On the Statistical Significance of Regional Economic Impacts from Recreational Fishing Harvest Limits in Southern Alaska

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ABSTRACT

Confidence intervals for regional economic impacts resulting from changes in saltwater sportfishing harvest limits are calculated using a stated preference model of sportfishing participation and a social accounting matrix (SAM) for southern Alaska. Confidence intervals are constructed to account for two types of input variation in impact estimates—sample variation in sportfishing-related expenditures and stochastic variation from parameters in the recreation participation model. For five of six policy scenarios examined, estimated impacts are not statistically different from zero. Tests for differences in estimated impacts between scenarios show that no statistical differences are found whenever stochastic variation is considered (statistical differences occur only when sample variation alone is accounted for). Due to the lack of statistical differences in this case, a comparison of economic impacts does not provide a clear-cut preferred alternative, and consequently other economic and non-economic criteria for evaluating policy scenarios should bear greater weight in policy decisions.

Key words: Recreational fishing, economic impacts, bootstrapping, stated preference choice experiment, and social accounting matrix model.

JEL Codes: R11, Q51, Q22, Q58.

INTRODUCTION

Pacific halibut (Hippoglossus stenoleptis), Chinook salmon (Oncorhynchus tshawytscha), and coho salmon (Oncorhynchus kisutch) are 'the primary saltwater finfish species targeted by recreational anglers in Alaska. These three species accounted for 65 and 61% of the total saltwater fish harvested in 2009 and 2010, respectively (Jennings, Sundet, and Bingham 2011). One of the primary tools used to manage the recreational harvest of these three species is angler bag limits. For Chinook and coho salmon, these bag limits vary by area (and additional size/length restrictions sometimes apply). For Pacific halibut in Alaska, recent regulations have differentiated between anglers using a charter or guide service and those that are unguided.

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Senior authorship is shared by Lew and Seung. The findings and conclusions herein are those of the authors and do not necessarily represent the views of the National Marine Fisheries Service, National Oceanic and Atmospheric Administration, or the US Department of Commerce.

Received April 15, 2013; Accepted March 10, 2014; Published online July 21, 2014. http://dx.doi.org/10.1086/677759

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This is due to concerns about overharvesting by the charter boat sector that has led to stricter harvest limits for charter boat anglers both in terms of the bag limit and size restrictions that began in 2007. Under the newly implemented Halibut Catch Sharing Plan (CSP) (78 Federal Register 75843), the regulations on charter boat anglers will be evaluated annually and adjusted to assist the charter boat sector in staying within its sectoral allocation (Federal Register 2013).

There are a variety of different criteria decision-makers consider in selecting among different harvest limit policies, including biological, environmental, social, and economic. Among the economic considerations, the economic impact of harvest limits is oft-analyzed, as it is required, to some extent, in many regulatory analyses (e.g., provisions of the Magnuson-Stevens Act, National Environmental Policy Act, Regulatory Flexibility Act, and Executive Order 12866). This article presents an analysis of the economic impacts from recreational harvest limit changes to Pacific halibut, Chinook salmon, and coho salmon in Alaska that explicitly addresses an issue frequently overlooked in regional economic models—input variation.

Regional economic models are often used to estimate the economic contribution of recreational fisheries in the U.S. and to evaluate economic impacts associated with fisheries management actions (Bohnsack et al. 2002; Chen, Hunt, and Ditton 2003; Criddle et al. 2003; Lew and Seung 2010; McKean, Johnson, and Taylor 2011; Sharma and Leung 2001). Several modeling approaches are available for conducting recreational fisheries-related economic impact analyses. Seung and Waters (2006a) review and compare the main approaches available in commercial fisheries applications, including input-output (IO) models, social accounting matrix (SAM) models, and computable general equilibrium (CGE) models, and their use in calculating economic impacts for primarily commercial fisheries. In recreational fishing contexts, IO models have been the most common regional economic impact modeling approach used (Storey and Allen 1993; Steinback 1999; Hamel et al. 2002; Bohnsack et al. 2002; Criddle et al. 2003; McKean, Johnson, and Taylor 2011). However, there have recently been a few studies that use SAM models (Arita et al. 2011) and CGE models (Lew and Seung 2010), for example.

Regardless of the modeling approach used, the outputs from economic impact models are generally reported as point estimates of impacts rather than a "range" of likely impacts that account for uncertainty, instead relying on sensitivity analysis and scenario analysis to evaluate the role of uncertain parameters or other assumptions. Given the fact that many inputs to regional models are estimated with statistical or measurement error, it seems prudent to acknowledge these sources of input variation in the outputs from these models.

In the case of estimating the economic impacts of outdoor recreation, there are, in general, three sources of variations in the model inputs: errors associated with IO coefficients, sampling variation, and stochastic variation. IO coefficients, which are derived from data such as IMPLAN, are subject to errors because they are typically based on secondary data [see Kop Jansen (1994) and Ten Raa and Steel (1994)]. Sampling variation refers to variation in expenditure estimates arising from the fact that data on the expenditures associated with outdoor recreation are typically collected from a random sample of outdoor recreationists via surveys. Therefore, expenditure estimates are random variables and the true distribution of the expenditures in the population is not known. The stochastic variation occurs because the outdoor recreation demand models often used to evaluate changes in behavior that represent

^{1.} We refer to these jointly throughout the article as sources of "input variation," as they represent the sources of variation in the inputs that constitute the exogenous shocks evaluated by economic impact models.

shocks to the economy typically are estimated using regression techniques that require stochastic assumptions. Therefore, the estimates from these models (changes in trips or participation, for example), which are often used to determine changes in recreational expenditures, are subject to stochastic variation.

