A Simple Procedure for Generating Confidence Intervals in Tourist Spending Profiles and Resulting Economic Impacts

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Abstract. This paper presents a simple bootstrap procedure to develop multivariate confidence intervals for tourist expenditure profiles and consequent estimates of economic impacts per thousand tourist visits. Mean expenditures from replicated visitor expenditure data included weights to correct for response bias. A covariance matrix for means of 50 expenditure items is estimated through 2,000 bootstrap replications for two separate visitation seasons. Confidence intervals assume multivariate normality of the expenditure means, and focus on endpoints defined by proportionate increases (and decreases) from the original sample data means. An empirical example is provided from summer and winter visitors to the Florida Keys. Ninety-five percent confidence interval endpoints for spending means were found at 3.87 percent above/below the original sample's point estimate for winter visitors and at 6.001 percent for summer visitors.

1. Introduction

Many public agencies have legal or policy mandates to consider the economic consequences of their management actions and infrastructure investments. Economic valuation often is used to evaluate the viability of the actions through a cost-benefit analysis. However, many of these agencies also have rural development goals that require justifying actions based on their resulting regional economic impacts. With economic impacts in particular, the viability of some decisions may center on how

a small set of related sectors are affected. Estimates of economic impacts may be especially important for generating local support for the agency and its policies.

Regional science practitioners have typically played a large role in guiding rural development activities. A special area of contribution has been in developing and refining the analytic tools used to predict and evaluate rural development policies. Over the years, these tools have been used by agencies, academics, and local political and economic ac-tors who need assistance in deciding how to invest in their rural region. Models of regional economies have been especially valuable in this re-gard.

Of all th e types of information used to make resource allocation or rural development policy decisions, estimates of the economic welfare and regional impacts generated by recreation/tourism visitation have been among the most contentious and difficult to quantify. Estimates of both of these measures are usually based on data obtained from surveys of visitors to public recreation sites. Travel cost or willingness to pay questions typically provides information for estimating economic values from demand functions (Smith 1993). Averaging the reported per trip expenditures across all surveyed visitors gives the information needed to construct final demand changes used in economic impact evaluations (Johnson and Moore 1993; Douglas and Harpman, 1995; Bergstrom, et al., 1996). Consequently, the estimators for both values and impacts are random variables.

Unfortunately, point estimates of average benefits or impacts per trip derived from a single sample of visitors may not be sufficient informa-tion for making good allocation or policy decisions. Understanding and accounting for the variability of such measures may also be necessary. For example, in a benefit-cost framework an analyst may need to know how likely it is that benefits will exceed project costs (Adamowicz, et al., 1989), in addition to knowing whether the expectation of benefits will exceed expected costs. This information may be critical if reversing the project decision is costly.

When evaluating a proposed investment for rural development, it is desirable to have information about both risks and rewards. Residents of the targeted region may want to know the chances that their fortunes could be reversed. Decision-makers who want to maintain their political status, will want to maximize the likelihood of an improvement in their constituents' situation. That is, the preferred investment may be the one that yields the most certain positive return beyond either the *status quo* or the next best option. The magnitude of the gain beyond that may well be a secondary issue. In these situations, having only point estimates of expected returns is not sufficient.

Determining the likelihood of estimated returns either above or be-low some reference point requires knowledge about the estimator's

distribution. However, the true distributions of estimators for impacts and benefits are not always easy to determine or describe. A fair amount of work has been done on evaluating the distribution of valuation estimates, and techniques have been developed for generating confidence intervals for estimators of benefits. These intervals are based on interpersonal differences in data obtained from visitor surveys. However, analogous research on variability in regional economic impacts of recreation or tourism is scarce.

This paper takes a step in addressing that scarcity. It illustrates a simple and easily-applied method by which confidence intervals for visitor spending profiles could be developed. The intervals are based on variation in data obtained from visitors. A resampling technique known as bootstrapping is applied to a sample of visitor expenditure data to generate a multivariate distribution for mean expenditure profiles. From the multivariate expenditure vectors that are at interval endpoints, it is possible to estimate confidence intervals for impacts on individual economic sectors.

This paper has eight sections beyond the introduction. Reviewing the typical processes for recreation economic research provides the background for understanding relevant sources of variation to include in confidence interval estimates. A review of research on the variability in recreation valuation shows that resampling techniques have been the most commonly applied set of methods.

