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Original Article

Measuring economic contributions of the marine recreational charter fishing sector using a resampling approach

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Policy makers and stakeholders often desire information on the economic impact of fishing, which is frequently measured through its contribution to the economy using regional economic impact models. The variance of fishery-related economic contribution estimates is seldom calculated but can improve the quality of policy information. In this study, we illustrate a resampling-based approach for calculating standard errors of contribution estimates within a social accounting matrix (SAM) model with inputs calculated from survey data with missing data. We estimate the contribution of the saltwater recreational charter fishing industry in Alaska to the economy for 2011–2013 and 2015. Statistical tests are then conducted to assess differences between estimates across the years. Of the years studied, the total output (sales) from the Alaska saltwater charter fishing industry in Alaska was found to be (statistically) largest in 2011 ($248 million in 2013 dollars) and lowest in the next year, 2012 (about $141 million in 2013 dollars). Subsequently, the total output increased in 2013 and then remained at a statistically similar level in 2015.

Keywords: Alaska, economic contribution, jackknife method, recreational fishing, sample weighting and data imputation, social accounting matrix model

Introduction

Saltwater charter boat fishing operations are widespread in coastal states across the United States providing for-hire fishing experiences to marine anglers. In 2015, for example, these businesses facilitated over 4 million fishing trips taken in US coastal states (NMFS, 2017). In Alaska, a state well known for its ocean and coastal fishing opportunities, virtually all saltwater charter fishing occurs in Southern Alaska, an area encompassing both Southeast Alaska and Southcentral Alaska, which roughly corresponds to International Pacific Halibut Commission (IPHC) Area 2C (Southeast Alaska) and Areas 3A, 3B, 4A, and 4B (Southcentral Alaska) (see Figure 1). Pacific halibut is a primary target species for charter anglers and is managed jointly by the North Pacific Fishery Management Council (NPFMC), the National Marine Fisheries Service (NMFS), and the IPHC. Other marine recreational species, including the other primary saltwater target, Pacific salmon, are managed by the State of Alaska. In recent years, over 350 000 Pacific halibut and 500 000 Pacific salmon have been harvested annually in Alaska with over half of these fish being harvested by charter boat anglers (Powers and Sigurdsson, 2016).

Recent socioeconomic research on the Alaska recreational charter sector has included efforts to better understand industry preferences for management options and compliance (Lew *et al.*, 2016; Chan *et al.*, 2018), baseline economic conditions (costs and revenues) of the industry (Lew *et al.*, 2015; Lew and Lee, 2018), spatial fishing patterns and their drivers (Chan *et al.*, 2017), harvest portfolio diversification (Beaudreau *et al.*, 2018), and the economic value of charter fishing for non-resident (tourist) anglers (Lew and Larson, 2015) and resident anglers (Lew and Larson, 2017). However, basic information about the economic contribution the recreational charter sector makes to the

