form. Finally, we ponder the question of the appropriate use of the travel cost method where most residents are local and travel and time costs are minimal.

The Chena River State Park Recreation Area

The State Park system in Alaska is experiencing a period of transition that is unprecedented. Visitor demand is continuing to increase while state budget cuts are constraining the amount of services and maintenance that can be provided by the park managers. To compound resource allocation issues, Governor Tony Knowles issued a hiring freeze for all non-essential state positions during the spring and summer of 1999. Many managers are facing difficult decisions regarding the management of state parks.

The entrance to the Chena River State Recreation Area is approximately 35 miles from Fairbanks, Alaska, the second largest city in the state. The recreation area totals almost 500 square miles in size. Major activities include both summer and winter involvement. Summer activities include camping, picnicking, and backpacking, hiking, running, and rock climbing, boating, swimming, and fishing, scenic and wildlife viewing and photography, horse back riding, and mountain biking. In addition, there is hunting, trapping and a rifle range. Specialized winter sports include dog-mushing, skijouring, and snowshoeing.

Regional rangers, superintendents and advisory committees have been contemplating initiating a user fee for the Chena River State Recreation Area, but are cautious that welfare of the community may be adversely affected. Additionally local managers fear that traditionally strong-willed Interior Alaskan residents would balk at the idea of explicitly paying for a government service. This original motivation for this study is the result of the desire of park managers and concerned citizens, who would like to know 1) the likely outcome of a user fee and 2) a way to allocate scarce resources more efficiently.

The Survey

The survey was developed through a series of seven focus groups and a sample of 100 people asked to participate in a pretest. Focus groups helped to ensure the survey was as unbiased as possible, as well as to identify certain areas of concern. The pre-testing sample enabled an appropriate bid range to be identified and further refined the survey instrument. Surveys were distributed at trailheads, parking lots, and a shooting range located in the recreation area on a rotating basis. The locations were systematically scheduled so as they would have the same number of weekend and weekday sampling. Sampling took place between May and September 1999.

To administer the surveys, a table was set up at the most frequented location at each site within the recreation area. The tables were supplied with bottled water, cookies, and trail information available to all visitors at each site, regardless of whether they filled out a survey or not. Park visitors were encouraged by volunteers to fill out a survey. Surveys were limited to visitors that were 16 and older (i.e., visitors that were old enough to drive). If a respondent agreed to take a survey, they were given a University of Alaska pen and an Alaska State Parks sticker. Respondents were asked to fill out the survey onsite, but were given a stamped return envelope if they preferred to mail it in. A total of 902 recreation area visitors were approached with a survey. In all, 800 surveys were handed out and 645 were completed. Out of the 645 surveys that were completed, 167 were returned via mail, the response rate for the surveys that were mailed was 52%. The overall response rate was 71.5%.

The 800 travel cost surveys were divided equally as to the out-of-pocket expense question. Half of the questions asked the respondent to "estimate how much **you personally** spent on this trip to the Chena River Recreational Area." The other question asked the respondent to "estimate how much your **whole group** spent on this trip to the Chena River Recreational Area." Round trip expenses were solicited for six different categories (Camping Fees/Lodging, RV/Car Rental, Food and Drink, Gasoline/Car Expenses, and Supplies) plus an "Other" category. Information on group size, number of children under 16, trip lengths, one-way travel mileage; in addition, one-way travel time was also requested. The survey concluded with a set of socioeconomic questions, such as age, income and education, and space for respondent comments.

Survey Data

In the initial cursory examination of the data, the average out-of-pocket travel costs per person is estimated for the two samples; those who were asked to give personal expenses and those who were asked to give their whole group expenses. The question of interest is whether the reported per-capita expenditures vary by type of question (for the per-capita expenses when the group expenses were solicited the group expenses were divided by group size). If so, then can the difference be explained by factors other than recall? For example, surveys were not generally given to children under the age of 16. Does this skew the data? The response rate was not 100% and many of the surveys were completed by the group driver/leader. Are the drivers over represented resulting in sample bias? Finally, in order to examine the possibility of wording bias, visitors that traveled alone (group size of one) were isolated to examine whether there was any differences between the responses for the individual and group of one expenses question. Table 1 shows a summary of the round trip out-of-pocket travel costs from the survey[1].

When the expenses are examined by category, all means differ at the 95% confidence level except camping cost which differs at the 90% level and misc. cost which has a p-value of 0.18. Viewing the individual data there is no discernable difference that would explain why the reported per-capita expenses differ between those respondents answering the personal expense question and those answering the group expense question.

The two differing survey treatments of costs lead to serious differences in estimated results. Travel cost equations were estimated for both the samples where the respondents answered the travel cost question where personal expenses were solicited and where respondents answered the question where group costs were solicited. Two travel cost equations were estimated in the form

$$(1) \qquad Trips = e^{(B_0+\beta_1 TC+\beta_2 Z)}$$

where Trips are per-capita annual trips, TC is per-capita travel cost, and Z are individual trip participation factors and socioeconomic variables. In the case of travel cost equations mean-level own-price elasticities measure the responsiveness of trips taken to travel costs

$$(2) \qquad E_p = \frac{\partial(Trips)}{\partial(TC)} \bullet \frac{TC}{Trips}$$

[1] In order to minimize the impact of outliers, all samples have the general restriction to visitors who traveled for 12 hours or less, 600 miles or less, incurred costs of $1,000 or less, and had a group size of 20 or less.

where mean-level own-price elasticity values reduce to

(3) $$E_p = \beta_1 \bullet \overline{TC}$$

The travel cost includes out-of-pocket costs and can include the value of round-trip time. For example, when trip time is valued at 50% of hourly wage rate, the formula for travel costs TC(50%) becomes

(4) $$\mathrm{TC}(50\%) = \mathrm{TC} + [(INC/HH)/2000]*Time*2*50\%$$

where INC is household income, HH is household size, and Time is one-way travel time in hours.

The results of two estimated travel cost equations are summarized Table 2[2]. Variable definitions follow in Table 3. In both sets of estimations (round-trip travel time valued at 0% and 50% of hourly wage) the travel cost estimates for the respondents filling out the personal and group expense question differ substantially.

The two travel cost estimates yield significantly different travel cost coefficients. In the case of travel time not being valued, the coefficient for the group expense is nearly 8 times the individual expense. This leads to a mean-level own-price elasticity three and one half times more elastic for the estimates in which respondents were asked to fill out the group expense. In the case of time being valued at 50% the differences are smaller due to the mitigating effect of the time value variable. Still, elasticities for respondents filling out the group expense are 2 and one-half times larger.

There is a probable reason that the impact multipliers and the mean-level own-price elasticities are larger (in absolute value) for respondents answering the group expense question. The relative variation in the expenses are quite a bit lower for respondents filling out the group expense question than the than the individual expense question. Therefore, in the estimation of the travel cost equation for respondents filling out the group question, it is taking a much smaller change in reported per-capita costs to have the same effect on trips as in the question where personal expenses are solicited.

Table 4 shows a summary of the round trip out-of-pocket travel costs from the survey using five scenarios that vary the level of sample restriction. (**Group Size** is the average size of the group, the **Cost per Person** is the out-of-pocket travel cost per individual, **Young** is the average number of youngsters (age under 16) in the group, **Drive** is the percentage of respondents who did all or most of the driving, and **#Obs** is the number of observations for each sample within the specified scenario).

[2] These travel cost equations are fairly simplistic and use for expository purposes only. More rigorous attempts at a travel cost estimation would take into account substitute sites and the multi purpose nature of the trips. Further, the trip variable should be divided by the population levels in the zones to alleviate estimation bias (Brown et al. 1983).

In Scenario 1 all of the respondents, except those restricted by the initial outlier restrictions, are included. The per capita expenditures for the individuals, that answered the question on how much they personally spent ($45.47), was nearly three times as high as the per capita expense for the individuals that filled out the group's expense ($16.66). Further restricting the influence of outliers gives a comparison of the medians that show per-capita median costs are also significantly larger for the respondents filling out the personal travel cost expense question than the group travel cost expense question. These differences held up when both Alaska residents and non-residents were examined with the spread slightly lower for residents and substantially higher for non-residents. Examining three other important statistics shows that the amount of young travelers, the group sizes, and the percent of the groups that drove to be fairly similar between the two samples.

An interesting observation that was evident in Scenario 1 was that the percent of respondents that filled out the questionnaire that asked "Did you do all or most of the driving" was 69% for both samples. This may seem high when the average group size was over 3.5 respondents per car. There are several possible explanations for the higher-than-expected percentage of driver-respondents. First, although the mean group averages are over 3.5 visitors per group, the median group size is closer between 2 and 3 indicating that outlier large groups are pulling up the average. Second, in handing out the surveys we witnessed groups that had more than one car. This was sometimes due to large groups and also to groups that needed two cars for a river float trip. Third, many groups had youngsters and we did not have children less than 16 years of age fill out the survey. Fourth, some non-drivers may have been taking care of a youngster and only the driver was free to fill a survey. And finally, the drivers may have been the dominant decision-makers and therefore somewhat more likely to fill out a survey.

In Scenario 2, the respondents were restricted to just the groups without children to see if the reported per-capita travel cost differences found in Scenario 1 had to do with children not filling out the survey. This could bias upwards the per-capita travel costs for the individuals filling out the survey that asked for the personal expenses as these averages would not have contained children who likely spend less than adults. However, there was virtually no difference in the spread when respondents with children were removed.

It is interesting then to examine whether the difference in reported travel cost expense comes from the fact that there was a larger proportion of drivers surveyed than might have been expected given group size. One way to examine this is to only look at the drivers (in groups without children). If there were a survey selection bias present, it would be expected that the spread between the per-capita travel cost for this question to rise. The reason for this is that if the drivers are paying most of the trip expenses then the per-capita expenses from the individuals answering the group question will be spread out among the group. The result for Scenario 3 indicates that the spread between per-capita travel costs does rise when the results are limited to the primary drivers. In this case the difference in reported per-capita expenses are $60.30 for individuals filling out the personal question vs. $20.60 for the individuals filling out the group expense question. This would indicate that there might be driver selection bias if the proportion of surveyed drivers is higher than the proportion of surveyed non-drivers.

If the sole difference between the reported expenses was due to the driver selection bias, then there should not be anomalies in the passenger responses. When only the passengers are examined (Scenario 4) it might be expected that the reported per-capita expense averages would be higher for the individuals answering the group expense question than for the personal expenses. The reason for this is that the respondents answering the personal expense question answer only about their own expenses while the individuals answering the group expenses are answering expense questions for the entire group (drivers included). At the very least, the reported expenses here should be much more similar than for the drivers. However, even when just the passenger surveys are included the per-capita expense averages are higher for the individuals that filled out the personal expense question ($19.98) than for the individuals that estimated the group expenses ($10.32). This would indicate that there might be some under-reporting of expenses for respondents trying to estimate the expenses of the entire group. The mean differences here are significant at the 90% level however, the differences in the medians (both $5.00) only have a p-value of 0.29. A further indication of the possible underestimation of fellow traveler expenses can be examined by comparing Scenario 3 and 4 for only those respondents filling out the group expense travel cost question. For respondents filling out the group expense question the resulting computed per-capita reported expenses are nearly twice when drivers answer the question ($20.63) than when passengers answer the question ($10.32)[3]. There should be no inherent difference in the reported amounts if group costs are estimated accurately. The only reasonable explanation for the reported differences in reported group expenses from surveyed drivers versus passengers is that the drivers are most likely better at accurately reporting many of the expenses than are the passengers.

Finally, in Scenario 5, the sample size was restricted to those surveys where the group size was 1.0. This was done to test whether there was something inherently confusing in asking individuals to fill out either expense question – their own personal expense versus the group expenses. The results here should be virtually identical if there is no bias due to how the question was asked. This was the case as the difference in reported per-capita expense between the two survey treatments was only 15 cents.

If it is established that the question format does lead to different answers, which, if either, is accurate? Table 5 shows estimated costs for individuals answering the group and personal expense by question group size. From this table, it is obvious that drivers pay most of the bills and that the passengers underestimate the drivers' expense. If one examines the personal expense question the drivers are paying 2-4 times the expenses as that of the passengers[4].

An interesting observation from this table is that the reported travel cost per-capita when drivers only are examined, seems to rise from the personal expense question. At first glance, it might seem that this would be a violation of the declining marginal cost principle. When both travel costs from drivers and passengers are examined from the

[3] Both the means and medians test different at the 95% level.

[4] Our more aggregated data found drivers paying 3 times that of passengers.

group expense question (and the passengers only from the personal expense question), declining (or at least non-increasing) MC seems to hold. The seemingly declining MC for the group expense question may also, in part, be a function of the respondents underestimating total group cost by an increasing amount as the groups get larger.