Research Process in Recreation Economics

In a typical study to estimate the economic value or regional economic impact of visitation to a recreation site, a (possibly stratified) random sample of n visits to that site are drawn. Intercept surveys occur as the recreation visit ends. At that time, the visitor is asked the questions needed for valuation estimation, including the number of annual visits to the site, travel distance and time, and substitute sites or activities. Either then or in a mailed follow-up survey, information about the amount of money spent on a set of k expenditure items for that visit is obtained. Invariably, not all of those contacted provide a full set of information, yielding m_v ($< n$) usable responses for valuation and m_e ($< n$) expenditure responses.

In welfare studies, an individual's trip price is computed from monetizing reported travel distance and travel time. This and other variables are regressed on annual visitation rates. Assumptions about functional form and error distribution determine the regression structure. For example, count data models reflect obvious restrictions on trip taking behavior. Average per trip consumer surplus is a function of the estimated coefficient on the price term.

Let **E** be the m_e x k matrix of expenditure data obtained for an impact study. To account for sample stratification and correct for non-response bias (Leeworthy, et al. 2000) a (m_e x 1) vector of weights, **W**, is constructed. The vector of average expenditures, **X**, is:

$$X = (\frac{1}{\sum\limits_{i=1}^{m} w_i})E'W \tag{1}$$

Expenditure items on surveys typically conform to the types of goods and services visitors purchase. However, models of regional economies are often based on industrial sectors. Seldom is there a one-to-one mapping of survey items to economic sectors. As a result, the k x 1 vector of mean expenditures must be "bridged" onto the j industrial sectors in the economic model. Let **B** be the k x j bridging matrix that maps **X** onto the industrial sectors. The vector **D** describes the demand shock to the economy from the average recreation visitor's purchases:

$$D = B'X \tag{2}$$

Input-output (I-O) models are widely applied and mathematically straightforward models of regional economies (Miller and Blair 1985). The demand vector for one visit may not have a measurable effect on a regional economy, so **D** is often scaled upward to represent a thousand visits. Given the standard **A** matrix of technical coefficients, the impact **P**, of the vector **D** on the economy is:

$$P = (I - A)^{-1} D \tag{3}$$

It is this vector that is of primary interest. Since I-O models are linear, economic impacts for a management action can be determined simply by scaling P to the expected change in the number of visitors.

Sources and Treatment of Variation

Estimates of impacts and valuation have similar sources of variation, and most are handled about the same way. Estimates of both measures are based on information provided by a random sample of onsite visitors. Consequently, both the mean sample characteristics and the weights that correct for stratification or selection bias are also random

variables. However, the intercept sample is usually treated as representative, and variation that might come from a different intercept sample is ignored. Measurement error that could exist in information collected from visitors (rounding or mis-remembering the annual number of trips, miles traveled, or dollars spent) is also ignored.

In valuation studies, th e economic construct of the individual's trip price is computed by monetizing travel time and distance. Time costs are assumed to equal a percentage (constant across individuals) of the visitor's hourly wage rate times the number of hours traveled. Monetary travel costs are usually computed as a cost per mile (again constant across individuals) times the number of miles traveled. Variation among individuals with respect to prices is then limited to reported differences in income and travel time/distance.

In impact studies, the bridging matrix (**B**) serves the same function as the monetizing formulae in valuation work. The construct of a final demand vector is created from reported spending on commodities. The transformation is accomplished by applying a set of coefficients relating categories of spending to economic sectors. These coefficients are assumed to be known and constant across all individuals.

At the heart of valuation work is the model of individual behavior defined by the regression. Assumptions about the error distribution, explanatory variables, and an appropriate functional form determine the model's structure. It is not known what the true structure may be, nor how it might vary across individuals. Any such differences across economic actors is assumed away. In impact analysis, the central element is the regional economic model. A matrix of technical coefficients is assumed to accurately capture the inter-linked behavior of industries. The true distribution of these coefficients across the firms in the region is unknown. It is assumed that the given set of coefficients applies equally to all firms in any industrial sector.

Due to the many sources of variation that could be included in the estimation process, the true probability distributions for the estimators of either values or impacts could be quite difficult to determine. Standard practices simplify the situation enormously. Reported estimates are contingent on a number of assumptions, and many of these assumptions remove sources of variability. The primary source of variation that remains is in the data provided by the surveyed individuals. Typically, these data include demographic characteristics, reported expenditures, and annual visit rates. Still, the problem is how to estimate the distribution of the estimator from only one sample of onsite intercept surveys.