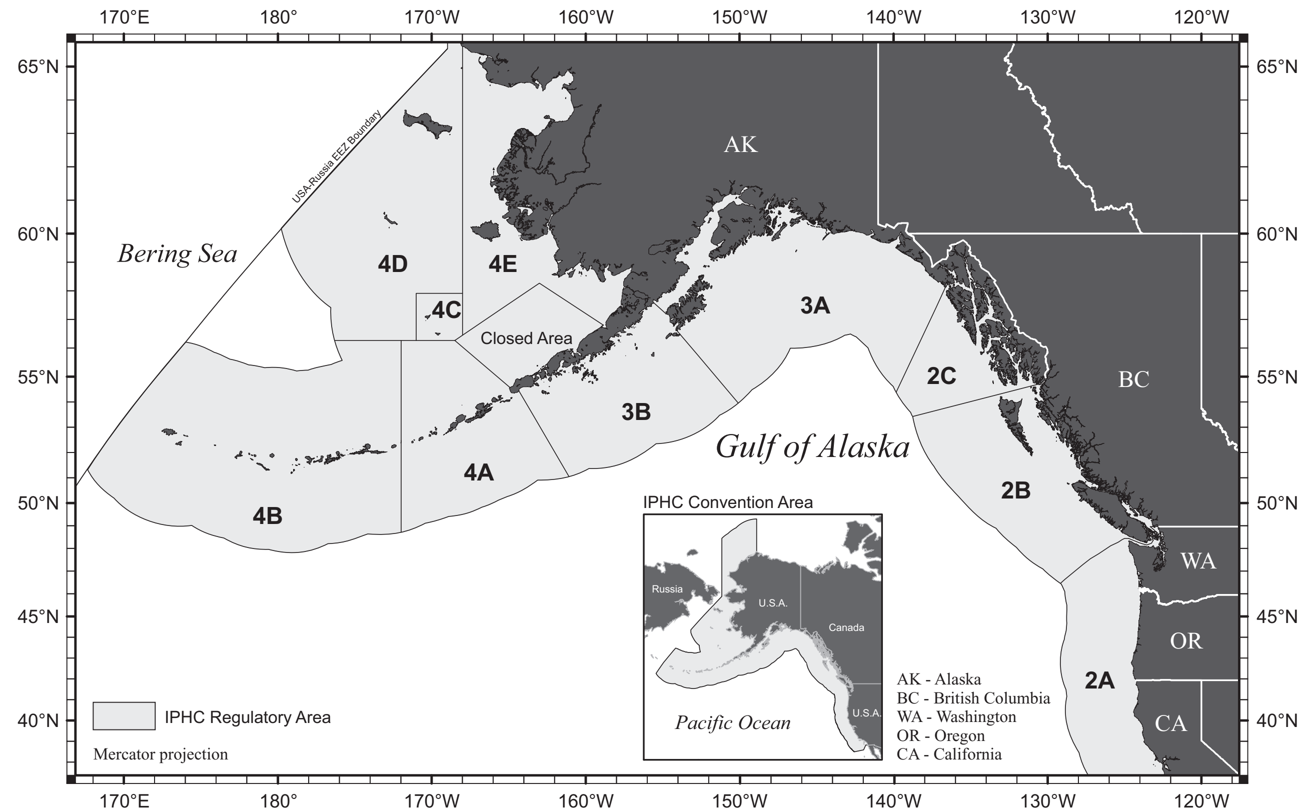

Figure 1. IPHC regulatory areas. *Source*: IPHC; https://iphc.int/the-commission.

economy is currently sparse but is valuable in allocation and other ongoing management discussions as it provides a baseline understanding of the size of the industry and what it contributes to aspects of the economy (employment, tax base, etc.) and provides context for the magnitude of potential impacts of shifting allocation shares between sectors.

Past efforts to estimate the economic contribution of the Alaska charter sector have been more inclusive in scope by including private boat and shore fishing and thus do not provide information that can easily be translated for the charter sector alone. For example, Lovell *et al.* (2013) estimate that the Alaska saltwater sport fishing sector as a whole, which includes the charter fishing sector as well as all non-charter (unguided) fishing, generated $483 million (in 2011 dollars) in total output (sales) in 2011. They also estimate the charter sector contributed $208 million (or 43% of the total) to overall output. The latter estimate was based on angler trip expenditures and may not account for other services charter businesses provide (wildlife viewing trips and transportation) that affect their costs and revenues. Because of this, it is unclear how accurate this estimate of economic contribution is for the Alaska charter sector.

Researchers generally do not report standard errors or confidence intervals around the estimates from regional economic models, such as in the case above, instead accounting for potential uncertainty in point estimates using sensitivity analyses on key parameters. However, this ignores the fact that the inputs used as "shocks" to regional models are generally estimated with sampling, statistical, or measurement error (English, 2000; Seung and Lew, 2013). Failing to account for the variance in economic impacts that result from the variance in the inputs precludes formal statistical testing of impact estimates and generally an understanding about the precision of the estimates.

This has prompted some research exploring ways of accounting for the variance of economic impact estimates attributable to the variance of inputs in Input–Output (IO)-based models. Weiler *et al.* (2002) proposed a simple approach using the endpoints of the confidence bounds on the inputs—in their case, estimates from a regression model—as input values to use in the regional model to generate impact estimates that are interpreted as the endpoints of confidence bounds on the estimated impacts. Several studies have employed this approach, including Orens and Seidl (2009) and Gabe and Lisac (2014). A computationally more intensive approach, based on bootstrapping, was introduced by English (2000). This simulation-based approach was used by Seung and Lew (2013) and Lew and Seung (2014) to estimate confidence intervals on the economic impact estimates resulting from predicted changes in marine recreational harvest limits in Alaska derived from a stated preference model of recreational fishing decisions. More recently, Seung and Kim (2018) used the approach in a study of recreational fishing in South Korea.

This study represents the first effort, to our knowledge, of estimating the specific economic contribution of the Alaska saltwater charter sector to the economy and differs from the work by Lovell *et al.* (2013) by specifically focusing on the economic contributions made by the charter sector and from much of the literature by estimating standard errors for the contribution estimates. We generated estimates of the economic contribution of the Alaska recreational charter sector to the economy during 2011–2013 and 2015 using expenditure data from surveys of Alaska charter businesses in a social accounting matrix (SAM) model of the Southern Alaska economy. By using data from charter businesses, rather than anglers, the full economic contribution of the sector on the Southern Alaska economy can be captured since the value of these businesses may not be fully captured by the angler expenditure data. Alaska charter businesses often provide non-fishing related services, such as lodging, transportation, and non-fishing tours (e.g. hunting and wildlife viewing trips), that are not captured in angler expenditure data.