Many of the previous economic impact analyses for outdoor recreation calculated only the point estimates, ignoring sources of input variation. There are only a few studies that consider this issue. English (2000) constructed confidence intervals in the regional economic impacts of recreational visits to the Florida Keys using an IO model and bootstrapping methods in order to account for sampling variation. Weiler et al. (2003) used the estimated covariance from a recreation demand model for the change in the number of visitors to estimate the confidence bounds and calculate the range of the economic impacts on a national park gateway community using an IO model. More recently, Seung and Lew (2013) developed methods to calculate the confidence intervals of the economic impacts from both sampling and stochastic variation within a CGE framework for a single harvest restriction change.

The present study applies the methods described by Seung and Lew (2013) to estimate confidence intervals for the economic impacts from a SAM model associated with six different bag limit policies for the major saltwater species targeted by recreational anglers off Alaska. Within that framework, sampling variation in recreation-related expenditure data and the stochastic variation embedded in estimated non-participation probabilities are incorporated in economic impact estimates by applying Monte Carlo-based 'simulation and bootstrapping methods. In this way, variation in estimated changes in recreation participation probabilities and in mean sportfishing-related expenditures is captured.² Using this approach, we assess the impacts of more restrictive fishing bag limits for Pacific halibut, Chinook salmon, and coho salmon in Alaska on non-resident anglers, who make up a large percentage of total anglers.3 The fishing bag limit changes we consider include reductions in the bag limit of one fewer or two fewer fish allowed to be harvested.4

Input variations resulting from the bag limit changes provide initial shocks to a SAM model specifically developed for southern Alaska. Southern Alaska, as defined here, is a region encompassing Southeast Alaska and Southcentral Alaska where nearly all recreational saltwater fishing occurs. The regional SAM model was used due to the model's advantage over the oftused IO model in that it can capture the distributional effects of an exogenous input shock on value added, households, and state and local government. The results show that when both types of variation are considered, there are no statistical differences between the economic impacts from the different bag limits considered.

The general approach followed herein is described in greater detail in Seung and Lew (2013). It involves using a bootstrapping approach to account for sample variation of mean expenditures

^{2.} Several important differences between Seung and Lew (2013) and the present study should be highlighted. This study uses more recent IMPLAN data (from 2008 instead of 2006) and examines multiple policy scenarios to assess the effect accounting for input variation has in policy evaluation. Although the CGE model used in Seung and Lew (2013) has theoretical advantages over a fixed-price model, such as an IO or SAM model, the SAM model is more commonly used since it has fewer data requirements and is, therefore, a useful model with which to illustrate the approach.

^{3.} Over 50% of anglers in Alaska are non-residents (Jennings, Sundet, and Bingham 2011).

^{4.} In 2006, the bag limit in Alaska for Pacific halibut was two per day, between one and three per day for Chinook salmon, and between three and ten per day for coho salmon, depending upon the area (Lew and Seung 2010).

and the Monte Carlo simulation-based approach of Krinsky and Robb (1986) to calculate variability in recreational participation changes arising from a stated preference choice experiment (SPCE) model.⁵ For each bootstrapped mean expenditure vector and draw from the distribution of recreational participation model estimates, input shocks (in the form of changes in angler expenditures) resulting from the bag limit changes are calculated and then mapped through the southern Alaska regional SAM model in repeated trials. That is, the model is run over a number of iterations with different bootstrapped expenditures and draws from the distribution of model-based recreation participation estimates being used in the SAM model in each iteration. The end result is an empirical distribution of economic impacts. Confidence intervals for the economic impacts are then calculated from these empirical distributions.

ACCOUNTING FOR INPUT VARIABILITY

Bootstrapping is a common resampling approach for approximating the standard error of a statistic (Efron 1979). The approach is straightforward. To illustrate, suppose we are interested in estimating the standard error of a function of the variables X, f(X). For the sample of N observations of X, we randomly select a total of N observations from the sample with replacement. The resulting set of resampled observations, X_b , is the bootstrap sample, which has the same number of elements as the original sample (i.e., N). Using the bootstrap sample, we calculate $f(X_b)$. This procedure is repeated R times, where R is a large number, and the set of $f(X_b)$ (i.e., $\{f(X_b)\} = f(X_b^1), f(X_b^2), \ldots, f(X_b^R)\}$) defines the bootstrap distribution of f(X). From the bootstrap distribution, confidence intervals or measures of dispersion can be calculated.

The first application of bootstrapping to a recreational economic impact analysis was done by English (2000), who used bootstrap samples to estimate standard errors on economic impacts associated with tourist spending in Florida using two approaches. First, he used each bootstrap sample in the economic impact model to generate an estimate of the economic impacts. He repeated this 1,000 times and generated an empirical distribution of the impacts. In the second approach, he calculated confidence intervals for each type of expenditure associated with recreational trips and for total expenditures, then calculated the economic impacts associated with each endpoint of the intervals, assigning the same relative allocation of expenditure categories as in the original sample. In this work we use the former approach, since the latter approach does not ensure that the confidence bounds on the economic impacts are precise at the specified level of α (Type 1 error). To this end, we draw R bootstrap samples for each of the expenditure categories (e.g., restaurant food expenses, lodging costs, fuel costs, etc.) and calculate the economic impact for each bootstrapped expenditure level in the regional SAM model. This results in R sets of economic impact estimates from which confidence intervals can be calculated.