Variability Research In Recreation Economics

Examining the variability in welfare or valuation estimates of recreation via resampling has been addressed by several research efforts. Most have followed a modified Krinsky-Robb procedure to accomplish the resampling. Creel and Loomis (1991) drew a random sample of 8,000 parameters from an assumed multivariate normal distribution with a mean and covariance matrix defined by parameters estimated in a travel cost demand equation. 90% confidence intervals for welfare measures were defined by a percentile method. Results were ordered and 5% of observations were removed from each tail.

Adamowicz, et al. (1989) created new dependent variables from the observed data matrix and random draws from a normal error term with mean zero and variance determined by the error in the regression for several functional forms of travel cost demand. Regressions on the new dependent variables yielded a new estimate of coefficients and ultimately welfare measures. Repeating this process 5,000 times for each functional form provided a distribution of welfare measures, from which means and standard deviations were reported.

Kling and Sexton (1990) followed a process similar to Adamowicz, et al., but drew a bootstrap sample from the empirical regression error distribution, rather than from an assumed normal error distribution. In addition, they eliminated bootstrap results wherein WTP was less than zero or greater than total income. For each of 16 data sets, one hundred bootstrap trials were generated, from which coefficients of variation were reported. Confidence intervals were calculated as if the bootstrap trial results were normally distributed.

Yen and Adamowicz (1993) combined the Krinsky-Robb procedure used by Creel and Loomis, with the theoretical restrictions to consumer surplus results of Kling and Sexton. For each of several models, 10,000 vectors of parameters were drawn. Ninety percent confidence intervals were reported, presumably calculated via a percentile method as the intervals are not symmetric about the mean of the simulation results.

Resampling has also been used to assess the variability of welfare estimates in some contingent valuation studies. Park, Loomis and Creel (1991) and Souter and Bowker (1994) used a Krinsky-Robb approach. In both applications, confidence intervals were based on 1,000 replicates and a percentile method for determining interval endpoints. Cooper (1994) used bootstrapping as well as Krinsky-Robb and analytic approaches to evaluate confidence intervals for welfare estimates from dichotomous choice CVM.

However, variability of results has essentially not been addressed in empirical research on the economic impacts of outdoor recreation or resource-based tourism. Current practices in recreation impact studies are to report means but not standard errors for the vector of visitor expenditures

(Uysal, et al., 1992; Johnson and Moore, 1993). Some studies report spending means for a number of visitor types that are expected to have homogeneous spending patterns (Propst, et al., 1992). One place to start would be to focus on the same source of variation included in research on recreation valuation: interpersonal differences in the visitor sample.

One recent study (English, 2000) did develop confidence intervals for total economic impacts. There, 1000 bootstrap estimates of average visitor expenditures were developed, and total economic impacts were estimated for each. Confidence intervals for total impacts (i.e., the sum over all economic sectors) were computed using several methods. A shortcut method was also tested wherein confidence interval endpoints for the average total visitor expenditures from the bootstrap datasets were developed, and then impacts were estimated from the endpoint values.

This paper extends that work, to present a method for developing confidence intervals for the multivariate vector of average expenditures (rather than for just total expenditures). From that, it is possible to obtain an estimate of interval endpoints for impacts at the sectoral level (rather than just for total impacts). To do so, this method makes use of both the Central Limit Theorem, and bootstrapped visitor expenditure datasets.

The Central Limit Theorem indicates that the mean from a random sample will be asymptotically normally distributed, regardless of the underlying distribution from which the sample is drawn, so long as that distribution has a finite variance. That is, over an infinite number of repeated samples from the same population, the vector of average expenditures per visitor will have approximately a multivariate normal distribution. Unfortunately, neither the mean nor the variance of that distribution is known, nor is it clear how quickly the convergence to normality occurs.

The bootstrap method (Efron and Tibshirani 1993) allows an analyst to obtain an approximation of the distribution of an estimator, in the absence of *a priori* information about the true distribution of the estimator or of the original data. From a sample of size n, a large number of new data sets are generated by drawing, with replacement, n observations from the original sample. For each new data set, the estimator is calculated. The resulting empirical distribution of estimator values is used to approximate its true distribution. For this paper, bootstrapping is used to develop an estimate of the asymptotic covariance matrix of the vector of average expenditures.