Due to the presence of unit and item non-response (i.e. missing data) in the survey data, the population-level expenditure estimates used as inputs to the regional economic model are generated after applying sample weighting and data imputation methods. A jackknife resampling approach (Efron and Tibshirani, 1994) that accounts for missing data is used to generate estimates of the standard errors of the economic contribution estimates. Employing this approach allows statistical tests to be conducted that examine whether there are statistical differences between total output estimates across the survey years. Of the years studied here, the total output (sales) from the Alaska saltwater charter fishing industry in Alaska was found to be (statistically) largest in 2011 and lowest in the next year, 2012. The total output increased in 2013, which was a statistically significant increase from 2012, and then remained at a statistically similar level in 2015.

The remainder of the paper is organized as follows: First, we describe the survey data and analysis undertaken to generate the primary SAM model inputs—population-level estimates of economic activity in the Alaska charter sector adjusted for unit and item non-response. Then, the SAM model is described, and the jackknife procedure for generating an empirical distribution of contribution estimates. This is followed by the presentation of the economic contribution estimates and jackknife standard errors resulting from the SAM model, as well as the formal testing for differences between economic contribution estimates across the survey years. The final section concludes with a discussion of the findings in the context of the allocation policy discussion and prospects for utilizing similar approaches in other fisheries.

Material and methods

Survey data and model inputs

In this section, we describe the data and methods used to generate population-level (charter sector) expenditure estimates. Annual expenditure data used in this study were collected from Alaska saltwater charter businesses in four surveys conducted in 2012–2014 and 2016 that collected information about costs, revenues, and employment in the previous season (2011–2013 and 2015). In what follows, we describe the general data collection approach, but additional details about the 2012–2014 surveys, and copies of the survey instruments, can be found in Lew *et al.* (2015) and about the 2016 survey in Lew and Lee (2018). Eligibility for inclusion in a given year's survey was limited to charter businesses that were licenced and active during the previous fishing season according to charter fishing activity recorded in the Alaska Department of Fish and Game (ADF&G) Charter Logbook Program (Powers and Sigurdsson, 2016), which is a mandatory program for all charter businesses and requires reporting of trip-level harvest and effort information.

The survey questionnaires used in each year are nearly identical, with only minimal variation in presentation and content to facilitate data consistency. Together, the four surveys collected annual business-level cost and revenue information for the 2011–2013 and 2015 fishing seasons, including disaggregate information on charter business revenues; fishing trip operating expenses; labour expenses; general overhead expenses; and capital, real estate, and equipment investments; and loan payments (see Supplementary Table A1).

Table 1. Summary of population-level estimates of total revenue and costs (in 2013 $millions) and jackknife standard errors (in parentheses).

Year	Total revenue	Total expenditure
2011	141.3 (4.2)	181.4 (7.5)
2012	114.2 (4.7)	108.2 (2.0)
2013	168.5 (9.5)	130.3 (2.8)
2015	114.3 (5.4)	120.6 (2.8)

The surveys were administered following a modified Dillman tailored design method (Dillman *et al.*, 2009) approach consisting of several mail contacts and a telephone interview. Details about the survey administration can be found in Lew and Lee (2018). For each of the survey years, the survey was administered during the winter and spring to coincide with the time when charter businesses are preparing for the upcoming season that typically begins Memorial Day weekend.

The 2012–2014 surveys were conducted as censuses of all active charter businesses in Alaska; there were 650 active charter businesses in the 2012 survey, 592 in the 2013 survey, and 572 in the 2014 survey. In contrast, the 2016 survey was administered to a stratified random sample of eligible charter businesses rather than to all eligible charter businesses to reduce survey fatigue among the target population, given that the survey had been conducted several times in previous years. The four sample strata were defined based on ADF&G management area (Southeast Alaska or Southcentral Alaska) and the number of guide licences and vessels registered to a business (one guide and one vessel only or more than one guide or vessel) according to ADF&G licence data. Simple random samples were drawn from each of the four sample strata so that the total sample consisted of 75% of the population of 561 charter businesses.

Unit response rates were 27% (174 respondents) in the 2012 survey, 24% (141 respondents) in the 2013 survey, and 22% (125 respondents) in the 2014 survey (Lew *et al.*, 2015). The unit response rate for the 2016 survey was 21% (87 respondents) (Lew and Lee, 2018). Note that the unit response rates for the 2012–2014 and 2016 surveys are below the benchmark level of 65% sometimes used to support ignoring any potential unit non-response bias (Dolsen and Machlis, 1991), suggesting that adjustments should be made for missing data in order for the population-level estimates to be calculated with confidence. Another concern with these data is the <100% item response rate, which reflects the percentage of individual respondents providing responses to individual questions. Across cost and revenue questions, the item response rate was about 45% in the 2014 and 2016 surveys and 50% in the 2012 and 2013 surveys. Thus, efforts were made to account for both unit and item non-response in the survey data to improve confidence in the population-level estimates used as inputs to the SAM model.