In the non-market valuation literature, the Monte Carlo simulation approach of Krinsky and Robb (1986) is commonly used to account for model-based stochastic variation in welfare estimates and other model outputs (e.g., elasticities) from maximum likelihood-based models (Park, Loomis, and Creel 1991). The approach is similar to bootstrapping, except that instead

^{5.} As pointed out by a referee, the Krinsky-Robb approach is not the only possible approach to measure variability (e.g., a delta method may also be employed). However, due to the non-linearity of the participation function and widespread use of the approach in non-market valuation studies, the simulation-based Krinsky-Robb approach is attractive.

Typical categories of expenditures associated with outdoor recreation include transportation, food, lodging, and other types of expense items.

of resampling from the data, the researcher takes random draws from the distribution of the estimated parameters, which is generally assumed to be asymptotically multivariate normal and centered at the parameter estimates, with covariance defined by the information matrix. Thus, compared to the data bootstrapping resampling approach above, it can be thought of as a parameter resampling technique. For each vector of parameters drawn, the function of interest (in this case, recreation participation levels) is calculated. This is repeated R times to generate an empirical distribution of the function of interest, which provides information about the dispersion of the function.

THE STATED PREFERENCE MODEL

The SPCE model estimated by Lew and Seung (2010) is used to calculate the probability of non-resident recreational fishing participation in Alaska. The model was estimated using SPCE data from a survey of non-resident anglers who fished in Alaska during 2006.^{7,8} In each of the four SPCE survey questions, respondents are asked to choose between two fishing trip options (Choices A and B) of differing durations, costs, fish targeted, harvest restrictions, and expected size and catch characteristics, as well as a non-fishing option (Choice C). Lew and Seung (2010) estimated a random parameters logit SPCE model assuming the deterministic portion of indirect utilities of the Choice $A(V_A)$ and Choice $B(V_B)$ saltwater fishing trips depends upon the fishing location (Southeast Alaska or Southcentral Alaska, the two regions where almost all saltwater fishing trips occur), the number of fishing days, fishing trip cost, bag limits, expected catch, and expected size of fish caught for three species-Pacific halibut, Chinook salmon, and coho salmon. The indirect utility of the non-fishing alternative (V_C) was modeled as a function of demographics. The estimation results suggested that utility was higher for saltwater fishing trips in Southcentral Alaska and increased in harvest (bag) limits and expected catch; for Pacific halibut and Chinook salmon, average fish size contributed positively to angler utility, but average fish size for coho salmon was not statistically significant in utility (see Lew and Seung 2010 for details). They showed how results can be used to estimate changes in fishing participation resulting from changes to the bag limits, which together with estimates of total number of anglers and the average fishing expenditures by each angler, can be used to estimate the exogenous shocks (total change in expenditures) associated with bag limit changes to popular saltwater sportfish species.

In this article, the estimated parameters from Lew and Seung (2010) were used to calculate the probabilities of fishing participation under the current bag limits for Pacific halibut, Chinook salmon, and coho salmon, as well as under several alternative counterfactual limits. However, in contrast to Lew and Seung (2010), we follow the procedure of Seung and Lew

^{7.} The survey was administered using a modified Dillman mail-telephone approach in early 2007 (Dillman 2000). The mail contacts consisted of an advance letter, an initial survey mailing (survey booklet, cover letter, map, business reply envelope, and a small monetary incentive), a reminder postcard, and a second full survey mailing. A follow-up telephone survey was also used to encourage participation. The survey was mailed to a random sample of 1,900 non-resident anglers who purchased fishing licenses in Alaska during 2006. The final response rate, excluding undeliverables, was 61.9%, consisting of 1,115 returned surveys, of which 1,097 included sufficient information for use in the SPCE model estimation. For more information about the survey and descriptive statistics of the sample, see Lew, Lee, and Larson (2010). For details on the SPCE model and estimation results, see Lew and Seung (2010).

^{8.} Stated preference choice experiments are a stated preference valuation technique that asks respondents to choose between several options that differ in their characteristics (or attributes) (Adamowicz, Louviere, and Williams 1994; Alpizar, Carlsson, and Martinsson 2001; Hanley, Wright, and Adamowicz 1998).

(2013) outlined above to account for two sources of input variation in constructing estimates of economic impacts to enable the calculation of confidence intervals around these estimates.

The specific form for the mixed logit-based probability of choosing to participate in a saltwater fishing trip for the estimated model is:

Pr[participation] =
$$\int [\exp(V_A(\theta)) + \exp(V_B(\theta))] / [\exp(V_A(\theta)) + \exp(V_B(\theta)) + \exp(V_C(\theta))] f(\theta) d\theta,$$
where θ is the vector of random parameters (which

where heta is the vector of random parameters (which corresponds to all non-cost parameters in V_B and V_{C_1} and the constant term in V_A). This form for the probability is identical to the probability derived from a simple multinomial choice model, but is evaluated over the distribution of the ran-

Using this, the percent change in participation resulting from a change in the fishing trip attributes, x, from x^0 to x^1 was calculated by the following:

%
$$\Delta$$
Pr[participation] = (Pr[participation|x¹]-Pr[participation|x⁰])/Pr[participation|x⁰]. (2)

The change in the number of anglers fishing in saltwater resulting from this change was calculated by multiplying %ΔPr[participation] by an estimate of the total anglers. To this end, we use the total number of non-resident anglers who purchased a license to fish in Alaska during 2006 (264,009), the year for which the survey data were collected.9

The Krinsky-Robb simulation approach is followed to account for the stochastic variation in the % Δ Pr[participation] estimates entering the SAM model. This is done by drawing R=1,000 parameter vector draws from the estimated multivariate asymptotically normal parameter distribution. For the r^{th} parameter vector drawn (r = 1, ..., R), the $\%\Delta Pr[participation]$ is calculated for the bag limit change, multiplied by 264,009, and then multiplied by the $r^{\rm th}$ bootstrap sample of average angler expenditures as described below. 10 This represents the $r^{\rm th}$ iteration's exogenous shock associated with the bag limit change that enters the SAM model.