When the estimated per-capita travel costs are examined from the drivers only from the personal expense question the principle of declining MC seems to be violated, however, it is not. For example, assume that the driver paid all (or nearly all) of the costs for the group. Then take the per-capita TC from the drivers' expense for the personal expense question, and divide them by the group size. The driver is paying about \$10.00 per person no matter what the group size is. This is not declining MC but it is not rising[5]. Taking another look at Table 5 (examining the medians) one will note that the median per-capita expenses from the personal expense for individuals of group size 1 is \$9.00. The median per-capita expenses reported for group size of 3.56 is \$20.00. This is consistent with the above findings if the drivers are footing most of the bill and we are getting driver selection bias. The larger the group is the more drivers will be paying and the "per-capita" expenses will seem higher than if we had proportionally sampled each driver <u>and</u> each of the other 2.56 passengers. Therefore, this phenomenon is only a re-enforcement of the driver selection bias.

What can be gleaned from these findings? It appears that passengers are largely unaware of many of the costs incurred by the drivers, so they may be under reporting the group expenses. Likewise, although by a smaller amount, drivers underestimate passenger expenditures[6]. The expenses from the personal expense question are likely to be more accurate. However, in our on-site selection, group expenditures from the personal expense question, are likely to be overestimated because of driver selection bias. Anything that could reduce (or account) for driver selection bias would lead to much more accurate travel cost estimates. Other possible solutions to this problem are to survey groups as single units although functionally, in our experience, this may be difficult and add in a bias against large groups. Another possible solution may be to sample drivers only and ask them about their group expenses, which may introduce only a small downward bias in group estimates (from underestimating passenger expenses). It should be noted that the per-capita cost is almost identical for Drivers asked to give whole group expenses and Passengers asked to give personal expenses.

[5] There may be some reasons that the per-capita costs may be slightly larger for groups of 2 or 3 than sole travelers as these groups may be more likely to camp (and pay camping fees, buying more food, etc.) and the individual more likely to be out enjoying a day trip.

[6] If one takes the per-capita costs in Table 5 for the group expense question and multiplies it by the number in the group you get estimated expenses that are just slightly under the reported per-capita expense when the drivers are questioned from the personal expense question. For example, for a group of 4, the driver from the group expense question reports a group expense of \$27.52 (6.88*4) while the individual has reported paying \$27.50. Thus, it may be that both of these individuals are really only estimating what they individually paid.

Stated vs. Revealed Preference.

Even ignoring the very serious problems in reported travel costs there is still the issue of whether travel cost was the appropriate means to evaluate this problem. From a management perspective s user fee needs to be evaluated in light of the potential gains of increased revenues from a user fee vs. the loss in visitation resulting from the increased fee. Using a travel cost method of evaluation where the vast majority of the participants are local, as in the case of the Chena River Recreational Area, may fail to estimate realistic human behavior on two fronts. First, there may be little variation in actual travel or time cost in which to obtain an accurate estimation. This is a particular problem when travel and time commitment costs are minimal. Second, local residents may have a strong reaction to any type of user fee when they feel that they have a right to continually use a recreational area free of charge (this is known as payment vehicle bias). To further examine the results of the revealed preference estimation, half of the respondents were asked to give their stated preferences.[7] They were asked whether they would reduce the amount of trips (and by how much) to the Chena Recreational Site if a user fee were initiated.

For the Contingent Decrease in Visitor (CDV) question, the survey question was in the form of

> If there were a $___ per car per day entrance fee, would you visit the Recreation Area less?
>
> YES NO
>
> If YES, how many fewer trips per year? _________#

There were 10 different bid amounts used in these questions, $1, 2, 3, 4, 5, 7.50, 10, 15, 20, 25. They were used based on the recommendation that bid amounts should fall approximately between the 15th and 85th percentile of "YES" votes, based on pre-testing (Kanninen, 1995). Alberini (1995) suggested that a smaller number of bids are preferable in order to increase the efficiency of the estimation techniques. Further, recommendations from Boyle, et. al. (1998) were followed in order to find the optimal distribution of the bid set. Finally, previous studies by Loomis (1987), and Giraud et. al. (1999) were used as a model for bid structure. The bid amounts and survey treatments were sorted so that the bid amounts were distributed sequentially. Survey treatments were also sorted so that each treatment was distributed throughout the summer in a systematic fashion. Partial summary of the results of the CDV questions is shown in Table 6.

When there was no bid amount the average number of trips per year was 5.27. Because of sampling variability, the number of trips per respondents by bid amount differs. A bid amount of just $1.00 decreased the number of trips by 27%. This may be evidence that a large percentage of the respondents would protest the placement of a fee of any kind by

[7] Only half of the respondents were asked the contingent trip reduction question because the other half were asked a contingent voting question instead.

reducing their visits, in other words, payment vehicle bias. This could be a result of respondents protesting a fee on the survey and may not reflect actual behavior if a fee were imposed.Larger bid amounts continue to decrease participation indication that there is also a significant trip reduction response to level changes in trip costs.

As reported before, the mean (median) travel cost for respondents filling out the personal and group expense ignoring question was $45.58 ($20.00) and $16.66 ($8.09), respectively. The time values for the two-way trip, valued at 50%, were $20.39 ($13.28) and $16.91 ($11.25) for those answering the personal and group expense question respectively. The total mean (median) cost when valuing time at 50% for those filling out the personal and group question are $65.97 ($38.75) and $33.57 ($19.34) respectively (see Table 7). Table 8 summarizes mean-level elasticities from the travel cost equations (see Table 2) and arc-elasticities calculated from the CDV question.

Although more sophisticated techniques can be used to calculate the own-price elasticities of demand for the CDV question, it is clear that there is a startling difference in the demand sensitivity between the two techniques. In the travel cost technique, at mean costs and depending on survey treatment and cost aggregation, own-price mean-level elasticities are very inelastic ranging between –0.025 and –0.135. The CDV arc own-price elasticities, calculated at mean cost levels (before and after the bid price is administered) are, in comparison, very elastic ranging between –1.07 and –4.92 dependent on survey treatment and bid level. If one uses median cost levels instead these elasticities would come down slightly less than half but still far above the travel cost elasticities. This indicates that those surveyed for the contingent decrease in visitation question have indicated that they would decrease trips at a drastically increased rate over what the travel cost equation indicates.

Conclusions

The results are troubling. The indications of this study are that travel cost estimates may vary widely with the technique used to solicit them, which can negate the accuracy of an otherwise careful and rigorous study. Champ and Bishop (1996) find that participant expense recall from surveys correspond to expense estimation from on-site diaries however neither one of the cost estimate biases that we have found question the recall of an individual's own expense. We found two potential biases in this study. The first arose with the tendency to over-survey drivers, in on-site sampling, which we coined "driver selection bias". This biases upward the estimates when the travel cost question solicits estimated costs that an individual personally spent. The second bias was a strong indication that group expenses are underestimated by passengers, which biases downwards the estimation of expenses when individuals are asked to estimate their entire group's expense. These two biases, in opposite directions, are found to be quite large and create a significant wedge between individuals answering the travel cost question on personal expenditures vs. groups expenditures with the per-capita travel cost estimation much higher for individuals answering the personal expenses vs. the group expense question.

The driver selection bias was a by-product of doing an on-site survey. It was found that drivers pay the largest proportion of trip costs and, if over-sampled, leads to an upward bias in estimated travel costs. The sampling technique employed here was to approach every visitor 16 or over visiting an activity area. As seen in Table 4, the sample over-represents visitors who did all or most of the driving (67% of respondents drove while the median group size was pretty close to between 2 and 3). There are a few possible explanations for this. Some groups had more than 1 car, many groups had youngsters and we did not have children under 16 years of age fill out the survey. It is plausible that some non-drivers may have been taking care of youngsters, leaving only the drivers were free to fill a survey. Group leaders (who often are the drivers) tended to fill out a survey for an entire group.

The downward estimated travel cost bias for the group expense question is not a function of the on-site survey technique. This bias is caused by group members' underestimation all other individual's expenses and especially that of the driver. For example, respondents filling out just the group expense question the estimated per-capita reported expenses are nearly twice as high when drivers fill out the survey than when passengers do. This is strong evidence that passengers underestimate driver expenses.

A question is also raised as to the appropriateness of the travel cost technique when most visitors are local and visitation costs are relatively low and when any type of costs may solicit strong right infringement sentiments. In a comparison of a contingent decrease in visitation rates vs. the travel cost method, there are wide differences in the responsiveness of trip changes to changes in costs for the stated and revealed preference technique. Own-price elasticities indicated substantial and significant increases in the sensitivity of visits to travel costs from the Contingent Decrease in Visitation technique in comparison to the travel cost technique. During this study, it was made apparent that many respondents do not find user fees as neutral costs. There may be significant payment vehicle bias, so the actual loss in visitor welfare would be much larger for a user fee, then from other costs associated with visiting a site.

Applied researchers using the travel cost method to value recreational site benefits need to be aware that even the most basic observable travel cost measurements may be open to interpretation and measurement error. Randall (1994) declaring that "TCM cannot stand alone (p.96)" suggests that, at the very least, TCM welfare estimates need to be calibrated with welfare estimates from other non-market techniques. Some recent works are examples of the effort to combine travel cost with a stated preference component (see Cameron (1992) and Layman et al (1996)). Although, these combination models, including Layman's "Hypothetical Travel Cost Method" techniques may improve upon the traditional TCM models their accuracy's are still heavily conditioned on a reliable measurement of travel cost. We find that this measurement, from survey data, is questionable even at the most basic level which further brings into question the appropriateness of using travel cost as a welfare measurement especially at a time when state preference techniques are being refined and becoming more accepted in literature.

If travel cost is to be used then perhaps best way to model the travelers would be to treat the group as the unit, controlling the group size by its inclusion as an explanatory variable. It would then be necessary, in on-site sampling, to question the entire group together as to their costs letting them discuss these costs (and travel time) and have them come up with a consensus. A decision-maker could then be identified to answer the remaining socioeconomic questions. This would obviously be a much more intrusive data collection technique and loss of observations would not only come from the aggregation, but also from the loss of participation. The advantages include the minimization of the driver selection bias effects, a correction for exclusion of children from the sample, and less variation in the data.

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Table 1

A Comparison of Mean Per-Capita Travel Costs from the Two Survey Treatments.

Sorted by	Personal Expense Question Mean Cost Per Person	Group Expense Question Mean Cost Per Person
Total costs	$45.57**	$16.66
Food cost	$13.21**	$5.47
Camp Cost	$4.57*	$1.97
Car cost	$10.26**	$4.72
Rent cost	$6.74**	$1.08
Supply Cost	$10.18**	$3.17
Misc cost	$0.65	$0.25

**Significantly different to Group Expenses per person at the 95% confidence level
* Significantly different to Group Expenses per person at the 90% confidence level

Table 2
Regression Output for the Travel Cost Treatments with Time Valued at 0% and 50%.

Dependent Variable = ln(TRIPS)				
Travel Cost Question	**Personal Expense Travel Time Value = 0%**	**Group Expense Travel Time Value = 0%**	**Personal Expense Travel Time Value = 50%**	**Group Expense Travel Time Value = 50%**
Variable	**Coefficient (t-Statistic)**	**Coefficient (t-Statistic)**	**Coefficient (t-Statistic)**	**Coefficient (t-Statistic)**
C	-1.3203	-0.5226	-1.3064	-0.5466
TC	-0.0007 (-1.94)	-0.005 3(-3.18)		
TC(50%)			-0.0007 (-2.00)	-0.0031 (-2.77)
INOMOTOR	0.7339 (6.86)	0.5999 (5.36)	0.7327 (6.85)	0.5828 (5.17)
ITAKE	0.8069 (5.28)	0.6354 (4.25)	0.8066 (5.29)	0.6190 (4.12)
IVIEW	0.4339 (3.94)	0.1216 (1.00)	0.4378 (3.98)	0.1314 (1.08)
IHIKE	0.4357 (2.89)	0.4870 (4.16)	0.4281 (2.82)	0.4908 (4.17)
AK	0.5807 (6.06)	0.5995 (5.59)	0.5769 (6.03)	0.6163 (5.86)
ED	0.0582 (3.35)	0.0160 (0.76)	0.0580 (3.35)	0.0156 (0.75)
INCCAP	0.0003 (0.11)	0.0024 (0.77)	0.0007 (0.00)	0.0039 (1.26)
# observations	232	235	232	235
R^2	0.45	0.33	0.45	0.32
Adjusted R^2	0.43	0.31	0.43	0.30
Mean-level TC	$45.58	$16.66	$68.60	$34.02
Standard Deviation TC	$89.55	$25.62	$103.4	$39.42
Mean-Level Own-Price Elasticity	-0.025	-0.088	-0.050	-0.135

Table 3
Variable Definitions

TRIPS Per-capita annual trips.