Population-level estimates accounting for unit and item non-response in survey data

There are few recreational expenditure studies that adjust estimates for sample non-response, with Leeworthy *et al.* (2001) and Lew *et al.* (2015) being a couple exceptions. In those studies, population-level estimates are adjusted for the fact that survey response rates are typically <100% and thus non-response bias, to the extent it is found, must be accounted for. Leeworthy *et al.* (2001) correct for non-response bias in a mailback (second stage) expenditure survey of Florida recreationists using information from an onsite exit interview (first stage) that identified the individuals who were sent the expenditure survey. Respondents from the first stage that did not respond to the second stage survey were treated as non-respondents and sample weights were constructed based on demographics and to adjust for the sample stratification approach used. Weights were then applied before generating economic impacts using an IMPLAN IO model.

In a study using the 2012 Alaska charter survey data also analysed here, Lew *et al.* (2015) develop individual weights for the sample of respondents to adjust for three things: (i) the probability of being selected for the sample (the base weight, w_1), (ii) differences between the respondent sample and non-respondent sample (non-response weight, w_2), and (iii) differences between the respondent sample and the population in terms of one or more known population totals (post-stratification weight, w_3). Auxiliary fishing catch and effort data on the sample and the whole population are used to calculate sample weights that correct for sample non-response (w_2) and to adjust the respondent sample to better reflect the population in several characteristics (w_1). The auxiliary data are from ADF&G's Charter Logbook Program database that includes information about when and where fishing occurred during the year, the amount of fishing effort, the species of fish harvested, clientele type (e.g. resident or non-resident, paid or unpaid), and the guides and vessels used.

Furthermore, Lew *et al.* (2015) compare several ways of handling item non-response in the generation of population-level estimates of total costs and revenues -zero imputation, mean imputation, hot deck imputation, and nearest neighbour imputation techniques. A K-nearest neighbour data imputation approach is preferred in their application because it takes advantage of the ample auxiliary information available about the sample that allows for good "donor" values to be used to replace missing values. This imputation approach involves finding the K (>1) item respondents that are the most similar to the item non-respondent using a distance function and randomly choosing a donor value from among them. More formally, for the jth item non-respondent, the researcher finds the K item respondents, called "nearest neighbours," that minimize the distance function (D_j) across all item respondents (N^r):

$$D_j = \sum_{i=1}^{N^r} |\mathbf{x}_i - \mathbf{x}_j| \quad (1)$$

defined for a set of auxiliary variables ($\mathbf{x}$) assumed to be related to the variable of interest (Chen and Shao, 2000). The donor value is then randomly drawn from the K "nearest neighbours."

In this study, we use the individual sample weights calculated in Lew *et al.* (2015) for the 2012–2014 survey data and Lew and Lee (2018) for the 2016 survey. These weights were calculated in these studies using the procedure outlined in Lew *et al.* (2015). The individual weights are represented by the $N^u \times 1$ vector $\boldsymbol{w}$ (where N^u is the total respondent sample size; that is, the unit respondents), which is a product of the three weights described above, w_1, w_2, and w_3. In this study, the base weight, which is equal to the inverse probability of being selected for the sample from the population (Brick and Kalton, 1996), is equal to one ($w_1 = 1$) for all surveys. Since the 2012–2014 surveys were conducted as censuses of the population, the base weight is 1. Also, since the 2016 survey was administered to a stratified random sample where 75% of each stratum was randomly sampled, the sample is self-weighting, so the base weight w_1 again equals 1.

To address item non-response, we adopt the K-nearest neighbour imputation approach (with $K = 3$) to impute values for missing survey responses. For a given year's survey dataset, this imputation approach is applied for each cost and revenue variable to fill in missing values. The data imputation involved several steps and used detailed charter business-level data from the Charter Logbook Program. First, three respondent classes were defined based on the number of client fishing trips taken during each year, which proxied for the size of the charter operation in that year. Second, to determine a donor value for a given question and item non-respondent, the distance function was minimized with respect to eight variables: (i) a dummy variable indicating whether fishing occurred in Area 3A (Southcentral Alaska), (ii) the number of fishing guides used, (iii) the number of calendar days fished, (iv) the total number of client fishing trips, (v) a dummy variable indicating whether crew fishing trips were taken, (vi) a dummy variable indicating whether some unpaid fishing trips were taken, (vii) the number of hours spent fishing for Pacific salmon, and (viii) the number of hours spent fishing for bottomfish (a category that includes Pacific halibut). Finally, a donor value is then randomly selected from the K nearest neighbours—the item respondents with the smallest distance function values from the item non-respondent. Additional details are provided in Lew and Lee (2018), Lew *et al.* (2015), and Lew *et al.* (2015). The end result of the data imputation is a rectangular dataset, $\boldsymbol{Y}$, with dimensions $N^u \times L$, where L is the total number of cost and revenue variables. Note that the weighting scheme described earlier leads to weighted mean estimates for the population that reflect adjustments for non-response and post-stratification concerns. That is, $\bar{Y} = (1/N^u)\cdot \boldsymbol{w}\cdot \boldsymbol{Y}$. Generating aggregate (population-level) estimates involves multiplying the population size (N) by the weighted mean estimate ($\mathbf{Z} = N\cdot\bar{Y}$). These population-level estimates of the expenditures of charter business are used as inputs in the SAM-IO model.