THE REGIONAL SAM MODEL

IO models have been a fundamental tool for regional economic analysis for the past half century. A standard IO model includes intersectoral flows of intermediate inputs, and thus captures a major source of economic linkages in an economy. However, the standard IO model ignores the income that flows from producing sectors to factors of production (value added), and then on to entities such as government and households, which generates endogenous demand for goods and services. A SAM model captures these flows in detail and can also

^{9.} Ideally, we would use an estimate of the number of potential Alaska anglers since the number who purchased a fishing 3. rucany, we would use an estimate of the number of individuals who would choose to buy a license and fish under the policy scenarios considered. Nevertheless, the number of fishing licenses sold to non-residents between 2000 and 2008 was within

^{10.} This procedure assumes independence of the two sources of variation; that is, sampling variation in fishing expento, this procedure assumes independence of the two sources of variation, that is, sampling variation in naming expenditures and stochastic model variation in participation estimates are assumed to be uncorrelated. This is reasonable in the offices and stochastic model variation in participation estimates are assumed to be uncorrelated. This is reasonable in the sense that the conditional indirect utility of fishing trips (represented by V_A and V_B) depends upon fishing trip attributes, sense may the continuous moment unity or using trips trepresented by 1/2 and 1/8/ depends upon using trip atmostes, including fishing costs (expenses), while the unexplained portion of utility captures other sources of variation. Thus, the model

investigate the distribution of factor income to various types of institutions and households (King 1985; Adelman and Robinson 1986). For example, some functions of a regional government are dependent on economic activity in the region, and a change in government revenue drives change in government expenditures in the region. This results in multiplier values that could be significantly larger than they would be if the regional government was treated as exogenous, as in a standard IO model.

The regional economy of southern Alaska is modeled with a SAM model. The southern Alaska SAM was generated using 2008 data and software from IMPLAN v.3.0. The resulting southern Alaska SAM has a total of 897 accounts, including 440 unaggregated IMPLAN production sectors producing 440 different commodities; 4 value added sectors (employee compensation, proprietary income, other property income, and indirect business taxes); 9 household categories (classified by income level); 1 state and local government sector; 1 federal government sector; 1 capital account; and an account for imports and exports to the rest of the world (ROW). The endogenous accounts include the 440 industry accounts, the 440 commodity accounts, the 4 value added accounts, the 9 household accounts, and the one state and local government account. The other accounts are exogenous. The structure of the southern Alaska SAM and the actual SAM are available upon request.11 Once the initial SAM was generated using 2008 data, we used nominal GDP ratios (Bureau of Economic Analysis) in order to adjust the data in the initial SAM to 2006 levels to be consistent with the year for which the sport angler survey data was collected.

MAPPING ANGLERS' EXPENDITURES INTO IMPLAN AND SAM SECTORS

Saltwater angler expenditures are categorized according to the type of angler: non-resident and resident anglers. Non-resident anglers lived outside of Alaska but fished in Alaska during 2006, while resident anglers lived and fished within the state. 12 In this study, expenditures by non-resident anglers are treated as exports because the expenditures, or the exports of recreational services, bring new dollars into the regional economy and generate multiplier effects as suggested by export base theory (Bergstrom et al. 1996; English and Bergstrom 1994; Miller and Blair 1985). 13 We assume the mix and amounts of expenditures by resident anglers do not change, as our focus is on changes in non-resident expenditures, all else assumed equal. 14

Information on the average angler expenditure was derived from results from the angler survey that collected information on trip-level expenditures by non-resident anglers as well as the SPCE data (Lew, Lee, and Larson 2010). This information was used to translate the change

^{11.} For further discussion of regional SAM models, see Holland and Wyeth (1993), Waters, Weber, and Holland (1999), and Seung and Waters (2006b).

^{12.} Note, however, that we do not account for changes to Alaska resident anglers resulting from changes in harvest policies in this article.

^{13.} In this study, the 21 different categories of sportfishing anglers' expenditures made by non-residents change when the fish catch limits change. These changes in expenditures are mapped to 440 different IMPLAN commodities. The resulting changes in expenditures on the 440 commodities are treated as changes in exports in our SAM model and are given as shocks to the model to calculate the economic impacts.

^{14.} Note though that our assumption can be interpreted to mean an increase in resident anglers' expenditures comes at the expense of reduced recreational spending elsewhere in the region (displacement effect). In this case, a decrease in resident angler spending is assumed to be offset by additional spending (equal in amount to the decrease in sportfishing-related spending) in other recreational activities.

in the number of anglers participating in saltwater fishing to a change in saltwater fishingrelated expenditures. The expenditure information obtained from the survey was grouped into three broad categories: (1) travel expenses to and from Alaska, (2) non-fishing expenses while in Alaska, and (3) fishing-related expenses while in Alaska. For our analysis, we only used the third category of expenditures, fishing-related expenses while in Alaska. We excluded the first category (travel expenses to and from Alaska) because most of the expenditure in this category is air transportation, and most air transportation expenditures occurred outside Alaska. We also excluded the second category (non-fishing expenses in Alaska) because they are not related to saltwater fishing. 15 The Alaska fishing-related expenses category was further divided into four subcategories: (1) all-inclusive fishing lodge/package costs (1 expenditure item), (2) transportation (7 expenditure items), (3) food and lodging (3 expenditure items), and (4) other fishingrelated expenses (11 expenditure items), resulting in a total of 22 expenditure items (table 1).16 To map the expenditure items into IMPLAN sectors, we first divided the "all-inclusive fishing lodge/package costs category" into the expenditure items in the other three subcategories based on the ratios of base-year levels of the expenditures on these items to the total expenditures. This resulted in a total of 21 expenditure items being mapped into IMPLAN sectors.