2. Data

The data used came from a study that estimated economic impacts and values for recreation visitation to the Florida Keys. Because of seasonal differences in visitation, weather, and resources uses, separate samples were developed for winter and summer. The summer survey period was during July and August of 1995. The winter sample period was December 1994 to May 1995.

An onsite random intercept survey, stratified by mode of travel (air, auto, cruise ship) provided demographic and activity information (Leeworthy and Wiley 1996). Each person contacted was given an expenditure questionnaire to fill out and mail back. Expenditure information was obtained for 50 different trip-related expenditure items, in five general categories: lodging (7 items), food (3 items), transportation (9 items), activities (22 items), and miscellaneous (9 items). For each item, respondents were asked how much they spent in the three-county South Florida area. Following Dillman's (1978) procedure, reminder postcards and second questionnaire mailings were made at two-week intervals. Of the 1,334 summer season contacts; 505 (37.86 percent) provided expenditure information. In the winter sample, 1,036 out of 2,250 contacts (46.04 percent) responded to the expenditure survey.

Tests for non-response bias were conducted and subsequent corrective weights were calculated (Leeworthy 1996; Leeworthy, et al., 2000). Individual characteristics related to both probability of expenditure survey response and to the amount of reported spending in south Florida was used to weight the expenditure sub-sample to the onsite contact sample for each season. For example, foreign visitors were less likely than domestic (U.S.) visitors to respond, but foreign visitors also spent more money per trip. Other significant variables for both seasons included race, age, and income. Weights equaled the product of a stratum weight to account for the sample design, and a non-response bias weight for a demographic category defined by combinations of race, age group, income class, and residence.

Bootstrap replicate datasets were developed from the expenditure sub-samples. Using the random number generating procedure in the SAS program's UNIFORM function, 2,000 bootstrap samples equal in size to the original expenditure sample (505 observations for the summer season; 1,036 for the winter season) were generated for each season by drawing entire observations with replacement from the original sample. For each bootstrap replicate, corrective weights were recalculated, using a process similar to that used in the original sample. That is, for each replicate, the proportion of cases in each of the demographic categories was calculated. Non-response weights for each category was the proportion of replicate cases in the category divided by the proportion of cases

in the onsite sample in that category. For the ith bootstrap replicate, the weighted average expenditure vector ($\mathbf{X_i}$) was calculated.

3. Analysis

It is assumed that the multivariate distribution of the 50 expenditure means is approximately normal, following the Central Limit Theorem. From the 2000 bootstrap replicates, a covariance matrix (S_B) for the average expenditure vectors was calculated. This serves as an estimate of the true covariance matrix (S). For a p-dimensional normal distribution, the 100(1-a)% confidence region around some mean vector (X) can be defined by all vectors μ such that:

$$n(\overline{X} - \mathbf{m})' S^{-1}(\overline{X} - \mathbf{m}) LE \frac{(p(n-1))}{(n-p)} F_{p,n-p}(\mathbf{a}) \tag{4}$$

where n is the number of observations from the distribution (Johnson and Wichern 1992).

In bootstrap analysis, the standard deviation of the sample of bootstrapped estimators serves as the estimate of the true standard error of the estimator. The two differ by /n. As a result, to define the confidence region for the estimator of interest here, the mean expenditure vector, a slight modification is made to the above formula. The 100 (1-a)% confidence region of mean expenditure vectors include all vectors μ that satisfy:

$$\sqrt{n}(\overline{X} - \mathbf{m})' S_B^{-1}(\overline{X} - \mathbf{m}) LE \frac{(p(n-1)}{(n-p)} F_{p,n-p}(\mathbf{a}) \tag{5}$$

The purpose of this exercise is to obtain a confidence interval around the mean expenditure vector generated from the original sample. Hence, that vector is assumed to be at the center of the estimated confidence region.

Unfortunately, the above definition yields an infinite number of solution vectors μ that lie on the surface of the 50-dimensional confidence region ellipsoid. Some selection process is needed to choose among them, in order to have a manageable set of results to discuss and compare. A first criterion might be to restrict the upper (lower) bound to have elements that are strictly greater (less) than the mean. Such a restriction avoids having an element in the upper bound vector that is less

than the estimated mean. The cost is to eliminate including negative covariation among potential substitutes, such as spending on hotel lodging and campsites.