The Southern Alaska SAM model

Several different models are available for conducting economic impact analysis for commercial and recreational fisheries. These models include IO models, SAM models, and Computable General Equilibrium (CGE) models. Since its development in the 1930s, economists have frequently used IO models for impact analysis related to regional economic development, resource management (including fisheries), and environmental issues. In an IO model, inter-industry transactions of goods and services used as intermediate inputs are captured. In recreational fishing contexts, IO models have been the most common regional economic impact modelling approach used (Storey and Allen, 1993; Steinback, 1999; Bohnsack *et al.*, 2002; Hamel *et al.*, 2002; Criddle *et al.*, 2003; McKean *et al.*, 2011; Seung and Kim, 2018).

One weakness of IO models is that the models miss the links among producing industries, factors of production (value added), and institutions such as households and government. By including these links, a SAM model can examine the distribution of factor income to various types of institutions, and therefore calculate the effects of the changes in the income or revenue of these institutions (King, 1985; Adelman and Robinson, 1986). Therefore, the multipliers from a SAM model are generally larger than those from an IO model. For further discussion of regional SAM models, see Holland and Wyeth (1993), Waters *et al.* (1999), and Seung and Waters (2006a). Although there are several studies that use a SAM model for commercial fisheries (Arita *et al.*, 2011; Seung and Waters 2013), there are few applications of the model to recreational fisheries (Lew and Seung, 2010, 2014).

A limitation of IO and SAM models for evaluating effects from specific policy changes or exogenous shocks is that the prices (factor prices and commodity prices) are assumed fixed, which precludes welfare effects from being calculated (e.g. changes in consumer or producer surplus). CGE models overcome this limitation by allowing prices to be endogenously determined. In this study, however, a CGE approach is not needed since our focus is on measuring the importance—in terms of economic contribution—of the whole charter business sector in its current state by considering the current state of the relationships (or linkages) among the industry and non-industry sectors. See Seung and Waters (2006b) for a more detailed review of regional economic impact studies using these models.

Since all charter businesses operate in Southern Alaska (Southeast or Southcentral Alaska), this study employs a SAM model covering Southern Alaska to generate estimates of the economic contribution of the Alaska saltwater charter business sector. To construct the Southern Alaska SAM model, we used data and software from IMPLAN 3.0. Note that IMPLAN version 3.0 is based on 2008 data. Since our analysis covers the period 2011–2015, an implicit assumption in the SAM model is that the production technologies of industries did not change significantly during the period between 2008 and the study period. There are a total of 897 accounts (industries, commodities, and institutions like households and governments) that constitute the economy in the model. These accounts include 440 unaggregated IMPLAN industries that produce 440 different commodities; four value added accounts (employee compensation, proprietary income, other property income, and indirect business taxes); nine household accounts (categorized by income level); one state and local government account; one federal government account; one capital account; and an account for imports and exports to the rest of the world (ROW). The last three accounts (federal government account, capital account, and ROW) are the exogenous sectors in the model with the other 894 accounts endogenous. The actual SAM is similar to the one used by Seung and Waters (2010). Both the actual SAM and details of the structure of the Southern Alaska SAM are available upon request.

The survey data included data covering four broad categories of expenditures: (i) charter trip operating expenses (six cost items); (ii) general overhead expenses (11 cost items); (iii) vehicles, machinery, and equipment (eight cost items); and (iv) building, land, and other real estate (eight cost items), as well as total revenue and total labour earnings for the charter boat sector (see Supplementary Table A1). To map the expenditure items to the 440 IMPLAN sectors, we relied on Gentner and Steinback (2008), Steinback and Brinson (2013), and Seung and Waters (2005). We allocated the labour earnings from the charter boat sector to households based on the base-year ratios of household incomes for the nine types of households. Then, for each household type, we applied the base-year ratios of expenditures on different commodities in IMPLAN. The mapping scheme is available upon request.

One unique feature of the Alaska economy is that industries in the state depend, to a large extent, on non-Alaska resident labour (Alaska Department of Labor and Workforce Development, 2016). The Alaska tourism industry is no exception. In 2014, the Scenic and Sightseeing Transportation industry, known as NAICS 487210 under the North American Industry Classification System (NAICS) and consisting of businesses primarily engaged in scenic and sightseeing activities on water, hired 53% of non-Alaska residents who earned 42% of total wages from the industry (Alaska Department of Labor and Workforce Development, 2016). However, these percentages also account for activities other than charter boat fishing. No information is available about non-residency rates of labour in the charter boat fishing industry. Therefore, in our study, we assume that 50% of labour income from the charter boat fishing industry flows out of the Southern Alaska region (results under alternative assumptions were qualitatively similar and are available upon request).