To derive the vector of changes in expenditures for 440 commodity categories used in the SAM model, the following steps were taken for each of the $r = 1, \ldots, R$ iterations of the model. First, the average expenditures per day (i.e., 21 mean expenditures) in the survey were calculated from the r^{th} bootstrap sample of expenditures from the survey data, and then allocated to 509 IMPLAN sectors using information in Table 4 of Gentner and Steinback (2008). As in Gentner and Steinback (2008), we distributed expenditure items containing more than one IMPLAN sector to individual IMPLAN sectors using the IMPLAN sectors' final demand ratios. To distribute generic grocery expenditure among different IMPLAN sectors, we used the personal consumption expenditure (PCE) activity database from IMPLAN (originally created by Bureau of Economic Analysis). Second, if the expenditures in IMPLAN sectors are commodity based, we applied transportation and retail margins to disaggregate the expenditures into different IMPLAN sectors. If the expenditures were industry based, the expenditures were converted into commodity-based numbers using a byproduct matrix from IMPLAN. Third, once all the anglers' average expenditures per day were converted into expenditures in 509 IMPLAN sectors following the procedure described above, the expenditures in the 509 sectors were mapped into the 440 IMPLAN sectors used in this article. 17 Fourth, to calculate the vector of sectoral shocks in the SAM model for the r^{th} iteration, the

^{15.} By ignoring the non-fishing expenses, the economic impact results in this study will be underestimated to the extent that non-resident sportfishing anglers spend money on items that are not related to sportfishing while visiting southern Alaska for sportfishing. In this case, the assumption that saltwater sportfishing was not the primary reason for the trip to Alaska may not be overly strong, as very few non-resident Alaska anglers who participated in qualitative testing activities (focus groups and cognitive interviews) indicated their trips to Alaska were for the primary purpose of saltwater fishing. Although saltwater sportfishing may have been a large driver, virtually all of the non-resident anglers involved in testing said they would have taken the trip to Alaska for other outdoor activities if they were unable to go saltwater fishing.

^{16.} Note that the standard deviations are generally larger than the mean, indicating wide dispersion in the distributions for these data.

^{17.} There are only 440 sectors in IMPLAN version 3, while Gentner and Steinback (2008) used an earlier version of IMPLAN which has 509 sectors.

Table 1. Survey Mean and Standard Deviations of Trip Expenditure Categories

Expenditure	Mean (S)	Std. Dev. (\$)
All-inclusive fishing lodge/package costs	401.74	1,325.23
Auto fuel costs	78.43	357.62
Auto rental costs	64.39	274.64
Bus/taxi fees	2.08	16.39
Train fares	4.76	49.79
Float/charter plane costs	23.80	163.78
Airline airfare (within Alaska)	166.59	553.59
Ferry costs	10.67	103.23
Lodging costs	138.05	496.67
Restaurant food and drink costs	84.62	196.81
Non-restaurant food and drink costs	49.31	171.75
Fishing/combination license fees	37.81	101.57
Fishing guide or charter fees	196.30	523.25
Fishing boat rental cost	20.18	168.32
Fishing gear and bait costs	24.23	251.52
Fish processing, freezing, packing or shipping fees	54.64	132.22
Ice costs	2.04	10.34
Fishing derby entry fees	1.59	9.12
Boat fuel, lubricants and repair costs	23.55	225.17
Moorage or launch fees	3.09	40.85
Gifts/souvenirs costs	76.61	280.53
Other fishing trip-related costs	60.75	1,050.90

average expenditures for 440 commodities from the rth bootstrapped sample were multiplied by: (1) the number of days per person or trip (=2.336 days/person or trip), (2) the total number of non-resident anglers who purchased a license to fish in Alaska (264,009), and (3) the $\%\Delta Pr[participation]$ for the r^{th} iteration of the Krinsky-Robb simulation, as noted above. Finally, for each of the R = 1,000 iterations, the sectoral shock for each of the 440 commodities was multiplied by the SAM multipliers for the commodity obtained from the SAM model to calculate the change in the total regional output.

ESTIMATING ECONOMIC IMPACTS FROM BAG LIMIT CHANGES

The resampling methods and economic models described above were applied to estimate confidence intervals for the economic impacts of changes in saltwater recreational fishing restrictions in Alaska (as measured by changes in total regional output). In Lew and Seung (2010), changes in the number of individuals who participated in saltwater fishing were estimated for several different single-species bag limit changes using data from a survey of anglers who fished in Alaska during 2006, but who were not residents of the state. Herein, both the bootstrapping approach of English (2000) and the Monte Carlo simulation approach of Krinsky and Robb (1986) were used to estimate confidence intervals around the economic impact estimates associated with six, single-species bag limit changes (reductions from 2006 limits) on nonresident anglers using data from Lew et al. (2010) and stated preference model results described in Lew and Seung (2010). Table 2, the content of which is from Table 6 in Lew and Seung (2010), presents the change in non-participation probability and the change in the number of participants for each of the six bag limit changes examined.