C Constant

INCCAP Per-capita by household

HH Total Members in a household

TC Travel Costs where time is not valued. This variable was created by combining the travel cost values from the personal expense question and the per-capita travel cost values from the group expense question.

TC(50%) Travel cost plus time valued at 50% of the hourly wage rate(see equation 3).

INOMOTOR This is an indicator variable marking non-motorized variables and equals 1 when the respondent indicated that they engaged in the following activities in Chena Park previous year: backpacking, camping, rock climbing, dog walking, dog mushing, non-motorized boating, picnicking, running, cross-country skiing, snow shoeing, and swimming.

ITAKE This is an indicator variable marking hunting type activities and equals 1 when the respondent indicated that they engaged in the following activities in Chena Park previous year: fishing, hunting, shooting and trapping

IVIEW This is an indicator variable marking viewing activities and equals 1 when the respondent indicated that they engaged in the following activities in Chena Park previous year: Bird watching, photography, scenic viewing and wildlife viewing

IHIKE Includes hiking. This category is separated because it is by far the largest single activity category

AK This is an indicator variable that equals 1 for Alaska residents.

ED This variable marks years spent in school starting in first grade (ending with 21+ years).

Table 4

A Comparison of Mean and Median Per-Capita Travel Costs from the Two Survey Treatments.

	Personal Expenses						Group Expenses					
Sorted by	**Mean Cost Per Person**	**Median Cost Per Person**	**Group Size (#)**	**Young (#)**	**Drive (%)**	**Obs (#)**	**Mean Cost Per Person**	**Median Cost Per Person**	**Group Size (#)**	**Young (#)**	**Drive (%)**	**Obs (#)**
Scenario 1 all	$45.57**	$20.00**	3.56	0.61	69%	283	$16.66	$8.09	3.88	0.76	69%	272
Scenario 1a residents	$35.07**	$20.00**	3.49	0.73	70%	203	$15.85	$8.18	3.93	0.85	70%	205
Scenario 1b non-residents	$95.33**	$28.00**	3.06	0.20	66%	50	$20.92	$9.38	3.31	0.36	66%	44
Scenario 2 no children	$47.33**	$15.00**	2.89	0.00	68%	209	$17.27	$8.22	2.93	0.00	68%	184
Scenario 3 no children divers only	$60.30**	$20.00**	2.54	0.00	100%	142	$20.63	$10.00	2.64	0.00	100%	124
Scenario 4 no children passengers	$19.98*	$5.00	3.67	0.00	0%	66	$10.32	$5.00	3.55	0.00	0%	60
Scenario 5 groups of 1	$25.97	$9.00	1.00	0.00	100%	30	$25.82	$12.25	1.00	0.00	100%	25

** Significantly different to Group Expenses per person at the 99% confidence level

* Significantly different to Group Expenses per person at the 90% confidence level

Notes: (1) The mean equality test is a t-test using unequal variances and the median equality test uses the Mann-Whitney *U*-test. (2) The observations for residents and non-residents do not add to the total observations, as some residencies were not determined.

Table 5
Reported Median Travel Cost per Person
By Group Size for the Group and Personal Expense Question

GROUP EXPENSE QUESTION

	Drivers only, no children			Passengers only, no children		
Gr Size	**# Obs**	**Days**	**TC Per Person**	**# Obs**	**Days**	**TC Per Person**
1	22	1	12.25	—	—	—
2	65	1	10.50	25	1	5.00
3	16	.5	7.67	8	.5	3.33
4	14	1.5	6.88	17	.5	5.00
5	Too few	Obs		3	.5	4.00
6+	Too few	Obs		Too few	Obs	

PERSONAL EXPENSE QUESTION

	Drivers only no children			Passengers only no children		
Gr Size	**# Obs**	**Days**	**TC Per Person**	**# Obs**	**Days**	**TC Per Person**
1	23	.5	9.00			
2	81	1	20.00	27	1	10.00
3	13	1	30.00	14	1	7.50
4	16	1	27.50	10	.75	7.50
5	Too few	Obs		2	.75	5.00
6+	Too few	Obs		2	.75	5.00

Table 6
Summary of the Contingent Decrease in Visitation (CDV) Questions Per Year

Bid Amount	No Bid	\$1	\$5	\$10	\$15	\$20	\$25
Observations	263	24	28	24	27	28	29
# Visits Before	5.27	6.58	4.04	3.80	8.59	3.86	2.79
# Fewer Visits	0	1.79	1.23	2.15	3.60	3.01	1.76
# Visits After	5.27	4.79	2.81	1.65	4.99	0.85	1.03
Remaining visits	100%	0.73%	0.70%	0.43%	0.58%	0.22%	0.37%

Table 7.
Individual and Group Travel and Time Costs Averages and Medians

		Individual Expense	Group Expense
Travel Cost	*Mean*	$45.58	$16.66
	Median	$20.00	$8.09
Time Value (50%)	*Mean*	$20.39	$16.91
	Median	$13.28	$11.25
Travel Cost + Time Value (50%)	*Mean*	$65.97	$33.57
	Median	$38.75	$22.78

Table 8
Summary of Mean-Level and Arc Own-Price Elasticities of Demand at $5.00/$25.00 Bid Rates

	TCM Whole Group Expenses[1]	TCM Personal Expenses[1]	CDV Whole Group Expenses[2]	CDV Personal Expenses[2]
Price Elasticity of Demand With Time Valued at 0%	-0.088	-0.025	-1.38/-1.07	-3.45/-2.14
Price Elasticity of Demand With Time Valued at 50%	-0.135	-0.050	-2.59/-1.70	-4.92/-2.89

Notes 1. The elasticities from the travel cost equations are calculated at mean-levels travel costs.

2. The arc-elasticities are calculated from

$$E_p = \left(\frac{Trip - TripB}{Trip + TripB}\right) \Big/ \left(\frac{TC - TCB}{TC + TCB}\right)$$

where Trip is the actual number of visits before the bid price was added, TripB is the stated number of visits after the bid price is added, TC is the travel cost before the bid, and TCB is the travel cost with the bid price.

Using Contingent Valuation to Value a Noxious Weeds Control Program: The Effects of Including an "Unsure" Response Category

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Using Contingent Valuation to Value a Noxious Weeds Control Program: The Effects of Including an "Unsure" Response Category

I. Introduction

The National Oceanic and Atmospheric Administration (NOAA) Contingent Valuation Panel recommended the inclusion of an explicit "would not vote" response category in addition to the "vote in favor" and "vote against" response categories of a referendum contingent valuation (CV) question (Federal Register Vol. 58, No. 10). The implications of this recommendation have not been extensively investigated and the Panel did not provide guidelines for interpreting the "would not vote" option.

Subsequent to the NOAA panel recommendation, researchers have experimented with response formats to closed ended CV questions which, in addition to the "vote in favor" and "vote against" response categories, allow for refraining from voting altogether, or allow for expressions of uncertainty (Carson et al., Wang). The common finding in these studies is that when respondents are explicitly given the option of expressing uncertainty about the CV question, many respondents choose this option. Carson et al (1998) conclude that the majority of the respondents who abstained from voting would have vote against the proposed plan, had they been offered only two response categories. These responses should, therefore, be recoded as votes against the proposed environmental plan and statistically modeled as such.

By contrast, Wang (1997) treats the "not sure" responses as distinct from the votes in favor and against the plan, and hypothesizes that, in fact, the "not sure" responses are the most informative about willingness to pay, since they reveal that the respondent's underlying willingness to pay amount is very close to the offer amount.

In this paper we explore three aspects of allowing respondents to express uncertainty about their vote on the program described in a CV survey. First, we examine how the distribution of responses to a contingent valuation question which includes an "unsure" response category compare to CV question with just the "vote in favor" and "vote against" response categories.2 We also examine the item non-response and determinants of the unsure responses.

II. Previous Research

Carson et al.'s working hypothesis is that inclusion of a "would not vote" option and recoding of those responses as "vote against" responses results in a distribution of response similar to that of a standard dichotomous-choice CV question. Two independent samples of respondents were administered versions of a CV survey about willingness to pay to prevent oil spills and the related damages to natural resources in Alaska.

Approximately 18 percent of the survey respondents chose the "would not vote" response category when the option was explicitly offered by the interviewer. The distribution of responses to the CV question was statistically similar between the standard dichotomous choice version and the version which offered the "would not vote" option, if the "would not vote" responses were conservatively re-coded as "would vote against."

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2 The Panel also called for research into alternative ways of presenting the "no vote" option. In this study we used an "unsure" response category as an alternative to

Moreover, median willingness to pay, the preferred welfare measure, was *not* statistically different between the standard dichotomous choice CV treatment and the treatment that included the "would not vote" option conservatively recoded as "vote against," when the "would not vote" responses were recoded as "would vote against." Carson et al. conclude that with a conservative interpretation of the responses inclusion of a "would not vote" option does not reduce estimates of willingness to pay relative to a standard dichotomous-choice CV response format.

Wang (1997) looks at the effects of including a "don't know" response category in addition to the standard "vote for" and "vote against" response categories. Wang develops a model for estimating mean willingness to pay that uses information provided by the "don't know" respondents and applies it to CV data collected via a mail survey. The model assumes that it is straightforward for people to answer "yes" ("no") to a dichotomous choice CV question when the offer amount assigned to the respondent is sufficiently low (high) relative to her true willingness to pay amount. By contrast, respondents answer "don't know" when the bid amount is close to their true willingness to pay. The corresponding statistical model is thus a variant of the ordinal probit (or logit), which identifies by how much willingness to pay must exceed (be less than) the bid for the respondent to say "yes" ("no").

Wang finds that for the four offer amounts used in the survey, a relatively large percentage (30%) of the respondents chose the "don't know" response category. Treating the "don't know" responses as "vote against" responses results in the lowest estimate of mean

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"no vote."

willingness to pay ($2.65). The ordinal logit model proposed by Wang uses the information from the "don't know" responses and produces an estimate of mean willingness to pay equal to $11.86, an estimate very close to the estimate of mean willingness to pay obtained from a standard logit model that removes the "don't know" responses from the willingness to pay estimates ($10.23). The standard error around mean willingness to pay is a bit less for the Wang model (1.527) than that from the model in which the "don't know" responses are removed (1.703). Despite this very small improvement in statistical efficiency, Wang concludes that the NOAA panel plea for including a "don't know" response category is appropriate, and recommends using information from the "don't know" respondents as described in his paper.

The study described in this paper is similar to the Carson et al. study in that we also implement a split sample design to allow for comparisons between a standard dichotomous-choice CV format and a format that includes an "unsure" response category in addition to the "vote in favor" and "vote against" response categories. An important difference between Carson et al. and this study is that this study implemented a self-administered mail survey whereas the Carson et al. survey was administered in person. We extend the type of analyses conducted in the Carson et al. study by including an estimate based on the Wang model which allows for use of the information provide by the "unsure" respondents, and make extensive use of the information gathered through debriefing questions to explore reasons for the "unsure" responses.

III. Reasons for Unsure Responses

In attitude surveys, researchers have found that a low education level is strongly correlated with a "don't know" response. Schuman and Presser (1981) suggest this finding is reflective of the respondent not having knowledge or an opinion about the issue at question. While CV questions are specific statements about preferences rather than attitudes, it is possible that effects similar to those found with attitude elicitation occur when respondents are not sure about how to respond to a CV question. The decision heuristics respondents use when they do not have an opinion, but are asked to express one, may lead to invalid responses.

Decision heuristics may also vary with respondents. To illustrate, when unable to answer a CV question that offers a dichotomous choice response format, one respondent may randomize the response (i.e., flip a coin), while another might adhere to the simple rule "if in doubt, vote against."

When the willingness to pay question follows the dichotomous choice format, there may be many reasons that make it difficult for respondents to answer the question. Respondents may not understand the information presented in the CV scenario, or may not believe or may object to certain aspects of the scenario. In-person surveys may encourage the respondents to give responses they think will please the interviewer or responses that are socially desirable. It has also been hypothesized that it may be difficult for respondents to answer a closed ended willingness to pay question when the posited offer amount is close to their true willingness to pay.

To sum, respondents may have many reasons for finding it difficult to answer dichotomous choice CV questions, and different ways in which they overcome these difficulties to provide a definitive answer. Unless we understand how such processes work, we run the risk of ascribing similar willingness to pay information to respondents whose "yes" or "no" responses are driven by reasons other than the size of their willingness to pay amounts vis-à-vis the offer amount.