Estimating standard errors of contribution estimates

Another goal of this study is to estimate the standard errors of economic contribution estimates. To this end, we employ a procedure similar to the bootstrapping approach employed by English (2000), Seung and Lew (2013), Lew and Seung (2014), and Seung and Kim (2018), but within a jackknife resampling framework. In the jackknife approach, we calculate the economic contribution for N^u different survey samples to create an empirical distribution for the contribution estimates from which standard errors can be derived. Each of the N^u samples leaves out a different respondent, resulting in N^u different samples consisting of N^u-1 respondents. For each of these (delete-1) jackknife samples, we calculate the population-level estimates of each cost and revenue category while adjusting for missing data (as described earlier). The resulting jackknife population-level estimates are then used as inputs to the SAM model, resulting in a point estimate of total output. This procedure is repeated for each of the N^u replicated datasets to generate an empirical distribution of total output that accounts for the variance embodied in the imputed survey sample data (Shao, 2002). The standard deviation of this jackknife empirical distribution is the standard error of the total output estimate.

Note that this procedure involves re-imputing missing data for each of the jackknife samples of size N^u-1. For a given variable, this potentially changes the set of item respondents available and therefore the randomly selected nearest neighbour may be different. In some cases where there are few item respondents, the deleted respondent may mean there are fewer than the minimum number of item respondents needed to conduct the *K*-nearest neighbour data imputation. In this study, this occurred for a few investment-related expenditures. As a result, the empirical variance estimates likely overestimate the true variance because it underestimates these categories.

Table 2. Economic contribution of charter boat sector (in 2013 $millions) and jackknife standard errors (in parentheses).

Variables	2011	2012	2013	2015
Total industry output	248.0 (12.0)	140.7 (2.8)	166.1 (3.6)	165.7 (3.5)
Value added				
Employee compensation	66.3 (3.2)	37.3 (0.7)	44.8 (1.0)	43.6 (1.1)
Proprietary income	12.1 (0.8)	6.2 (0.1)	7.3 (0.2)	8.1 (0.1)
Other property income	41.5 (2.3)	22.4 (0.5)	26.0 (0.6)	27.3 (0.5)
Indirect business tax	12.0 (0.6)	6.8 (0.1)	8.1 (0.2)	7.9 (0.2)
Total value added	132.0 (6.7)	72.6 (1.4)	86.1 (1.9)	86.8 (1.8)
Total household income	77.3 (3.9)	42.7 (0.8)	50.9 (1.1)	50.9 (1.1)
State and local government revenue	19.1 (1.0)	10.8 (0.2)	12.8 (0.3)	12.4 (0.3)

Results

Table 1 presents the population-level estimates of Alaska charter sector total costs and revenues for 2011–2013 and 2015 after adjusting for missing data through sample weighting and data imputation.

The contribution of the charter boat sector was first computed based on the population-level estimates of the expenditures to total regional output, value added, household income, and state and local government revenue. Table 2 details the estimated total output for the Alaska charter sector in 2011 is $248 million. All values in the table are in 2013 dollars. The total output in 2012 decreased by a large magnitude—to $141 million—and then increased in 2013 to $166 million. Between 2013 and 2015, there was little change in total output. Other variables show a similar trend. For example, the total value added income ranges from a high of $132 million in 2011 to a low of $73 million in 2012, followed by a large increase in 2013 and then a similar value added level in 2015. Table 2 also includes the jackknife standard errors of the estimates.

Formal statistical tests are possible given the jackknife-based empirical distributions of total output. We employ a method of convolutions (MOC) approach (Poe *et al.*, 2005) to formally test whether there are differences between different years. This involves developing precise confidence intervals for the difference between two total output estimates. To construct the method of convolutions confidence interval (MOC-*CI*) for year A and year B (where A and B $\in$ {2011, 2012, 2013, 2015}), each of the $N^u{}_A$ and $N^u{}_B$ jackknife estimates are used to simulate the empirical distribution of the difference between total output from A and from B. Every possible difference between the total output values of the year A and year B samples is calculated and collectively used to form an empirical distribution of the total output difference from which confidence intervals can be determined. If the MOC-*CI* for a particular difference in total output estimates contains zero, then one cannot reject the null hypothesis that the total contribution between the 2 years is the same.

The 95% MOC-*CI*s representing the pairwise comparisons of the economic contribution estimates for different years are presented in Table 3. Only one MOC-*CI* contains zero, the comparison between 2013 and 2015. This suggests that one cannot reject the null hypothesis that the total output estimates in these 2 years are statistically the same. Given the magnitude of total output differences seen in Table 2 and the size of the associated jackknife standard errors, this result is not surprising. Since the MOC-*CI* does not contain zero for any other pair of years, the total output between those other years are statistically different (at the 5% level). The fact that the MOC-*CI* is strictly positive for all comparisons with 2011 suggests the 2011 total output estimate is greater than in 2012, 2013, and 2015. The strictly negative MOC-*CI* in comparisons of 2012 with 2013 and 2015 indicate the 2012 estimate was lower than in subsequent years.

Table 3. Pairwise total output differences in total output across years: 95% confidence intervals (in 2013 $millions).