Figure 1 shows an example of an elliptical confidence region for two typical expenditure variables, X_1 and X_2. The ordered pair, (X_1^*, X_2^*) represents the original sample mean for these two variables. Perhaps the simplest option for selecting a point on the confidence ellipse that con-forms to the criterion listed above is to start from the original sample mean and move along the line whose slope equals the ratio of the two means, X_2^*/X_1^*. In Figure 1, this is the dashed line. Moving propor-tionately from the sample mean toward or away from the origin to de-fine the confidence endpoints is easy to explain, provides interval end points that are symmetrical about the mean, and puts the widest inter-vals on the items on which visitors spend the most money. In a more general context, this particular solution vector for the upper bound is defined by the following constrained optimum:

$$\text{Max } \boldsymbol{m} = (1+ p)* \overline{X}$$

$$s.t. \sqrt{n}(\overline{X} - \boldsymbol{m})' S_B^{-1}(\overline{X} - \boldsymbol{m}) = \frac{(p(n-1)}{(n-p)} F_{p,n-p}(\boldsymbol{a}) \qquad (6)$$
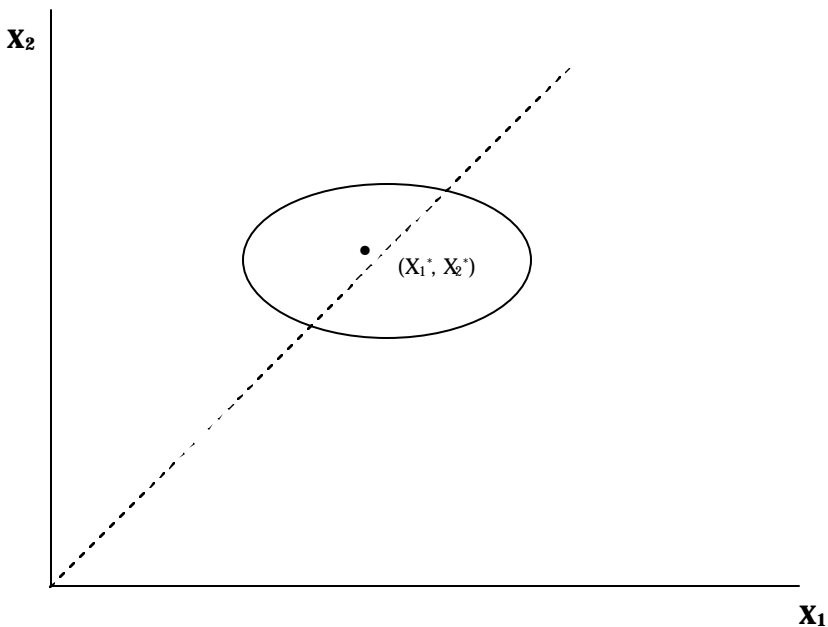

Figure 1. Example confidence region for typical expenditure variables, X_1 and X_2.

For both the summer and winter season, the expenditure vectors that satisfy the above optimum were calculated. Lower bounds for μ were obtained by subtracting the maximizing percentage, p, from unity and multiplying by the original sample mean vector. Then, the spending profile bounds were bridged to economic sectors, and economic impacts for the original sample mean, and four confidence bound expenditure vectors (upper and lower, winter and summer) estimated via IMPLAN.

4. Results

In the winter season sample, the confidence region limit was reached by adding or subtracting 4.873 percent to the original mean expenditure vector (Table 1). The five expenditure items that had the greatest variation were: non-government hotels (+/- $7.48), restaurants (+/-$6.49), home or condo rentals (+/- $1.83), car rental (+/- $1.76), and grocery store purchases (+/- $1.50). Summing over the interval bounds for all 50 expenditure items, this confidence interval ranges from $661.93 to $729.75. These are $33.91 higher/lower per person than the original sample mean.

For the summer sample, the confidence bound was reached at 6.001 percent of the original sample mean. The five expenditure items showing the widest interval included: non-government hotels (+/- $6.93), restaurants (+/- $6.40), boat rental (+/- $2.73), home/condo rentals (+/- $2.52), and car rental (+/- $1.77). The sum of all expenditures at the lower bound was $585.42, and $656.76 at the upper bound, or $35.67 above/below the original sample mean.