Confidence intervals for the total regional output changes were calculated using two different methods—the normal approximation approach and the bias-corrected percentile approach (e.g., English 2000):¹⁸

Normal Approximation Method

Let λ be the value of the estimator of interest from the original sample and σ^* be the standard deviation of the estimator distribution in the bootstrap samples. Then, the confidence intervals for the normal approximation is given as $\lambda \pm z_{\alpha/2}\sigma^*$, where α is the desired level of confidence and $z_{\alpha/2}$ is the $(100 \cdot \alpha)^{th}$ percentile point of the standard normal distribution.¹⁹

Bias-corrected Percentile Approach

The bias-corrected percentile (BCP) approach puts less reliance on the assumption of normality of the bootstrap distribution in the calculation of confidence intervals and is based upon the quantiles of the empirical bootstrap distribution of estimates. BCP-based confidence intervals are derived as follows. Let $\lambda^*(r)$ be the value of the estimator for λ obtained from r^{th} bootstrap sample, Φ the standard normal cumulative density function (c.d.f), $F(\lambda^*)$ the empirical c.d.f for $\lambda^*(r)$, and $z_0 = \Phi^{-1}\{\Pr(\lambda^* \leq \lambda\}$. Then, for a desired level of confidence, α , the lower and upper bounds on the confidence interval are equal to $F(\lambda^*)$ evaluated at the $\Phi\{2z_0 + z_{1-\alpha/2}\} \times 100$ and $\Phi\{2z_0 + z_{1-\alpha/2}\} \times 100$ percentiles, respectively.

For each of the bag limit changes, three different models were run that differ in the treatment of input variation. Model 1 included only sampling variation associated with recreation-related expenditures. Model 2 excluded sampling variation of expenditures and instead accounted for stochastic variation in fishing participation probabilities. Model 3 accounted for both types of input variations.

RESULTS

Before presenting the results from models I to 3, the point estimates of changes in total regional output from running the SAM model for each of the six policy scenarios without consideration of any input variation (hereinafter referred to as model 0), which is consistent with current practice in the literature, are presented in the second column of table 3. 20 The decrease in total regional output associated with a reduction of one fish in the bag limits for Chinook salmon, coho salmon, and Pacific halibut ranges from \$12.0 million associated with the Chinook salmon bag limit reduction to \$20.8 million for the Pacific halibut bag limit reduction. For a reduction of two fish, the decrease in total regional output ranges from \$24.9 million for Chinook salmon to \$44.6 million for Pacific halibut.

^{18.} For more detailed explanations of these methods for calculating bootstrapped confidence intervals, see Diciccio and Efron (1996).

^{19.} Since the normal approximation approach assumes the bootstrapped empirical distribution is roughly normally distributed, we conducted Komolgorov-Smirnov (KS) two-sample criterion D tests (Mood, Graybill, and Boes 1974; Deshpande, Gore, and Shanubhogue 1995) to ensure this approach was appropriate. The tests could not reject normality at a 5% significance level for the distributions of the economic impacts for all six bag limit change scenarios, regardless of whether the impacts are calculated based on (1) only the sampling variation in mean expenditure data, (2) only the stochastic variation in non-participation probability, or (3) both types of variation.

^{20.} A recent study estimated the output (sales) contributed by marine recreational angling in Alaska during 2011 to be approximately \$483 million (Lovell, Steinback, and Hilger 2013). Comparing the range of regional output estimates to this estimate suggests that policy changes have a small, but non-trivial effect on overall output. However, the overall effect on the broader economy is likely small when viewed in terms of the state's GDP (\$51.2 billion in 2011).

Table 2. Reductions in Anglers' Participation

Policy Scenario-Bag Limit Change	Non-participation Probability (%)	Decrease in Number of Participants			
1 fewer Chinook salmon 2 fewer Chinook salmon	0.856	2,261			
1 fewer coho salmon 2 fewer coho salmon 1 fewer Pacific halibut 2 fewer Pacific halibut	1.786 0.991 2.002 1.488	4,716 2,615 5,286			
		3.192	8,426		

Table 3. Means and Standard Deviations of Reductions in Total Regional Output (S million) by Model

Policy Scenario-Bag Limit Change	Model 0 Baseline SAM	Model 1 Expenditure Variation Only		Model 2 Stochastic Variation Only		Model 3 Both Sources of Variation	
	Mean	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2 fewer Chinook salmon 1 fewer coho salmon 2 fewer coho salmon 1 fewer Pacific halibut 2 fewer Pacific halibut	11.96 24.94 13.83 27.96 20.78 44.57	11.97 24.97 13.84 27.99 20.80 44.62	0.58 1.22 0.67 1.36 1.01 2.17	12.93 25.84 14.64 28.51 21.91 45.73	18.32 18.15 17.84 16.42 20.17 21.68	12.90 25.82 14.62 28.50 21.89 45.73	18.38 18.19 17.93 16.53 20.25 21.79

Using the methods described above, empirical distributions comprising 1,000 simulated estimates of the change in total regional output were generated for each of the six policy scenarios under the three models that differ in the input variation treated. The bootstrap means and standard deviations are presented in table 3. For the model 1 distribution of total regional output, the means for all policy scenarios are all within 1% of the estimate of total regional output change when input variation is ignored (i.e., the model 0 estimates). Moreover, the bootstrap standard deviations are all small relative to the mean, on the order of 5% or less of the magnitude of the mean. However, for models 2 and 3, the bootstrap means depart from those of model 0 by between 2 and 8%. Additionally, the bootstrap standard deviations are considerably larger, reflecting the influence of the stochastic variation contributed by the stated preference model.

From these distributions, confidence intervals were calculated using the two methods of confidence bound construction for the change in total regional output. Table 4 presents the 95% confidence intervals that result from the three models that account for input variation. Note that the two methods used to calculate confidence bounds—the normal approximation and bias-corrected percentile methods—lead to very similar confidence intervals. As the table shows, across both confidence interval types, regardless of the method used, the confidence

^{21. 90%} confidence intervals were also calculated and are available upon request; however, no qualitative differences exist between the 90 and 95% confidence, intervals.