Year comparison	Lower bound	Upper bound
2011 and 2012	83.71	130.80
2011 and 2013	58.17	105.89
2011 and 2015	58.45	105.93
2012 and 2013	−33.67	−16.75
2012 and 2015	−33.68	−16.62
2013 and 2015	−9.47	9.28

Discussion

Based on the estimates in this study, the saltwater recreational charter fishing sector is small relative to the commercial seafood sector, which has been estimated to contribute $4.4 billion (total output) to Alaska's economy during 2015 (NMFS, 2017). In contrast, during the same period (2015) the charter fishing sector is estimated to have had a total output of about $166 million, which is about 4% of the contribution made by the commercial sector. Note, however, that the Alaska seafood industry includes many more fish and shellfish species than are targeted in the recreational charter fishery and spans a much larger geographic region—virtually all recreational charter fishing occurs in the Gulf of Alaska region, while commercial fishing occurs in the Bering Sea and Aleutian Islands region as well (Fissel *et al.*, 2017). Therefore, it is difficult to make a direct comparison of the recreational charter and commercial sector economic contributions. In addition, note that harvest by the recreational sector (including charter and non-charter recreational fishing) relative to the commercial sector suggests a similarly small impact from the recreational sector on stocks. Over our study period, the proportion of total combined recreational and commercial harvest attributable to the recreational sector for Pacific halibut was between 10 and 20% and for Pacific salmon was <1%.

Comparisons to the 2011 estimates by Lovell *et al.* (2013) can be made. The $248 million estimated total output for the charter sector in 2011 is larger than the point estimate of $208 million in Lovell *et al.* (2013) that was obtained through an analysis of angler expenditures. The estimate in this study includes consideration of non-fishing activities undertaken by the fishing business, while the earlier estimate does not. Thus, it is unsurprising that this study's estimate exceeds the one in Lovell *et al.* (2013). Furthermore, a Student's t-test for equality of the point estimates is rejected ($p < 0.01$), suggesting the charter business activities not directly arising from revenue from anglers play a significant role in the total output in the sector. Modelling differences may also explain some of the difference since Lovell *et al.* (2013) used an IO model and this study used a SAM model. As mentioned earlier, a SAM model takes into account the distributional effects, and thus the economic effects or contribution from a SAM model is generally larger, all else equal.

Overall, the results suggest a statistically significant reduction in the economic contribution of the charter sector between 2011 and 2012. This reduction in economic contribution likely reflects the 9% decrease in the number of active saltwater charter businesses in 2012 compared to 2011 (Powers and Sigurdsson, 2016). In addition, significant management changes in the charter recreational halibut fishery may have also contributed to the 2011–2012 decrease (to our knowledge, there were no significant changes in Pacific salmon management in Alaska during the same period). Starting in 2007, more stringent halibut harvest restrictions were imposed on saltwater charter anglers, first in Area 2C, then in 2014 in Area 3A too. Specifically, in Area 2C the number and size of fish that could be harvested on recreational charter vessels changed from two fish per day of any size (prior to 2007) to two fish with one having a size limit (2007–2008), to one fish of any size (2009–2010), and eventually to one fish with a size limit (2011-current) (Lew and Larson, 2015). The most restrictive harvest restrictions occurred in 2011, when charter anglers in Area 2C were limited to one halibut no longer than 37 inches (which translates into a fish weighing about 23 lbs). Therefore, charter anglers were only able to bring home smaller halibut. Since total output in 2011 was highest among years studied, this may seem counterintuitive except that charter anglers often book their next trip months, if not a full year, in advance (Lew and Lee, 2018), before harvest regulations are announced. As a result of this lagged response, charter anglers who fished in 2011 may not have wanted to book a trip for 2012 after the very restrictive halibut regulations they experienced in 2011 if their primary goal was to fish for and harvest large halibut and they believed that restrictions would be the same or worse in 2012. Therefore, we would have expected charter angler demand to be lower in 2012 or for there to be a shift to primarily non-halibut charter trips, which may have contributed towards both the lower number of active charter businesses and lower economic contributions by the charter industry that year.

Our results also indicate that after 2012 the contribution in 2013 and 2015 were statistically larger than the 2012 contribution (Table 3). The contribution increase in 2013 relative to 2012 can be explained by a significant increase in general overhead expenses, such as expenditures on repair and maintenance, utilities, and non-wage payroll costs (Supplementary Table A1). In sum, general overhead expenses in 2013 increased by about \$10 million compared to 2012. The roughly equal estimate of economic contribution in 2015 compared to 2013 occurred despite a decline in overall expenditures from 2013 seen in Table 1. Note that the decline in total expenditures did not carry through to the 2015 economic contribution estimate because large decreases in some expenditure categories were offset by smaller increases in other expenditure categories that have larger multipliers.