Confidence bounds for total industrial output impacts in the winter season ranged from $661,930 to $721,750 per 1,000 visitors (Table 2). These figures are about 4.87 percent on either side of the impact estimate derived from the original sample mean. In the hotel and lodging sector, the 95% confidence interval bounds were $145,980 to $160,940 per 1,000 visits. In the restaurant sector, confidence interval bounds were at $126,770 and $139,750 per 1,000 visitors.

For the summer season, the expenditure vectors at the 95 percent confidence bounds yielded industrial output impact estimates for the "Hotels and other lodging" sector of $179,300 per 1,000 visits at the lower bound, and $202,200 per 1,000 visits at the upper bound. Impacts to the restaurant sector were between $108,800 and $122,700 per 1,000 visits. For all sectors, the upper bound for impacts was about 6 percent above the impact estimate from the original sample mean.

Interval bounds for impacts in the hotel sector for the winter sample were at $237,800 and $262,300 per 1,000 visits. Interval endpoints for the restaurant sector were at $135,800 and $149,700 per 1,000 visits. In this

sample, impact bounds for each sector and for the sum across all sectors were about 4.88 percent above or below the impact estimate of the original sample mean.

Table 1. Original sample per person per trip expenditure means and multivariant 95% confidence bounds based on a percentage of sample mean for spending in South Florida for selected items, summer and winter season.

| | MEAN EXPENDITURE PER PERSON PER TRIP | | | | | |
| | SUMMER | | | WINTER | | |
Expenditure Item	Original Mean	Lower Bound	Upper Bound	Original Mean	Lower Bound	Upper Bound
Non-government Hotels	115.54	108.64	122.47	153.46	145.98	160.94
Home/Condo Rentals	41.95	39.43	44.46	37.36	35.53	39.18
Campsites	9.13	8.58	9.68	29.19	26.77	30.61
Restaurant food/drink	106.66	100.26	113.06	133.26	126.77	139.75
Beverages bought at store	13.82	12.99	14.65	12.70	12.08	13.32
Food bought at store	27.13	25.50	28.75	30.77	29.27	32.27
Car rental	29.57	27.79	31.34	36.19	34.43	37.95
Gas/Oil for cars	20.13	18.93	21.34	23.28	22.14	24.41
Airfare, package tours	17.83	16.76	18.90	11.58	11.01	12.14
Boat rental/charter	45.44	42.71	48.17	3.95	3.75	4.14
Boat fuel/oil	18.83	17.70	19.96	5.06	4.81	5.31
Diving activities	12.35	11.61	13.09	4.78	4.55	5.01
Clothing	20.89	19.64	22.14	23.59	22.44	24.74
Souvenirs/gifts	17.75	16.69	18.82	19.18	18.25	20.11
Total, All Items	**621.09**	**585.42**	**656.76**	**695.84**	**661.93**	**729.75**

Table 2. Sectoral-level total economic impacts for industrial output in three-county South Florida economy per 1000 visitors, for original sample mean expenditures and 95% confidence bounds, for selected economic sectors (in thousands of 1993 dollars).

| | SUMMER | | | WINTER | | |
Economic Sector	Original Mean	Lower Bound	Upper Bound	Original Mean	Lower Bound	Upper Bound
Air Transportation	36.0	33.9	38.2	34.1	32.4	35.7
Wholesale Trade	23.7	22.3	25.1	26.1	24.8	27.4
Auto Dealers/Service Stations	47.6	44.8	50.5	38.6	36.7	40.5
Restaurants/Bars	115.8	108.8	122.7	142.7	135.8	149.7
Miscellaneous Retail	19.3	18.2	20.5	28.1	26.7	29.5
Real Estate	23.2	21.8	24.6	37.9	36.1	39.8
Hotels and other lodging	190.7	179.3	202.2	250.1	237.8	262.3
Auto rental/leasing	33.6	31.6	35.6	40.8	38.8	42.8
Amusement/Recreation	76.2	71.6	80.8	40.5	38.5	42.5
Total All Sectors	**970.6**	**912.3**	**1,028.8**	**1,085.7**	**1,032.8**	**1,138.6**

5. Discussion

This paper demonstrates a simple, straightforward method to develop approximate confidence intervals for average expenditure profiles for recreation visitors. The method applies a bootstrap procedure to respondents to expenditure surveys, in order to generate a distribution of multivariate mean expenditure profiles. Since the primary interest in

such an effort is in the means for each bootstrap replicate of the original data, it is possible to make use of the Central Limit Theorem, which indicates that the distribution of mean expenditures will be multivariate normal.