In this paper, we investigate two related questions. First, had the "unsure" response category not been explicitly offered, how would "unsure" respondents have answered a standard dichotomous choice CV question? Second, why are some respondents "unsure" about how they would vote?

We formalize possible plausible explanations for the "unsure" responses in a series of working hypotheses, and attempt to accept or refute the hypotheses by conducting statistical analyses of the responses to the payments questions from the two treatments.

Hypothesis 1. *Respondents who choose the "unsure" response category would have voted against the program in the absence of such a category.* Proponents of this hypothesis argue that some respondents feel that it is socially unacceptable, or offensive to the interviewer, to turn down the plan. The "unsure" response category provides a more socially gracious way of not supporting the program in question. It is unclear that providing a socially desirable response is an issue with a mail survey, but we feel that this hypothesis is worth investigating. The implication of this hypothesis is that "unsure" responses should be recoded as votes against the program.

Hypothesis 2. *"Unsure" responses are completely uninformative about willingness to pay.* Hence, they should be deleted from the sample used for statistical analysis.

Hypothesis 3. *Respondents who choose the "unsure" response category would vote in favor of the program in the absence of such a category.* Proponents of this hypothesis argue that some respondents may be in favor of the program in general but have some reservations (such as the cost of the program). When forced to provide a definitive response to the CV question they would "vote in favor," however they are a bit unsure and will give this response when it is offered explicitly. It is also possible some respondents feel compelled to say that they are in agreement with the program for fear that saying otherwise, or simply expressing their uncertainty about the benefits of the program, will offend the interviewer or not be socially unacceptable. The implication of this hypothesis is that "unsure" responses should be recoded as votes for the program.

Hypothesis 4 (Wang, 1997). *"Unsure" responses are very informative about willingness to pay: respondents who select this response category have willingness to pay amounts that are close to the bid.* If so, the "unsure" responses should be retained in the usable sample, modeled as distinct from the votes in favor and against, and modeled as implying that the underlying willingness to pay is close to the bid offer.

Hypothesis 5. *Respondents will select the unsure response category when they have considerable uncertainty about their income, their ability to commit to spending money within their household, and about the benefits of the program.* This proposed explanation calls for relating "unsure" responses to the subject's expressed uncertainty about these matters, or to respondent characteristics, such as education or age, related to such uncertainty.

These explanations are not all mutually exclusive, and different explanations may be valid for different study participants.

IV. Study Design

The study implemented a split sample design. The two treatments were parallel in all aspects except the response format to the CV question. The final survey instrument was developed after conducting seven focus groups and a small pretest.

The topic of the survey was controlling invasive plant species or noxious weeds on National Forests. Noxious weeds are "a threat that affects 49 percent of the nation's imperiled or endangered organisms" (Stolzenberg 2000). Despite the seriousness of the threat posed to biodiversity by noxious weeds and the considerable coverage of this topic in the media, the focus groups revealed that many people were relatively unaware of the noxious weeds problem. It was therefore necessary to provide study participants with a substantial amount of information prior to asking them about their willingness to pay for a program to control noxious weeds in National Forests. After providing information about each topic (i.e National Forests and Noxious Weeds), study participants were asked a series of questions designed to measure their previous experience and attitudes.

The focus groups participants also made it clear that we needed to describe National Forests (to avoid confusion with public lands owned and managed by other entities), define what noxious weeds are and describe how the program to control noxious could be implemented. Study participants were told that the Noxious Weeds Control Program would be financed with revenue from a special one-time tax. As it would take many years of treatment to control the noxious weeds, the revenue from the tax would be placed in an interest earning trust fund, and the funds would be used over the next ten years to implement the Noxious Weeds Control Program. The CV question was posed as a vote on a national referendum to impose a one-time tax to fund the *Noxious Weeds Control Program* and read as follows:

> If the ***Noxious Weeds Control Program*** is implemented, the cost to your household would be $ (offer amount). Would you vote in favor or against the program? ***(Circle one number)***

In Treatment 1, the standard dichotomous choice response format ("vote in favor," "vote against") was administered. In Treatment 2, the response format included an "unsure" response category in addition to the "vote in favor" and "vote against" categories, for a total of three response options. In both treatments, one of five offer amounts ($5, $10, $25, $50, $75) was randomly assigned to the CV question.

The survey included a series of debriefing questions after the willingness to pay question. The intent of these questions was to better understand some of the reasons for and issues related to the response to the willingness to pay question. Respondents were asked to rate on a likert scale from 1 to 4 (1=definitely true, 2=somewhat true, 3=somewhat false, 4=definitely false) how true they thought the statements were about why they responded as they did to the willingness to pay question. These likert scale items were branched so respondents who answered "vote in favor" to the willingness to pay question were given one set of statements and respondents who answered "vote against" received a different set of statements. There were also eight statements that both "vote in favor" and "vote against" respondents were to answer. The "unsure" respondents in Treatment 2 were asked to respond to all the debriefing statements. There was also a series of questions that were developed to measure attitudes toward the environment in general.

The data were collected via mail surveys. Since this research was for methodological purposes and we do not generalize the results, we used a convenience sample to compare the responses to the payment questions obtained from the two alternative approaches. We recruited participants via ads placed in the general news section of three Sunday newspapers.[3] The ads offered $10 for completing a mail questionnaire on a "current Colorado issue." The ad did *not* mention noxious weeds or National Forests. A total of 891 Colorado residents responded to the ad and were mailed surveys. Seven-hundred-forty-three surveys were returned, for a response rate of 84%.

V. Results

Before comparing responses to the CV question for the two treatments, we compared the distributions of the responses to the survey questions prior to the CV question and the demographic questions to assess whether the respondents in the two treatments are

[3]The ads ran in the Denver Post and the Rocky Mountain News (two Denver based daily newpapers) and The Gazzette (a Colorado Springs daily newspaper).

representative of similar populations. As shown in Table 1, the respondents in Treatment 2 are very similar in virtually all respects (demographics, rates of visitation of national forests, attitudes towards forests and environment, and prior knowledge of the weeds problem) to those the respondents in Treatment 1. This result suggests that the differences in the responses to the payment questions between the two treatments (if any) are due to treatment effects rather than response effect.

V.1. Responses to the willingness to pay question

In Treatment 1, 76% of the valid responses were "vote in favor" compared to 62% of the valid responses in Treatment 2. In treatment 2, 13% of the valid responses were "vote against" and 25% were "unsure." This result is consistent with previous studies that found that when an explicit opportunity to express uncertainty is provided, a non-trivial percentage of respondents chooses the response category rather than providing a definitive response to the willingness to pay question.4

One response a study participant may have when he feels conflicted or uncertain about how to respond to a dichotomous choice CV question is to skip the question. If this is the case, explicit inclusion of an "unsure" response category should reduce item non-response. We find that in Treatment 1 (vote in favor/vote against) 5% of the study participants did not answer the CV question. In treatment 2 (vote in favor/vote

[4] This finding also confirms that numerous "not sure" responses can be observed in *any* survey that explicitly allows for such response category, and not just with in-person surveys, where, it has been suggested, respondents may opt for the "not sure" response when they are truly against the plan, but are reluctant to say so for fear of offending the interviewer or

against/unsure), the item non-response on the CV question is 2% (Table 2). The difference in item non-response for the two treatments is significant (χ^2 =4.125, p=.039).

This result has two important implications. First, given the relatively large fraction of "not sure" responses, it would appear that explicit inclusion of an "unsure" response category does not just attract people who would have skipped the question anyway. Second, whether or not including an explicit "not sure" response category is advantageous, in terms of reducing item non-response and in turn providing more useable observations, depends on how the "unsure" responses are treated in the statistical modeling of the data. If information from the "unsure" respondents is used in deriving estimates of mean willingness to pay (as in Wang 1997), decreasing item non-response is very important. If "unsure" respondents are excluded from the sample of usable observations, including an "unsure" response category will inevitably reduce the usable sample size (the loss of observations in our case would be of 25% of the original number of respondents).

V.2. Comparisons of the two treatments

The next step in the analysis is to compare the distribution of response to the payment question for the two treatments. The intent of these comparisons is to answer the question of what respondents would do if they were not explicitly provided the "unsure" response category. Treatment 1 with the standard dichotomous choice response format serves as the benchmark for assessing the most appropriate way method of dealing with the "unsure" responses.

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appearing to be socially or politically incorrect.

There are four options for dealing with the "unsure" responses. One option is to take the conservative approach and recode the "unsure" responses as "vote against." This approach implicitly assumes that if the "unsure" response were not explicitly offered, all the "unsure" respondents would choose to "vote against," and is in agreement with hypothesis 1.

The second option is to remove the "unsure" responses from the data set and only use the "vote in favor" and "vote against" responses. While this approach eliminates the need for the analyst to decide what to do with the "unsure" responses, it comes at the cost of losing a substantial amount of data. This option is in agreement with hypothesis 2.

The third approach is to recode the "unsure" responses as "vote in favor" responses. This approach is appropriate if there is evidence that "unsure" respondents are similar to respondents who "vote in favor" in the dichotomous choice treatment, and is thus implied by hypothesis 3.

The final option is to keep the "unsure" responses as they are and estimate mean willingness to pay using a model such as suggested by Wang (1997). We investigate the appropriateness of each of the four options.

V.3 Recoding the "unsure" as "vote against"

For both versions of the survey, the percentage of "vote in favor" responses to the willingness to pay question is highest at the lowest offer amount, declining as the offer amount increases (Table 3). In treatment 2, the percentage of "unsure" and "vote against" responses increase with the offer amount, reaching 32% and 22%, respectively, at the top offer amount of $75. This result would seem to suggest that the "unsure" responses could be interpreted and reclassified as if they were "vote against" responses. However, when we do so, the split between "vote in favor" and "vote against" at the various bid levels reproduces the distribution of responses from the standard dichotomous choice in Treatment 1 for only three of the five offer amounts (Table 3).

Comparisons of the estimates of mean willingness to pay also suggest that recoding the "unsure" responses as "vote against" results in an estimated mean willingness to pay that is statistically different from mean willingness to pay from the standard dichotomous choice data.5 As shown in Table 4, estimated mean willingness to pay is $78.15 based on the Treatment 1 data (dichotomous choice). When the unsure responses in Treatment 2 are recoded as "votes against", the estimated mean willingness to pay is $61.65. These two estimates are not statistically different at the 5% significance level.

A multinomial logit (MNL) model which predicts the likelihood of selecting each of the three possible response categories as a function of respondent characteristics, acceptance of the scenario and environmental priorities and a vector of response-specific coefficients is used to explore how these variables relate to the response to the willingness to pay question. If the relationships are similar between the regressors and both the "vote against" or

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5 The mean willingness to pay is computed using a fully parametric approach. Specifically, we fit a probit model where the dependent variable is a dummy indicator that takes on a value of one if the respondent voted in favor of the Noxious Weeds Control Program at the stated offer amount, and zero otherwise. The right-hand side of the model includes the intercept and the offer amount. This procedure assumes that the latent WTP variable is normally distributed, and recovers mean/median WTP as minus the coefficient of the bid, divided by the intercept (Cameron and James 1987). The standard errors are calculated from the covariance matrix of the probit estimates using the

"unsure" responses to the willingness to pay question, this can be viewed as support for the approach of re-coding the "unsure" responses as "vote against." The MNL model assumes that each response is associated with a level of utility:

(1) $$V_{ij} = \mathbf{x}_i \beta_j + \varepsilon_{ij}$$

where V is indirect utility, x is a vector of individual characteristics or attitudes, β is a vector of alternative-specific coefficients, and ε is a vector of i.i.d. error terms that follow the type I extreme value distribution. The subscripts i and j denote the individual and the response category, respectively. It can be shown that the probability that response k is selected by respondent i is:

(2) $$\Pr(k) = \frac{\exp(\mathbf{x}_i \beta_k)}{\sum_{j=1}^{3} \exp(\mathbf{x}_i \beta_j)}.$$

The MNL model is useful in that it allows one to identify what kind of individuals are more likely to select each of the possible response category, but has the disadvantage that it is not possible to recover estimates of mean willingness to pay. The MNL was one of the tools that led Carson et al. to conclude that persons who declined to vote in one of their two versions of the Alaska oil spill contingent valuation survey should be interpreted as having meant a vote against the proposed program.

Estimation results from the MNL model are reported in Table 5. The model shows clearly that the offer amount is one of the strongest determinants of the "unsure" and "vote against" responses. The positive coefficients of this variable indicate that as the bid increases

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delta method (explained in Cameron 1991).