Table 4. 95% Confidence Intervals for Reductions in Total Regional Output (\$ million)

Policy Scenario-Bag Limit Change	Confidence Interval Type	Model 1		Model 2		Model 3	
		Lower	Upper	Lower	Upper	Lower	Upper
1 fewer Chinook salmon	Normal approximation	10.83	13.11	-22.98	48.85	-23.14	48.94
	Bias-corrected percentile	10.87	13.11	-22.47	49.75	-23.17	. 52.60
2 fewer Chinook salmon	Normal approximation	22.58	27.35	-9.75	61.43	-9.85	61.49
	Bias-corrected percentile	22.67	27.34	-10.42	61.88	-10.74	63.58
1 fewer coho salmon	Normal approximation	12.52	15.17	-20.34	49.63	-20.54	49.77
	Bias-corrected percentile	12.57	15.16	-22.58	51.01	-22.98	50.29
2 fewer coho salmon	Normal approximation	25.31	30.66	-3.69	60.70	-3.91	60.91
	Bias-corrected percentile	25.41	30.65	-6.39	59.85	-6.84	62.59
1 fewer Pacific halibut	Normal approximation	18.81	22.79	-17.65	61.47	-17.82	61.59
	Bias-corrected percentile	18.89	22.78	-15.29	65.03	-15.71	64.58
2 fewer Pacific halibut	Normal approximation	40.35	48.87	3.22	88.23	3.00	88.46
	Bias-corrected percentile	40.51	48.86	6.89	90.98	7.46	93.06

bounds for model 1 are much narrower than for models 2 and 3 (by an order of magnitude). Moreover, the model 1 confidence intervals suggest that at the 5% level total regional output reduction is statistically positive for each of the six policy scenarios. The confidence intervals for models 2 and 3 are very similar in width, with the model 3 confidence intervals being slightly wider. In contrast to the model 1 bounds, the confidence intervals for models 2 and 3 overlap zero in all but one case, suggesting that at a 5% level of significance, we cannot reject the hypothesis that the economic impact of each of these policy changes is statistically zero. The one policy scenario for which the 95% confidence interval does not contain zero is the two fewer Pacific halibut case.

Given these results, decision makers may also wish to know whether there are statistical differences among the results for policy scenarios. To this end, we employed the method of convolutions (MOC), a computationally intensive but precise method for estimating the difference between two (independent) distributions (Poe, Giraud, and Loomis 2005). In this case, we applied the MOC to calculate the confidence intervals associated with the difference in total regional output for various pairs of policy scenarios. The resulting 95% confidence intervals were used to evaluate whether the difference in total output change between each pair of policy scenarios was statistically different from zero (i.e., the MOC confidence intervals do not contain zero at a given level of significance). The results of these tests for significance of the difference in total regional output are presented in table 5. The two right-most columns clearly show that there is no statistical difference between any two of the policy scenarios for estimates based on models 2 and 3. For model 1, however, nearly all have statistically significant differences (in the expected direction), with the lone exception being two fewer Pacific halibut versus one fewer coho salmon, which has a difference in regional output that is not statistically different from zero.

^{22.} We use a complete combinatorial approach to the method of convolutions (Poe, Giraud and Loomis 2005) to precisely calculate the confidence interval for difference between the economic impacts of two different policy scenarios. To this end, the difference between each of the R economic impact estimates calculated using the bootstrapping/Monte Carlo approach described above for Policy A is differenced with the R estimates for Policy B, resulting in an empirical distribution of the difference consisting of $R \times R$ elements. Confidence intervals can then be identified from these empirical distributions, and tests conducted on whether or not zero is contained within the confidence intervals at different levels of α .

Policy Scenario B	Model 1	Model 2	Model 3
2 fewer Chinack colmon			Model
	~	0	0
	-	0	0
	-	0	0
		0	0
	-	0	n
	-	0	0
2 fewer coho salmon	_	0	0
l fewer Pacific halibut	_	0	, 0
2 fewer Pacific halibut		0	0
	т	0	0
	-	0	0
	+	0	0
	0	0	0
	+	0	n
2 fewer Pacific halibut	+	0	0
2 fewer Pacific halibut	_	0	U
	2 fewer Chinook salmon 1 fewer coho salmon 2 fewer coho salmon 1 fewer Pacific halibut 2 fewer Pacific halibut 1 fewer coho salmon 2 fewer coho salmon	2 fewer Chinook salmon 1 fewer coho salmon 2 fewer coho salmon 1 fewer Pacific halibut 2 fewer Pacific halibut 1 fewer coho salmon 2 fewer coho salmon 1 fewer Pacific halibut 4 fewer Pacific halibut 5 fewer Pacific halibut 6 fewer Pacific halibut 7 fewer Pacific halibut 9 fewer Pacific halibut 1 fewer Pacific halibut 1 fewer Pacific halibut 2 fewer Pacific halibut 1 fewer Pacific halibut 1 fewer Pacific halibut 1 fewer Pacific halibut	2 fewer Chinook salmon

Notes: + = MOC-based confidence interval for difference in total regional output between A and B does not contain zero and is positive, indicating the total regional output reduction from A is statistically greater than B.

- = MOC-based confidence interval for difference in total regional output between A and B does not contain zero and is negative, indicating the total regional output reduction from A is statistically less than B.

0 = MOC-based confidence interval for difference in total regional output between A and B contains zero, indicating no statistical difference between the total regional output reduction from A and B.