This method develops confidence interval endpoints that are a constant percentage higher or lower for all expenditure items from the original sample mean. Combining that method with the linearity inherent in I-O economic models means that the confidence interval bounds for economic impacts will the same percentage above or below the point estimate generated from the original data as are the interval bounds for the expenditure vector. However, it is not clear that this simple result will necessarily hold for either non-linear computable general equilibrium models or for other choices of determining interval bounds.

An obvious question to developing the bootstrap replicates is: "Why not just use covariance matrix from the original data?" To begin with, the distribution of individual expenditure observations is not necessarily normal. For example, a number of observations will have zero values. As a result, the multivariate confidence interval obtained by assuming normality is much wider. For example, for the winter sample, if the covariance matrix from the 1,036 original observations is used to approximate S, and this distribution is (incorrectly) assumed to be multivariate normal, then interval endpoints are reached at +/- 21.546 percent of the original mean vector. Since the interval from the covariance matrix references the distribution of individual profiles, not the distribution of the mean profile, the greater variability should be expected. Applying the covariance matrix interval greatly overstates the variability of estimated impacts from tourism visitation.

Confidence intervals generated by this method are based on the same source of variation as are interval estimates currently reported in research on economic values for recreation resources. Many practitioners in regional science have extensive quantitative training, so the techniques involved here should not be very difficult. By including confidence intervals in reports of impact results, analysts can have comparable information for both of the primary economic metrics (values and impacts) used in decisions about the use of resources that support outdoor recreation. The additional information provided by these confidence intervals could assist rural development specialists in evaluating and generating local support for tourism-based alternatives.

Implications for Policy and Research

It is noteworthy that the percentages that define the intervals are smaller for the winter data set (4.873 percent) compared to the summer data set (6.001 percent). In part this difference exists because the original

sample size in the winter (1,036 observations) was nearly twice as large as the sample size in the summer (505 observations). One area of further research would be to more fully examine the nature of the relationship between original sample size and the width of the expenditure confidence interval. If general guidelines can be established, this information may help researchers decide on sample sizes for tourist visitor studies. Collecting data from visitors is the most costly part of such studies.

Another area for future research could be to identify the types of tourists and tourism development combinations that have not only high levels of average spending per visitor, but that also have lower variability in mean spending profiles. Understanding variability in spending may help explain why tourism works in some areas and fails in others. Additionally, information on the relative constancy in visitor purchase patterns may help local entrepreneurs decide whether or not to invest in tourism-related businesses.

This paper has shown that little additional effort is required to obtain some information about the range of expected impacts of recreation and tourism visitation. Given the relative ease with which these intervals were generated, it is curious that confidence intervals have been so notably absent in reported research results of tourism's impacts. It is not that the techniques are overly complicated. Based on personal experience, it seems likely that practitioners realize that variations in spending across visitors is not the only source of error in tourism impact estimates, and disdain a partial accounting of the range of possible outcomes.

However, there may be ways to address this need. For example, estimating the amount of expected tourist visitation is an obvious source of error. Further, it is not always possible to develop confidence intervals for visitation that are based on statistical procedures. Estimates of the volume of visitation are often simply educated guesses. *Ex ante* estimates of how visitation will change in response to a policy change are seldom any more scientifically based.

The lower bound of spending per visitor derived in the method described here could be combined with a reasonable, conservative estimate of expected visitation levels. Their product would give an overall lower bound for total tourism-based final demand. An analogous process would yield an upper bound. Any economic model, not just an input-output model, could then be used to determine the regional impacts for each bound.

Regional scientists have long been at the forefront in providing information and tools to address resource issues where rural development concerns are paramount. Development from the first small input-output model to more detailed or multi-region I-O models and non-linear CGE models has been one way regional science has improved its tools to meet the changing needs of its clients. The need for such information continues as rural areas struggle with changing resource uses and population

characteristics. If anything, there is a need for more depth in the types of information that can be brought to bear on such issues. This paper has presented a simple and inexpensive means to further broaden the typical set of economic impact data. Such an addition would seem timely, given the increased attention to the local effects of policies and management actions being considered by many resource-management agencies.

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