(and holding all else unchanged) the likelihood of selecting the "unsure" and "vote against" response categories, instead of a "vote in favor," increase. It is also important to note that the coefficients of the bid are virtually the same for the "unsure" and "vote against" response options: the appropriate Wald statistic takes on a value of 1.42, failing to reject the null hypothesis of no difference at all conventional significance levels. This result is very similar to that previously obtained by Carson et al. (1998).6

Similar results—in the sense that the coefficients associated with the "unsure" response are statistically indistinguishable from the corresponding coefficients for the "vote against" response—are seen with DEFKNOW, DEFSIDE, HARMIMP and DONAT. The coefficients of all of these variables are negative and significant, implying that persons who state they know their future income (DEFKNOW=1), would like to know more about the potential side effects of weed control techniques (DEFSIDE=1), are more seriously concerned about the harm caused by noxious weeds to wildlife (HARMIMP=1) and contribute money to environmental organizations (DONAT=1) and are less likely to respond "unsure" or "vote against" to the willingness to pay question than to respond "vote in favor."

The MNL model also indicate that respondents with higher incomes are more likely to respond with a definite "vote in favor" or "vote against" than persons with lower income, that persons that said they need more information about the effects caused by weeds are more likely to select the "unsure" response category, and that dissatisfaction with the available information about how the program would be funded leads people to respond "vote against"

6 The statistic is distributed as a chi square with one degree of freedom under the null hypothesis of no dfference and for large sample size. The 5% critical level is 3.84.

the Noxious Weeds Control Program.

Concern about the effects of weeds on plants and soil do not seem associated with selection of any one of the response categories in particular, nor do ratings of national forests as habitat for plants and wildlife. Longer residence times in the state of Colorado appear to reduce the likelihood that a respondent will announce to be against the plan. We were rather surprised that familiarity with at least some common species of noxious weeds (as witnessed by having seen the plants shown in the pictures) does not affect the likelihood of choosing any one of three response categories. Overall the results of the MNL analysis suggest that the variables related to responding either "unsure" or "vote against" to the willingness to pay question are very similar, supporting hypothesis 1.

We conclude that while conditional analyses (i.e., the MNL model) support hypothesis 1, unconditional analyses based on the percentage of respondents in favor and against the program (after "unsure" responses in Treatment 2 are recoded conservatively as votes agaainst the plan) do not support hypothesis 1.

V.4 Removing the "unsure" responses from the data set

Inclusion of the "unsure" response category reduces the percent of both the "vote in favor" and "vote against" responses relative to the standard dichotomous-choice response format (Table 2). Carson et al report similar findings, and note that, when the "would not vote" response are excluded, the split between the "yes" and "no" in the remainder of the sample is similar to that observed when only two response categories are offered.

In this study, we find that dropping the "unsure" responses from the data provides statistically similar distribution of responses to the willingness to pay question between the two treatments at three of the five offer amounts (Table 3). When the "unsure" responses are dropped from the usable sample, the distribution shift to the right and in turn, increases both mean willingness to pay and the dispersion of willingness to pay estimate. Mean willingness to pay is now $103.61, but this estimate is not statistically distinguishable from that the $78.15 implied by the data from Treatment 1 respondents (Table 4).

V.5. Re-coding the "unsure" responses as "vote in favor"

Recoding the "unsure" responses to "vote in favor" results in an estimate of mean willingness to pay of about $140. This estimate of mean willingness to pay is significantly higher than the estimate of $78.15 from Treatment 1.

When comparing responses of "unsure" respondents to "vote in favor" respondents for a series of likert scale items developed measure the reasons for the response to the willingness to pay question, we see an interesting pattern. On four of the five items, contingency table analysis suggests that the distribution of response for the two groups ("vote in favor" and "unsure" respondents) is statistically different (Table 6). The consistent pattern is that more "vote in favor" respondents chose the extreme point on the scale which corresponds to "definitely true." Relative to the "unsure" respondents, more "vote in favor" respondents said it was "definitely true" that the program was worth the stated amount, that they wanted to show their support for the environment in general, that the goals of the program were an important consideration when deciding how to vote, that preserving the health of National Forest was very important to them. These results seem intuitive and suggest that "unsure" respondents are different from respondents who "vote in favor."

This is confirmed by the results of the MNL model in Table 5, which suggests that the relationships between the independent variables and responding either "vote in favor" or "unsure" to the willingness to pay question are significantly different. There is no evidence that in the absence of an explicit "unsure" response category, the "unsure" respondents would "vote in favor" or that the "unsure" respondents are similar to the "vote in favor" respondents.

V.6 Retaining the "unsure" responses

The model proposed by Wang (1997) allows for retaining the information provided by the "unsure" respondents. In this model, the "unsure" responses are distinct from both the "votes in favor" and "vote against" responses. Indeed, "unsure" responses are very informative about the underlying distribution of willingness to pay because they signal that the respondent's maximum willingness to pay is very close to the offer amount. Wang's model assumes that respondents vote in favor of the program if their willingness to pay amount is sufficiently greater than the offer amount—in fact, if it exceeds the offer amount by more than a certain amount. In a simpler specification of the model, the "threshold" (denoted as t1) that must be exceeded for the respondent to announce that he would be in favor of the program is held the same across all respondents. In a more complex specification, the threshold may be allowed to vary across respondents as a function of their economic circumstances, attitudes and beliefs, and acceptance of the scenario.

The model is completed by assuming that people that are against the program hold willingness to pay values that are sufficiently smaller than the offer amount. These persons will answer a firm "vote against" only if their willingness to pay is less than the offer amount, minus an appropriate threshold. For identification purposes, this threshold, denoted as t2, is assumed symmetric around mean willingness to pay with respect to the threshold t1. Finally, all persons whose willingness to pay lies between (bid-t2) and (bid+t1) will answer "unsure" to the willingness to pay question.

The contributions to the resulting likelihood function are thus:

(3) $$\Pr(yes \mid B_i, \mathbf{x}_i) = \Pr(WTP_i > B_i + t_1) = \Pr(x_i\beta + \varepsilon_i > B_i + t_1) =$$

$$= \Pr(\varepsilon_i / \sigma > -x_i\beta / \sigma + B_i / \sigma + t_1 / \sigma),$$

(4) $$\Pr(no \mid B_i, \mathbf{x}_i) = \Pr(WTP_i < B_i - t_1) = \Pr(\varepsilon_i / \sigma < -x_i\beta / \sigma + B_i / \sigma - t_1 / \sigma)$$

and

(5) $$\Pr(not\ sure \mid B_i, \mathbf{x}_i) = \Pr(B_i - t_1 < WTP_i < B_i + t_1)$$

$$= \Pr(\varepsilon_i / \sigma < -x_i\beta / \sigma + B_i / \sigma + t_1 / \sigma) - (\Pr(\varepsilon_i / \sigma < -x_i\beta / \sigma + B_i / \sigma - t_1 / \sigma).$$

If one assumes that willingness to pay follows the normal distribution, the three contributions become:

(4) $$\Pr(yes \mid B_i, \mathbf{x}_i) = \Phi\left(x_i\beta / \sigma - B_i / \sigma - t_1 / \sigma\right),$$

(5) $$\Pr(no \mid B_i, \mathbf{x}_i) = \Phi\left(-x_i\beta / \sigma + B_i / \sigma - t_1 / \sigma\right)$$

and

(6) $$\Pr(\textit{not sure} \mid B_i, \mathbf{x}_i) = \Phi\left(-x_i\beta/\sigma + B_i/\sigma + t_1/\sigma\right) - \Phi\left(-x_i\beta/\sigma + B_i/\sigma - t_1/\sigma\right),$$

where Φ denotes the standard normal cdf.

The results of the Wang model for normal willingness to pay are reported in Table 7. In this specification, the thresholds are allowed to vary with respondent characteristics. For the sake of simplicity, we work with a specification of the threshold that is linear in respondent characteristics or variables capturing acceptance of the scenario:

(7) $$t_1 = \mathbf{z}_i\delta.$$

Because this function is linear, all coefficients are identified only if the variables that enter in the determination of the threshold (the $\mathbf{z}_i$ s) do not overlap with variables than enter in the expression for mean willingness to pay (the $\mathbf{x}_i$ s).

The results make intuitive sense and confirm some of the insights learned from the MNL model. Mean willingness to pay increases significantly with respondent confidence about his or her future income (by \$34), with respondent need for more information about the side effects of weed control (by \$97; presumably, this signals seriousness about undertaking the program), and is typically greater among persons who contribute to environmental organizations (by about \$33). Concern over wildlife impacts of uncontrolled noxious weeds also tends to increase willingness to pay (by about \$55). By contrast, skepticism about the funding of the noxious weeds program reduces willingness to pay by about \$49.

The "unsure" region—the band around the bid within which the respondent is unable to provide a firm "vote in favor" or "vote against" response—is made considerably tighter (by about $15) by each year of formal education and by personal experience with the species of weeds, although the effect of the latter (about $5) is less pronounced. Other research (Krupnick et al. 2000) finds that, holding all else constant, women are more likely to respond "unsure" to a trichotomous choice question. We do find that males seem to have somewhat tighter uncertainty regions, but the effect is not statistically significant. We also experimented with including among the determinants of the thresholds variables that capture the respondent's experience with vote situation, but neither a dummy for voting in national elections nor one for voting in local elections was found to have any explanatory power for the thresholds.

The estimated mean willingness to pay based on the Wang model $102.36 and the standard error is $13.94. The asymptotic t-test to compare the mean based on the Wang model to the estimate of mean willingness to pay based on the standard dichotomous choice data (which is equal to $78.15) results in a statistic of -1.4955. The difference between the two means is *not* statistically different.

V.7. Why are respondents unsure?

One way of attempting to explain the "unsure" responses is to link them to observable characteristics of the respondents that might plausible influence their ability to provide firm information about willingness to pay (such as age, education, income) and the information they provided in answering the Likert-scale debrief questions.

Uncertainty about future income (or ability to commit money on behalf of the household) or uncertainty about aspects of the provision of the program could result in choosing the "unsure" response category when answering the vote question. To test this conjecture, several statements about the respondent's future income, ability to make decisions about spending in his or her household, and knowledge of the resource quality implied by the plan were included in the questionnaire. The respondent was asked to circle whether he "definitely" or "somewhat" agreed with each of the statement, or "definitely" or "somewhat" disagreed. We compare the percentage of respondents who find the statement "I know what my income will be in the near future" somewhat or definitely false.7 As shown in Table 8, among the 85 respondents who chose the "unsure" response category to the willingness to pay question in Treatment 2, 29 disagree with that statement (35 percent). By contrast, only 16 percent of the people who answered "vote in favor" to willingness to pay question felt uncertain about their future income. This suggests that uncertainty about income is one, but not necessarily the most important, of the reasons for choosing the "unsure" response category. This conclusion is further confirmed by the fact that 32% of the people who answered "vote against" disagreed with the statement about knowing their future income. A similar story emerges about the respondent's recognition that he or she makes spending decision in their household. More of the "unsure" respondents (62%) relative to the "vote in favor" (52%) and "vote against" (50%) respondents agreed that they needed more information about the problems that the weeds cause;

Looking for further insights into the reasons for choosing the "unsure" response

7 In these analyses, we pool together the "definitely" and "somewhat" response categories.

category to the vote question, we group together firm "vote in favor" and "vote against" respondents, and compare their answers to questions about resource quality in the absence of the program with those provided by "unsure" persons. Table 9 shows the measures for which the distribution of response for the "unsure" respondents is significantly different from the distribution of response for study participants who provided a definitive ("vote in favor" or "vote against") answer to the willingness to pay question. With respect to the statements about the reasons for having National Forests, relative to the "vote in favor" and "vote against" respondents, fewer of the "unsure" respondents thought it is extremely important that National Forest provide habitat for plants or habitat for fish and wildlife and the distribution at the low end of the scale (not at all concerned) is equivalent for the two groups. A consistent pattern is seen with the statements about the respondent level of concern about the various impacts of noxious weeds. Fewer of the "unsure" respondents said they were "extremely concerned" about the decreased soil stability, harm to wildlife, and decreased water quality. The "unsure" respondents were more likely (73% versus 50% of the "vote in favor" or "vote against" respondents) to say it was definitely or somewhat true that they needed more information about the problems weeds cause. It appears that the difference between the respondents who were able to provide a definite response to the willingness to pay question and those who said they were "unsure" is that "unsure" respondents find the reasons for having National Forests to be less important and they are less concerned about the impacts of weeds.

VI. Conclusions

The NOAA Panel recommended inclusion of a "no answer" response category, in addition to the "vote in favor" and "vote against" response categories. The Panel also recommended additional research in "alternative ways of presenting and interpreting the no-vote option" (Federal Register vol. 58, no. 10, p. 5910). This study has allowed us to compare the dichotomous choice format with a response format that includes an "unsure" response category in addition to the "vote in favor" and "vote against" response categories. We found that inclusion of the "unsure" response category changes the distribution of response to the willingness to pay question relative to the dichotomous choice format. If the "unsure" responses are conservatively recoded as "vote against" or if they are removed from the data set, we did not find the distribution of the "vote in favor" and "vote against" responses to be similar to the standard dichotomous-choice treatment.