The results clearly show that, in the case examined here, the stochastic variation from the recreation participation model, which is accounted for in both models 2 and 3, leads to much wider confidence intervals than the sampling variation from the expenditure data. Comparing the confidence intervals from models 2 and 3, which differ only in the inclusion of input variation from the expenditure data in model 3, suggests that the contribution of the expenditure data's sampling variation is small, since the confidence bounds are nearly identical. This means that if only the sampling variation in mean expenditures is taken into account, the resulting range of economic impacts may be misleading. Looking only at the model 1 confidence bounds, decision makers may believe that there are significant differences between different bag limit policies, which is seen formally by an examination of the confidence intervals for the differences in total regional output generated for two different policies with the MOC analysis.

Yet when the stochastic error associated with the recreation participation model is included (models 2 and 3), it becomes clear that the comparison of economic impacts across policy scenarios may not yield statistically significant differences. That is, estimates from the regional SAM model may lead to different point estimates for each policy scenario, but due to the input variation used to generate the estimates, the policy scenarios are not, in fact, statistically different in terms of total regional output. In this particular case, decision makers would be wise to use other criteria (e.g., economic efficiency, cost-effectiveness, distributional equity, political tractability, etc.) to decide between policy alternatives because the variation endogenous to the regional impact model used to generate estimates of the economic impacts is too large to yield statistically distinct estimates for each policy scenario. Furthermore, for models 2 and 3, it is clear that the input variation is sufficiently great to lead to the finding that none of the total regional output estimates for the policy scenarios are statistically different from zero.

DISCUSSION

Recreational fishing valuation studies are increasingly producing results that can be used in evaluations of harvest policy changes on fishing values and participation (e.g., Anderson and Lee 2013; Larson and Lew 2013). Linking these valuation models to economic impact models to evaluate economic impacts on regional and national economies is likely to continue and increase (e.g., Loomis 2006; Lew and Seung 2010), particularly in the U.S. where such information is often required as part of regulatory analyses associated with federal fisheries management decisions.²³

However, when calculating regional economic impacts from recreational fishing, and outdoor recreation generally, it is common practice for economists to calculate only the point estimates of the impacts (model 0), ignoring the potential range of the impacts arising from the input variations, such as sample variation and stochastic variation as considered in our study. This study used bootstrapping and Monte Carlo methods to account for sample variation and stochastic model variation, respectively, in two input components—expenditure data and estimates from a recreation participation model. Using these methods, we incorporated the variation endogenous to the processes used to estimate exogenous shocks for six Alaska non-resident saltwater sportfishing bag limit change scenarios. A regional SAM model was employed to calculate the range of regional economic impacts from the exogenous shocks, and confidence bounds on the economic impacts were constructed. The ranges of the economic impacts were estimated for each of the six bag limit changes on non-resident anglers. We compared results for the confidence intervals associated with the change in total regional output calculated with one or both of the two different types of variations (sampling variation in expenditure estimates and the stochastic variation from the recreation participation estimates).

An important finding is that the confidence intervals of the estimated change in total regional output calculated with the stochastic variation associated with the recreation participation model (models 2 and 3) are significantly wider than those obtained with the variations in expenditures only (model 1). A formal comparison of differences in economic impacts for different policies across the different model assumptions show that no statistically significant differences exist between policy scenarios when stochastic variation is included. This means that accounting only for variation in mean expenditures may produce misleading information about the likely range of economic impacts.

Furthermore, even though we have shown the important implications of accounting for two common sources of variation inherent in the inputs for a particular application of a recreation-based economic impact modeling exercise, it does not account for potential variation due to IO coefficients in IMPLAN or other important sources of variation that may be present. For example, as to the latter, in this study the percent change in total participation was calculated by assuming a constant total number of total anglers (264,009). Clearly, changes in recreational fishing policy may influence whether or not individuals will choose to fish at all, affecting the total number of anglers who fish and spend money on fishing-related activities in Alaska. To

^{23.} Consideration of economic impacts is a requirement as delineated in Title III, Section 3 of the Magnuson Stevens Fishery Conservation and Management Act (U.S. Public Law 109-479), which requires that conservation and management measures "to the extent practicable, minimize adverse economic impacts on communities" (104-297, 109-479). In addition, assessing economic impacts in regulatory analyses is often required under the National Environmental Policy Act, Regulatory Flexibility Act, and Executive Order 12866.

the extent that stochastic variability associated with this participation decision can be accounted for, confidence intervals associated with economic impacts of recreational fishing policies may be even wider. Thus, in future research it may be useful to identify and measure other potentially important sources of input variation to assess their relative contributions to the overall variation in economic impact estimates.

In order to make informed decisions, decision makers need to be aware of the accuracy of the estimated impacts associated with the estimates attached to policy scenarios. To this end, they need information on the source and magnitude of variations embodied in the data sources and underlying models used to estimate the exogenous shocks in economic impact models. Our results show that the range of regional economic impacts from changes to outdoor recreation could be much wider than previously thought, and underscore the importance of being aware of caveats in interpreting the economic impact results that are used by policymakers in natural resource management decisions.

In the case of Alaska recreational fishing, visitors to Alaska for saltwater sportfishing spend a large amount of money in the state. Their spending generates economic impacts throughout the state that are not trivial. Federal fishery managers and state and local policymakers alike are naturally interested in how changes in harvest limits for saltwater sportfishing will affect the economic activity in the region. Our findings suggest that due to considerable input variation in the recreation participation model, comparisons of the economic impacts of alternative bag limit policies may not be meaningful, at least in this case. However, to the extent that future analyses can reduce the stochastic error in model estimates, and hence the width of the confidence intervals around the estimates, economic impact estimates may be important considerations in these types of decisions. For the time being though, the economic impact estimates in this article, and the associated confidence bounds, appear to provide ample evidence that point estimates should not be used to compare alternative bag limit policies.

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