We found that a substantial number of respondents across the range of offer amounts, chose the "unsure" response category to the willingness-to-pay question. This result is consistent with previous studies (Carson et al, Wang) and supports the call for research to better understand *why* respondents choose the "unsure" response category. Our study suggests that the causes of uncertainty are complex and likely vary among respondents. We recommend efforts be made during the design phase of the contingent valuation survey instrument to minimize uncertainty related to the information provided in the scenario, yet we acknowledge that even the best designed contingent valuation surveys are likely to leave some respondents unsure about how to respond to the willingness-to-pay question. Given this situation, it seems appropriate continue researching the effects of inclusion of an "unsure" response category. Research to develop models to include the "unsure" responses in the willingness to pay estimates would particularly useful. Research is also needed into the determinants of "unsure" response to closed-ended contingent valuation questions.

From a statistical perspective, inclusion of an "unsure" or "no vote" response category has not been found to be superior over the standard dichotomous-choice format. Given the limited statistical tools currently available for interpreting these unsure responses and the lack of a theoretical model for motivating the "unsure" responses, the standard dichotomous choice format has an advantage over the trichotomous response format. We did not find evidence of a simple decision heuristic whereby unsure respondents "voted against" when forced to make a decision in the dichotomous-choice format. We found that some of the individuals who chose the "unsure" response category would likely answer "vote in favor" while others would choose "vote against" in a standard dichotomous choice situation. Given our current inability to appropriately model "unsure" responses, it may be better to use the standard dichotomous-choice format in actual CV applications as suggested by Carson et al.

Table 1: **Comparison of Treatments**

	Treatment 1 (vote in favor/vote against)	Treatment 2 (vote in favor/vote against/unsure)
Ever Visited or Seen a National Forest?		
Yes	92%	95%
No	5%	3%
Unsure	3%	2%
Prior to this survey, had you heard about noxious weeds?		
Yes	52%	56%
No	48%	44%
In the last year have you contributed money to an environmental organization?		
Yes	25%	22%
No	75%	78%
Demographic Measures:		
Percent Female	39%	43%
Mean Age	48 years	46 years
Mean Years in CO	24 years	24 years
Educ:		
Eighth or less	0%	0%
Some high school	4%	3%
High school graduate	11%	10%
Some College or technical school	31%	27%
Technical or trade school graduate	9%	9%
College graduate	24%	26%
Some graduate work	7%	10%
Advanced degree	14%	14%
Household Income:		
less than $10,000	9%	8%
$10,000-19,999	12%	14%
$20,000-$29,999	15%	15%
$30,000-$39,999	13%	12%
$40,000-$49,999	12%	13%
$50,000-$59,999	13%	11%
$60,000-$69,999	8%	5%
$70,000-$79,999	4%	5%
$80,000-$89,999	4%	6%
$90,000-$99,999	5%	4%
$100,000-$149,999	4%	5%
over $150,000	2%	1%

Table 2: Response to Willingness to Pay Question by Treatment

	Treatment 1 (vote in favor/vote against) n=379	Treatment 2 (vote in favor/vote against/unsure) n=345
Vote in Favor	72%	61%
Vote Against	23%	12%
Unsure		25%
No Response	5%	2%

Table 3: Response to Willingness to Pay Question by Offer Amount

	Treatment 1 (vote in favor/vote against)	Treatment 2 (vote in favor/vote against/unsure)		
		No recoding	Unsure dropped	Unsure recoded as no
$5	n=72	n=65	n=55	n=65
Vote in favor	89%	78%	93%	78%
Vote against	11%	6%	7%	22%
Unsure		16%	χ^2=.537[8]; p=.464	$\chi^2=2.76^1$; p=.097
$10	n=74	n=66	n=50	n=66
Vote in favor	86%	67%	88%	67%
Vote against	14%	9%	12%	33%
Unsure		24%	$\chi^2=.061^1$; p=.805	$\chi^2=7.77^1$; p=.005
$25	n=75	n=64	n=49	n=64
Vote in favor	79%	70%	92%	70%
Vote against	21%	6%	8%	30%
Unsure		24%	$\chi^2=3.80^1$; p=.051	$\chi^2=1.28^1$;p=.258
$50	n=65	n=73	n=51	n=73
Vote in favor	74%	51%	72%	51%
Vote against	26%	19%	28%	49%
Unsure		30%	$\chi^2=.025^1$; p=.875	$\chi^2=7.80^1$;p=.005
$75	n=73	n=69	n=47	n=69
Vote in favor	49%	46%	68%	46%
Vote against	51%	22%	32%	54%
Unsure		32%	$\chi^2=4.10^1$;p=.043	$\chi^2=.123^1$; p=.726
Overall	n=359	n=337	n=252	n=337
Vote in favor	76%	62%	83%	62%
Vote against	24%	13%	17%	38%
Unsure		25%	$\chi^2=4.88^1$;p=.027	$\chi^2=14.745^1$;p=.00

[8]Testing the distributions of responses at the specified offer amount between Treatment 1 and the Treatment 2 with "unsure" recoded as described in the column heading.

Table 4: Mean WTP by Treatment.

	Treatment 1 (vote in favor/vote against)	Treatment 2 (vote in favor/vote against/unsure)		
		Unsure recoded as yes	Unsure dropped	Unsure recoded as no
Mean WTP (Standard Error)	**$78.15 (8.23)**	**$140.61 (30.97)**	**$103.61 (17.82)**	**$61.65 (8.71)**

Asymptotic t tests for the difference in mean WTP

	T statistic	Statistically different?
Treatment 1 v. treatment 2 with "unsure" recoded as "vote in favor"	-1.96	Yes, at 5% significant level
Treatment 1 v. treatment 2 with "unsure" dropped	-1.30	No
Treatment 1 v. treatment 2 with "unsure" recoded as "vote against"	-1.38	No

Table 5. Multinomial logit model of responses. Treatment 2. Omitted category: "vote in favor." N=339.

Variable	UNSURE Coefficient (T statistic)	NO Coefficient (T statistic)	Likelihood ratio statistic that coefficients are both equal to zero[a] (P value in parentheses)
Constant	2.56276 3.57	0.39655 0.41	14.2429 (0.001)
Bid level	0.02421 3.88	0.03358 4.23	23.4486 (less than 0.001)
Household income (thou.dollars)	-0.01482 -2.55	0.00692 1.09	10.6162 (0.005)
DEFKNOW (Respondent knows future income)	-0.96480 -2.68	-1.05015 -2.23	8.8001 (0.012)
DEFWEED (Respondent needs more information about the problems caused by weeds)	1.20869 3.07	-0.11612 -0.24	11.3701 (0.003)
DEFSIDE (Respondent needs more information about the side effects of weed control techniques)	-2.04829 -3.46	-3.45762 -5.22	29.0606 (less than 0.001)
DEFPROG (Respondent needs more information about how the program would be funded)	0.71191 1.50	1.78596 2.90	8.8405 (0.012)
DONAT (Respondent contributes to environmental orgs.)	-0.98205 -2.13	-0.95317 -1.65	5.9756 (0.050)
SOILIMP (respondent is extremely concerned about the soil stability impacts of noxious weeds)	-0.35196 -0.74	0.20489 0.34	0.8535 (0.653)
WATERIMP (respondent is extremely concerned about the water quality impacts of noxious weeds)	0.23084 0.48	0.01861 0.03	0.2529 (0.881)
HARMIMP (respondent is extremely concerned that noxious weeds will harm wildlife habitat)	-2.02458 -4.02	-1.53207 -2.56	17.5873 (less than 0.001)
PLANTIMP (respondent is extremely concerned about the effects of noxious weeds on native plants)	0.41126 0.86	-0.95961 -1.62	4.3016 (0.116)
HABPLANT (respondent strongly agrees with the statement that national forests provide habitat for plants)	-0.69582 -1.84	-0.18445 -0.37	3.4875 (0.175)
HABLIFE (respondent strongly agrees with the statement that national forests provide habitat for fish and wildlife)	-0.37773 -0.82	0.38169 0.54	1.6835 (0.431)
LIVECO (years lived in Colorado)	-0.00759 -1.01	-0.02634 -2.31	5.4608 (0.065)
Log likelihood	-226.06		

[a] Each likelihood ratio test is distributed as a chi square with two degrees of freedom under the null hypothesis.

Table 6: Comparing "unsure" respondents to "vote in favor" respondents

How true is each statement?		Definitely True	Somewhat True	Somewhat False	Definitely False
I felt the ***Noxious Weeds Control Program*** would be worth the amount I was asked to pay. (χ^2=110.85;p=.000)	Unsure	10%	64%	23%	3%
	Vote in Favor	75%	23%	1%	1%
I would vote for the program to show my general support for the environment (χ^2=119.25; p=.000)	Unsure	10%	69%	16%	5%
	Vote in Favor	80%	17%	1%	1%
The goals of the ***Noxious Weeds Control Program*** were an important consideration when deciding how to vote (χ^2=37.01;p=.000)	Unsure	27%	60%	12%	1%
	Vote in Favor	65%	32%	2%	1%
The use of herbicides was an important factor when deciding how to vote (χ^2=2.078;p=.556)	Unsure	32%	48%	14%	5%
	Vote in Favor	31%	42%	18%	9%
Preserving the health of the National Forests is very important to me (χ^2=14.681;p=.002)	Unsure	74%	23%	3%	0%
	Vote in Favor	90%	9%	0%	1%

Table 7. Wang model of responses. Treatment 2. N=339.

Variable	Coefficient	T statistic
β coefficients		
Constant	-15.9407	-0.760
Household income (thou.dollars)	-0.0195	-0.074
DEFKNOW (Respondent knows future income)	34.4657	2.369
DEFWEED (Respondents needs more information about the problems caused by weeds)	-10.7381	-0.864
DEFSIDE (Respondent needs more information about the side effects of weed control techniques)	96.6999	3.880
DEFPROG (Respondent needs more information about how the program would be funded)	-49.8911	-2.684
DONAT (Respondent contributes to environmental orgs.)	32.6722	1.977
SOILIMP (respondent is extremely concerned about the soil stability impacts of noxious weeds)	5.5245	0.340
WATERIMP (respondent is extremely concerned about the water quality impacts of noxious weeds)	-4.2428	-0.263
HARMIMP (respondent is extremely concerned that noxious weeds will harm wildlife habitat)	54.6235	2.855
PLANTIMP (respondent is extremely concerned about the effects of noxious weeds on native plants)	12.7086	0.799
HABPLANT (respondent strongly agrees with the statement that national forests provide habitat for plants)	13.6427	0.997
HABLIFE (respondent strongly agrees with the statement that national forests provide habitat for fish and wildlife)	-6.3212	-0.400
Standard deviation of WTP (σ)	72.4869	4.870
γ coefficients		
Constant	81.0222	3.732
Education	-12.5910	-1.775
MALE	-16.1810	-1.428
SEEN1 (Respondent has seen the noxious weeds)	-4.2811	-1.967
MEAN WTP:	**$102.36 (s.e. 13.94)**	

Table 8: Reasons for vote on the Noxious Weeds Control program (all respondents). Treatment 2

Statement	Percent of "vote in favor" respondents who agree	Percent of "vote against" respondents who agree	Percent of "unsure" respondents who agree
I know what my income is in the near future	84%	68%	65%
I make the spending decision in my household	90%	79%	66%
I need more information on the problems that weeds cause	52%	50%	62%
I need more information on the possible side effects of the methods that would be used to control weeds	90%	57%	79%
I need more information about how the program would be funded	71%	70%	72%

Table 9: Comparing "unsure" respondents to "vote in favor" and "vote against" respondents

Importance of reasons for having National Forest....		**Not at all important**	**Slightly important**	**Important**	**Extremely Important**
Habitat for Plants (χ^2=12.13; p=.007)	Unsure	1%	4%	37%	58%
	Vote in Favor and Vote Against	1%	2%	19%	78%
Habitat for Fish and Wildlife (χ^2=14.11; p=.003)	Unsure	1%	5%	18%	76%
	Vote in Favor and Vote Against	1%	1%	8%	91%
Level of concern about impacts of noxious weeds....		**Not at all Concerned**			**Extremely Concerned**
Decreased Soil Stability (χ^2=7.70; p=.053)	Unsure	4%	21%	42%	33%
	Vote in Favor and Vote Against	2%	12%	38%	48%
Harm to Wildlife (χ^2=19.28; p=.000)	Unsure	1%	45%	38%	48%
	Vote in Favor and Vote Against	2%	4%	21%	73%
Decreased Water Quality (χ^2=12.65; =.005)	Unsure	5%	14%	29%	52%
	Vote in Favor and Vote Against	2%	5%	25%	68%
How true is each statement?		**Definitely True**	**Somewhat True**	**Somewhat False**	**Definitely False**
I need more information about the problems weeds cause (χ^2=15.72; p=.001)	Unsure	26%	47%	23%	4%
	Vote in Favor and Vote Against	16%	34%	30%	20%

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VALUES, VALUES, VALUES

Reflections on the Nature and Use of Non-Market Values

Philip R. Wandschneider

Abstract: In a variation of the (in)famous triad of location, location, location, one might say that all that matters when doing non-market valuation are values, values, values. Usually, in W-133 workshops discussions focus on issues of operationalizing value observations (stated or revealed) into useful data. But what are we really measuring? Does what we measure have social relevance? Should it? How should the validity of this information be checked, and how should the information be used. In this paper I will briefly review the nature of the underlying value concept we attempt to measure, some conceptual issues in operationalizing these measures, and some issues in public choice concerning the validation and use of these measures. The paper is based partly on personal experience with using CV in contentious social circumstances. The purpose of the paper is to discuss some issues in moral philosophy and methodology related to contingent valuation specifically, and economic valuation in general.

INTRODUCTION

A great deal of the professional effort of applied economists is devoted to improving methods for measuring economic values. This is as true of marketing economists estimating demand systems as it is of non-market specialists estimating recreational values or environmental damages. But exactly what is it that we are measuring? Clearly economists are not measuring the same kind of thing that chemists measure when the analyze chemical compositions or astrophysicists measure when examining the spectra of distant objects. And yet, measurements of economic values have real world implications. Policy actions can turn on estimates of economic value.

This essay comprises some thoughts about the nature of economic values based on the author's experience with the regulatory use of economic values and a liberal borrowing of notions from the philosophy of science, epistemology, and the writings of economists of greater experience and stature. If estimates of economic value are not based on the physical properties of things, what are they? How can they be measured, who should decide what they are, and who decides how they are to be used? This essay will explore some notions of value and attempt to help clarify the role of the researcher and the discipline in the policy process. I will briefly explore three questions, with most of the essay devoted to the first question. The first question is epistemological; what are the epistemological and scientific grounds for discovering and measuring economic values? The second question is moral; what is the ethical status of measures of economic value? The third question is political; how should estimates of economic value be used in the policy process?

The case which provoked these thoughts was a contingent valuation study of the benefits from a state rule to reduce smoke from burning of grass seed crops in Eastern Washington (Wandschneider et al,). Washington state law requires a study of economic benefits and costs of a proposed environmental regulation. The state Department of Ecology contracted with researchers at Washington State University to provide this analysis. The resulting analysis supported the proposed regulation with a finding that estimates of economic benefits of the rule exceeded estimates of costs. Economic benefits were estimated using a contingent valuation study. In reaction to the study, stakeholders who believed that they would be harmed by the regulation attempted to overturn the benefit cost analysis by appeal to the university itself and by appeal of the regulation within the framework of administrative law procedures. Opponents of the benefit cost study criticized both the particular methods of the cost benefit study, and, more generally, the use of contingent valuation. In a very modest way the situation parallels the vigorous debate over using contingent valuation which arose because of the Exxon Valdez mishap. The Exxon Valdez debate generated polar positions, with some, even in the economic community, questioning the legitimacy of contingent valuation economic value estimates (especially for "passive use" values), while others defended the method (See Portnoy, Hanemann, Smith, Diamond and Hausman, McFadden, inter alia.).

THE SCIENTIFIC GROUNDS FOR THE MEASUREMENT OF ECONOMIC VALUE

In considering the scientific nature of estimates of economic value, topics can be organized into three subjects. These are not strictly separable topics, but they provide a convenient organization for the discussion. This section, the main part of the essay, considers: conceptual/epistomological matters; operational/measurement issues; and confirmation/validity issues.

The Epistemological Status of Economic Values

Let us first consider what it is that is being measured in estimating economic values. At one level there is a simple answer. What is measured is what the measurement instrument measures. While this proposition is true, it is true at a tautological level and begs the question (although it has important empirical implications). The underlying question concerns the nature of the thing that one wishes to measure. One can then ask the question of whether the measurement has successfully captured this property.

So we must ask, what is the economic value of something? In addressing this question, one cannot avoid some rather deep metaphysical and epistemological questions. It is immediately clear that the economic value of a thing is not a physical property of the thing. Let us define an economic value as *a magnitude assigned to a thing or action indicating its worth (to the agent assigning the value).* Notice the unusual quality of value compared to physical properties of objects. To measure a physical property of something, one addresses one's instrument to the object[1]. But for a value assignment, does one measure a property of the thing, or an aspect of the observer (the agent assigning value)?

The branch of epistemology dealing with value claims is called axiology. Axiology is largely defined by two polar positions concerning the nature of the entity "value." The *objectivist* position is that value resides in the value object, and that the observer is assigning value based on his or her perception of that "intrinsic" value. This position must be based on an idealistic metaphysical presupposition. An idealist believes that the fundamental nature of reality admits of certain non-material phenomenon. Perhaps the most famous idealist is Plato who asserted that the ultimate Reality comprises ideal objects -- e.g., the perfect sphere -- and that the material objects we experience in daily life are but weak reflections of the deeper Reality. The metaphysical foundation of other idealists rests on spiritual foundations; the ultimate reality is God (e.g., C.S. Lewis). Reality is whatever God says it is. The idealist interpretation of the valuation process is therefore that the observer is somehow able to understand (apperceive) this non-material quality which is a property of the valuation object itself, or, perhaps the connection of the

[1]Actually, the situation for physical properties is more complicated. For one thing, one might argue that perception or belief about the nature of an object is at least partly subjective. For another thing, modern quanturm theory raises the possibility that the state of nature might not be independent of the observation.

valuation object with a deeper Reality (God, the Ideal). The apperception process does not rely on the normal senses, which can detect no aspect of these ideal properties.

On one count, the objectivist position may seem attractive because it grounds the value concept in something that is absolute and "Real." The operational task becomes one of finding a mechanism to measure this magnitude. However, the objectivist position raises the considerable challenge of how to infer a material measurement from an immaterial essence. This is counter to the usual materialist epistemology of science. Science rests on a materialistic premise that the world we observe is the only reality. Their are no hidden, deeper realities. Everything can be understood and explained in terms of logic and observable entities.[2] Thus the idealist-objectivist position creates a conundrum - values are defined things, but they are things that cannot, in principle, be observed by the ordinary senses even augmented by instruments.

In contrast to the objectivists, the *subjectivists* hold that value resides entirely within the observer. All values are expressions of some subjective, emotional state of the observer. The pure subjectivist position implies that values are fundamentally arbitrary. Value measurements are at best measures of the emotional state of the observer and provide no information about the value object. An illustration of this subjectivist view is the discussion of "warm glow" in the valuation literature. Warm glow occurs when a valuing agent assigns a value to an object because it makes him/her feel good. The assigned value is a nearly meaningless, ad hoc emotional expression. It measures nothing about the value object at all. The pure subjectivist would see all valuation as "warm glow" (or cold void?). The pure subjectivist position spells doom for attempts at measuring economic values.

Subjectivism is clearly the position of some critics of the contingent valuation method (CVM). No amount of improvement in operational techniques will satisfy such critics because there is nothing to measure. However, it should be noted that the pure subjectivist position is different from the position of those who might accept that an economic value can be measured, but who believe that such measurements should be rejected on ethical grounds. I discuss this issue later.

Ironically, the polar positions of both objectivist and subjectivist would seem to leave the scientific study of economic values in a bad place. However, alternative positions exist. One alternative philosophical position is that of the pragmatists. Pragmatists believe that assigning a value to an object is an interactive process between a community of observers and the value object. A value assignment requires both (a community of) observers and objects. Economic valuation must rest on something like the pragmatist's epistemological position. A value assignment is a social fact. In some sense it resides inside (is subjective) the observer, but it refers to the object and so is not merely a subjective, emotional expression. The implication of such a view is that, while economic value is not a defined property (like mass), there is something material to measure. This material thing comprises a relationship between the object and the observers, so an economic value is necessarily a contingent property. The nature of the economic value property depends on the relationship between observers and value object.

The Nature of Economic Values

Assuming something like the pragmatist's position, the question is, what is the nature and stability of the property, economic value. Are economic values stable or even "fixed," or are they constructed on the fly - are they arbitrary and ad hoc. Economics has followed two tracks in attempting to answer this question: a theoretical approach based on hedonic psychology, and an operationalist approach grounded

[2]However, scientific models can have theoretic terms which are not observable as long as the overall model can be justified using experiential data. See, e.g., Hausman, 19__

in observation. Revealed preference theory attempts to join the two - unsuccessfully according to Hausman (1999).

An operationalist approach defines what is measured in terms of the measurement instrument[3]. An economic value is whatever is measured by the tools that we have which measure value. It would seem that there is no need for theory. However, such a completely atheoretic approach is unsatisfying because the measurements have little meaning. Suppose one measures a value of P for object X. Who is to say how long and under what conditions this magnitude is valid? Without a theoretic structure, one does not know how to interpret economic value observations. Consider either a revealed or stated preference value. If it is simply an empirically observed action or recorded utterance, how are we to know under what conditions it holds? Repeated observations may give us some clue about stability, but how do we distinguish an accidental string of similar observations from true underlying stability. We are faced with the classical (Hume's) problem of how to gain demonstrable inductive knowledge.

The hedonic psychology approach provides a systematic explanation for behavior and economic value[4]. Using this theory of a self-interested, hedonic agent, an economic value can be characterized as a stable, existing property - given a stable relationship between observer and object. A theoretic meaning is assigned and the operational objective becomes a search for a sound method to measure the conceptually defined thing. Unfortunately, the theoretic property which confers meaning to economic value, utility, is not directly measurable. Moreover, it is not clear, on a priori grounds, how well defined and stable this utility structure is. Current economic micro-theory assumes that people can only rank alternatives. While the rankings can be represented by a utility index under certain assumptions, the magnitudes of the utility index have little significance. In theory, they are valid only up to a monotonic transformation. If the magnitudes attached to economic valuation are only valid up to a monotonic transform, what information does a numeric measurement (a price or willingness to pay) convey?

Perhaps surprisingly, a numeric value does convey information. However, the information is a good deal more convoluted than is sometimes portrayed. Suppose we are able to measure a true economic value consistent with the standard ordinal utility theoretic structure. What a numeric price or willingness to pay value says is that, under certain regularity conditions, certain kinds of money measures will generate an ordering that is consistent with the ranking of the valuing agent. That is, the magnitude of the money measure has meaning only within the context of measuring all other things of interest with the same measuring scheme under the same "initial conditions."

Let us repeat for emphasis. The magnitude of the economic value is non-unique. It is not arbitrary, since the price for thing C must place it in an overall ranking consistent with the internal preference ranking of the valuing agent. However, an infinite number of price structures can theoretically produce the same ranking. In empirical work, this raises a number of issues.

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[3]Extreme operationalists deny the existence of anything which is not measurable. Thus early behavioral psychologists denied the existence of any internal brain processes (a black box), and even defined thought as some kind of not-yet-detected sub-vocalizations.

[4]Economists tend to be somewhat schizoid, teeter back and forth between a purely empiricist, operationalist view and a theoretic psychological model built around the hedonic calculus. In principle, the two should inform each other. In fact some claim that the utility index is recoverable from only choice data based on the weak axiom of revealed preference - but see Hausman for contrary view. In fact, there has been considerable work to use the theoretical structure to inform empirical studies, including empirical value studies. The extensive literature on the theory and measurement of the various concepts of consumer surplus exemplifies this connection. However, economics is not yet a mature science with theory being constantly confronted with evidence and adjusted accordingly.

- How do we know that the measured price (revealed or stated preference), correctly places the value object in the right ranking; what conditions are necessary to assure consistency of measurement? The considerable literature on surplus measures and compensation tests addresses these issues.
- The question of whether the sum of all price times quantity exhaust the total budget is not per se at issue. The purpose of the budget constraint is to see that the respondent is answering under the same conditions as are used for pricing all the other objects which the target object is to be ranked against. However, the budget constraint is only one of a set of incompletely understood conditions required to assure that the prices are consistent.
- More generally, we must calibrate any empirical values, specifying the circumstances under which they apply.
- Under what conditions can we aggregate the price/ranking of different agents. How do we know they are all using the same valuation scheme?

An obvious illustration of the non-uniqueness of economic value measures is the difference between willingness to pay and willingness to sell (accept compensation). In fact, in principle, there are a half dozen theoretic measures of the value of a welfare change to an indiviudal[5]. A large literature exists about the relative merit of these measures (which ones will produce the most utility-consistent ranking), and the circumstances under which they approximate each other. Without entering that discussion, the point here is that, according to the accepted standard economic micro-theory, the measurement of economic value is, in principle, fuzzy.

In summary, there is a kind of Heisenberg's uncertainty principle for economics - any value we measure is not unique and has meaning only as a relative quantity in relationship to all other values. At a deep, conceptual level, economic values are embarrassingly slippery. Any particular measurement is, in principle, a contingent value. There exists no underlying unique value to be measured. One must pay careful attention to the context in which the value is measured. Different contexts may invoke different comparisons and hence different numeric magnitudes for the economic value of a thing. In fact, two different empirical measurements, elicited on two different occasions may BOTH be valid - but in different contexts.

Three final points. First, while this argument has been developed within the framework of ordinal utility, having cardinal-measurability for utility improves things, but cardinal utility is still unique only to an affine transformation. With stronger measurability, information on intensity becomes meaningful. Still, we do not know what the relative values are unless we know the "exchange rate" between agent ones internal utility metric, the exterior metric, and agent B's metric. Moreover, the fundamental non-uniqueness of economic values remains - unless we are prepared to assign absolute values to things like the objectivists do.

Second, it must be emphasized that the fuzziness of economic value measurement does not mean that such values are entirely arbitrary. In fact, given the multitude of objects which must be ranked, the freedom to assign arbitrary values is drastically reduced. If one values a new car at $30,000, one clearly cannot value a can of soup at $60,000 with any kind of consistency.

Finally, it must be acknowledged that the economic utility hedonic may not be the correct psychological model. Perhaps the human valuation system works differently. For example, perhaps

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[5]In mathematical terms, the magnitude of a welfare change is determined by a line integral, which depends on the path of integration.

value assignments are based on what people think prices should be, or perhaps altruism is important.

Operational Issues in Measuring Economic Values

So the conceptual investigation leads to the conclusion that any empirical measurement of economic values will have some potential fuzziness to it, and that applied studies must carefully assess and report the circumstances under which they measure values, as the values will be contingent. Now we should ask whether operational measures of economic value can be constructed. Broadly speaking the experience of economics is that economic values can be measured but that there are many obstacles and challenges to obtaining sound empirical measures. (See, for example, the NOAA panel report (Arrow, et al), Mitchell and Carson, or Diamond and Hausman, Freeman, or any of a large number of other works for discussions of these difficulities.) Difficulties exist in measuring revealed preference, market values and even more difficulties exist in measuring the economic value of non-marketed goods and services. Of course, the primary purpose of the W-133 research project is to address these difficulties for the non-market case. Overall, economists have developed an impressive set of techniques for measuring economic values, but challenges remain.

In summary, the discussion at the conceptual level says that some ambiguity is unresolvable and numerical values are inevitably contingent. On top of this is a layer of operational question that doubtless will occupy economists for many years. Operationally, we are very unlikely to get a precise measure of the underlying economic value - even were it to "sit still" so we could take a picture of it. Still, at least with operational problems, we know that greater effort will be rewarded with improved estimates of values.

Problems in Testing and Confirming Knowledge about Economic Values

Since economic value research is plagued by both conceptual and operational uncertainties, how are we to determine whether our theories about economic value and our protocols and the resulting estimates of economic value are "good." Actually, there are two questions here - one of scientific validity and one of practical use. Let us postpone the discussion of the practical/policy use of estimates of economic value and turn to the issue of judging scientific validity. Specifically, let us focus on how we can know if we have a "good" estimate of economic value - how can we determine if the measurements are correct?

The issue of confirming putative scientific knowledge is an issue of scientific (economic) methodology. Current understanding of economic methodology is that scientific procedures can neither demonstrably prove, nor disprove a theory. Of course, simple factual assertions can be demonstrably proven by direct experience. Also, logical systems can be evaluated to determine whether they are valid in the sense of consistent. However, assertions generated by a theory depending on scientific laws cannot be demonstrably proven. This difficulty is due to the impossibility of proving an inductive law of nature (the problem of induction, Hume's problem) on the one hand, and the difficulty in disproving a theory on the other hand. The difficulty in proving a theory stems from the necessity to specify initial conditions and to posit auxiliary assumptions in order to subject a theory to an empirical test. (This is sometimes called Duhem's problem.) The presence of context means that what Lakatos calls "immunizing strategies" can be found to "protect" a theory by claiming that the initial conditions had changed or that an auxiliary hypothesis didn't hold. For instance, it is very difficult to disprove the rationality theorems of economic theory because instances of possible irrationality can often be ascribed to changes in preferences or other conditions.

The point of this discussion is that the community of scientists, economists in this case, must determine how to test proposed economic knowledge - within the framework of proper scientific methods. Professional value judgements are required to determine when a particular theory, hypothesis or finding passes the test.[6] The scientific community must have a "loss-function" to decide when a theory (provisionally) passes the test (this is another kind of value that enters the value discussion).[7] Knowledge is (provisionally) confirmed if the methods used to generate it have satisfied the conditions set by the community of scholars. Thus, theories and protocols are expected to pass tests of logical consistency, of replicability, of empirical correspondence, and consistency with the existing body of knowledge. Scientific panels (peer review) adjudicates and enforces these procedures, but it is not the review process, but the protocols and tests in conformance with the rules of the "scientific method," that establish the legitimacy of knowledge. "Good research" is therefore defined by adherence to the specific protocols and general methods of science (economics), not (per se) by peer review. Peer review is "the good housekeeping stamp of approval" of science.

Turning to the issue of the estimation of economic values, the conclusion from this discussion of general principles of scientific methodology is that it is the discipline itself, based on the "rules of science" which establishes the conditions for determining the legitimacy of estimates of economic values. The discipline establishes the groundrules for distinguishing "good estimates" of economic value from bad estimates. In doing so, the discipline follows the general methodological principles of the scientific methods as well as many specific rules which define good theory building and good empirical protocol. Obvious instances of this in the non-market valuation field include influential pieces which set standards such as Mitchell and Carson, and the NOAA panel (Arrow, et al.). Meetings of the W-133 research group are important for precisely this reason - they help establish the theories, protocols and procedures which comprise the acceptable tool kit of non-market valuation.

For concreteness, consider a brief list of some of the theory and measurement issues currently under debate in the profession. These include procedural issues like: what is the best elicitation mode/format; how should don't know and undecided responses be treated, how should non-commodity linked values like altruism and "warm-glow" be detected and counted. They also include specific issues of survey design and of econometric estimation.

THE NORMATIVE/ETHICAL STATUS OF ECONOMIC VALUES

Suppose one can measure economic value empirically. Suppose one has consensus that the value is measured in a legitimate fashion and so is a valid measurement. What is the normative significance of the measurement of economic value? What moral weight should be put on the value. As noted earlier, in principle, one may believe that an economic value can be measured but then declare it morally irrelevant. For instance, in pretests people often say that they cannot, will not, or should not "put a price" on air quality. However, when people are put in a CVM context, most people will, in fact, confess to a value. It would seem that these people are capable of generating an economic value but that they are denying its legitimacy. We are faced with yet another level of values. What is the normative value

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[6]The problem is more complicated. Some philosophers of science believe that, while demonstrable knowledge is impossible, degrees of confidence can be assigned to knowledge propositions. Others believe that knowledge can be falsified, but not demonstrably affirmed (popperism). Still other believe that the science community sets tests which a theory can be said to have provisionally passed. See, e.g., Hausman.

[7]In a now classic article, Rudner established that scientists cannot avoid the necessity to makae value judgements - judgements about whether a theory or hypothesis is accepted or not. Some scholars argue that such scientific value judgements are a unique and separate category of value judgements.

(significance) of the estimated economic value?

Standard normative economics (welfare economics) rests on the Utilitarian ethical system. From the Utilitarian perspective expressions of willingness to pay are not only social facts, they are the proper indicator of the ethical worth of things. Therefore, from this point of view, there is no question about the normative significance of economic value estimates, they are the proper measure of the moral value of things, at least when they are constructed in the proper way.

We must be careful here. Utility is not only a positive, psychological theory (or in revealed preference mode, an operational, behavioral model) which explains behavior, but an ethical theory. Positive utility theory says people do what pleases them. Normative utility theory says that what pleases people is good. This is a source of confusion for economists and non-economists alike and, as a result, positive and normative economics are often blurred.

Let's briefly review the main tenets of Utilitarian ethical theory. The strong Utilitarian position is based on the normative assumption that the only information normative significance concerns the utility of individuals. Things are of value only to the extent that they generate utility value (pleasure) to individuals (non-paternalistically). General qualities of society, like income distribution, are of value only to they extent they please individuals. Environmental values are anthropocentric; endangered species are only of value to the extent they are valued by someone. Virtue (e.g., altruism) is important only if it gives pleasure.

General social value is simply an aggregation of these individual values. For the English neoclassical school, individual values were cardinal and interpersonally measurable and could be aggregated by simple summation. For modern ordinal utilitarianism, numeric values cannot be mathematically combined because they are non-comparable. Still, one can identify increasing welfare, which is indicated by a Pareto improvement.

In principle, economic estimates of value can quantify these ethical properties. The economic value is both the empirical value of a thing and a measure of the normative value -worth - of the object. In practice, there are a number of problems in determining whether the measured value is the "right" value. The empirically observed market price may not be the ethically proper, efficient price.

So let us review. The Utilitarian perspective says that economic value estimates have normative significance and so can presumably help distinguish between good and bad social situations and thereby help us make social decisions. However, not all economic values (prices) are correct. Estimates of economic value must be corrected to conform to the ethical theory if they are to be used to evaluate social policy. An additional difficulty is that we know from economic theory and our earlier discussion of values, that economic values are contingent so that there is no unique "best." (Thus, in general equilibrium theory there are an infinite number of Pareto optimal allocations, each of which can be associated with a different set of prices and a different "initial condition" of wealth distribution.)

While Utilitarianism gives us a link between estimated, quantified economic values and normative significance, not everyone accepts it. Following is a brief list of some of the objections to Utilitarianism (See, e.g., Sen and Williams, Weinz)

- Are we willing to say that process and rights do not matter, only the consequences count? Who "creates" the pollution is not important.
- Are we willing to say that motives (virtue) and right behavior (duty) do not matter? Upright behavior has not special claim.
- Do we wish to banish non-utility information, such as the physical state of people or the distribution of material goods? Is there no difference between consumption of jam and heroin,

except in their utility consequences?

- Are we willing to say that deservedness does not matter, the manner of acquisition of an economic asset does not matter?

POLITICAL/POLICY GROUNDS FOR USE OF ECONOMIC VALUES

Once estimated, how should economic values be used? How they are used is in program and project analysis, in regulatory benefit cost analysis, in judicial actions, in administrative and enterprise allocation decisions, and so forth. But what determines when and how they should be used.

Of course, use of estimates of economic values should depend partly on the quality of the estimates. Are the estimates sound, reliable? Use should also depend on the perceived ethical relevance the values. But while the positive and normative standing of value estimates matters, ultimately the political process determines there use. One might say that the final test of validity of an economists estimate of value is a test of praxis - is it used in the policy process.

CONCLUSIONS

Many of the topics discussed in this essay could lead to a pessimistic view about the program of assigning economic values, particularly non- market values. More considered thought should lead to a council of caution and care, not despair. For instance, it is undeniable that estimates of economic value rest on metaphysical and ethical foundations with which not everyone will agree. This does not mean that economic values convey information of no empirical or ethical significance. Rather, it means that economic values do not have a unique claim on empirical and ethical truth. Policy might be informed by other values, but this is exactly what a pluralistic, democratic process does.

Much of this essay was devoted to an exegesis of the inherent fuzziness of estimates of economic values. This inherent fuzziness is especially irksome to non-market valuation analysts, because it provides an opportunity for critics to attack the method. It must be admitted that there is some truth to much of the criticism of non-market valuation, partly because results are sometimes presented with a false precision. Clearly, economic values are not absolute, exact and unique. Clearly it is also prudent to use precision in the estimation and calculation phase of analysis. But for policy purposes measurements of economic values should be presented with caveats because we know that the values are fuzzy. Value estimates should be presented as contingent, not absolute; in terms of upper and lower bounds rather than point estimates.

But the overall most important implication of this essay is the importance of continued research into economic valuation. The economics discipline has a social responsibility, beyond any scientific curiosity, to develop the procedures, theories, and protocols by which validity can be assigned to estimates of economic value.

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