A contributing factor to increased spending in 2013 and 2015 relative to 2012 is the increase in charter trip demand that corresponds to changes in charter angler harvest restrictions for Pacific halibut after 2011. The 2012 and 2013 Area 2C harvest regulations were relaxed compared to the 2011 levels (discussed above) and have remained relatively stable in recent years. In these years, charter anglers were still only allowed to harvest one halibut, but that halibut could be either small ($<$43 lbs) or large ($>$162 lbs). In the years since, the thresholds for the small and large fish have been slightly modified. Recent research suggests that charter anglers, particularly non-residents, value the ability to catch a large halibut (Lew and Larson, 2015). Thus, the loosening of the restrictions in Area 2C allowing charter anglers to catch a trophy-size fish, may have enticed anglers to book charter fishing trips after the 2012 season in Area 2C, where non-residents make up a large percentage of charter anglers (Lew *et al.*, 2010). Given charter anglers in Area 3A continued to be able to harvest a large trophy fish even after 2014 (when a maximum size restriction was placed only on the second halibut harvested), it is unclear what effect, if any, charter specific regulations may have had on overall charter trip demand in Area 3A in recent years.

A second factor that may have contributed to an increase in charter sector economic contributions between 2012 and 2015 is the implementation in 2014 of the Pacific Halibut Catch Sharing Plan (CSP) for Areas 2C and 3A (78 Federal Register 75844). An important aspect of the CSP for the charter sector is that it instituted an annual and transparent process for evaluating and determining charter-specific management measures, like the bag and size limits, which could have contributed to a more stable regulatory environment for charter businesses. With the decline in the size of the charter sector slowing in recent years, remaining charter businesses may have seen the post-CSP implementation period as a time to expand, which is evidenced to an extent by the increase in capital investments by the sector in 2015 (Lew and Lee, 2018).

Statistical comparisons using the empirical distributions of economic contributions were a principal focus of this research. Unlike previous studies utilizing bootstrapping methods (English, 2000; Seung and Lew, 2013; Lew and Seung, 2014), these empirical distributions were estimated using a jackknife procedure. The jackknife procedure involved re-imputing missing data for each jackknife sample, then calculating the contribution estimate associated with the jackknife sample. In cases where the jackknife procedure is applied to disaggregate expenditure categories with high rates of item non-response, it is possible for the jackknife sample to no longer have the minimum number of "nearest neighbour" data points to enable imputation via the *K*-nearest neighbour approach. In our case, this occurred in a couple cases, which introduces bias in the jackknife standard errors. Note that this would occur under bootstrapping as well, as the bootstrapped samples are simple resamples of the original data. One way to avoid this issue would be to aggregate over related expenditure categories within the same sector to prevent running up against the nearest neighbour data imputation constraint. A drawback of doing this is that it introduces an aggregation bias resulting from a loss of data resolution (Lahr, 1993). The trade-off between the bias introduced through the data imputation approach and the bias from aggregating over expenditure categories likely differs across applications, and an evaluation of alternative approaches for treating missing data and their effects on estimating the variance of economic contribution estimates is left to future research.

Concluding remarks

This study is the first to estimate the full economic contribution of the Alaska saltwater charter fishing sector to the economy and to illustrate the application of a jackknife resampling approach for accounting for the variance of the estimates from a SAM model in the presence of missing data. Standard errors are calculated that indicate the estimates of total output are measured fairly precisely, with statistical tests showing the Alaska charter sector contributing the most to the Alaska economy in the first year within the study period (2011) and the least in the year immediately following (2012). Economic contributions in 2013 and 2015 were statistically equal and larger than the 2012 estimate.

While several possible reasons for the economic contribution trends are discussed, most relating to fishing regulations related to Pacific halibut, a more rigorous analysis is needed that more formally analyses the structure of economic decision-making in the charter sector to be able to say more definitively what the role of regulations are given the potential for confounding factors of broader socioeconomic conditions, input markets, other political decisions, biomass changes and stock availability of targeted species, and angler preferences. Future research to better understand the role these factors have on the economic impact of the charter sector in Southern Alaska would benefit policy discussions regarding saltwater sport fisheries, such as the upcoming review of the Pacific halibut allocation between the charter and commercial sectors planned for 2021 by the NPFMC (see https://www.npfmc.org/research-priorities-3/). For this review, the Southern Alaska SAM model and jackknife approach developed here provide the basic tools necessary for generating point estimates and standard errors of the economic impact of allocation changes for the charter sector. However, a presently absent but necessary piece needed to operationalize such an economic impact analysis is the link between different Pacific halibut allocation amounts and their effects on charter businesses' labour decisions, costs, and revenues, which represent the "shocks" that propagate economic impacts. Under the CSP, halibut allocations to the recreational charter sector translate into harvest restrictions on charter boat fishing, which currently take the form of limits on crew harvest, daily, and annual limits for charter client anglers, and restrictions on when charter fishing trips for halibut can occur (IPHC, 2018). These charter-specific regulations are not tied to specific allocation levels, but are determined by the NPFMC in a public process described in the CSP (78 Federal Register 75844). To the extent a decrease in the halibut allocation to the charter sector occurs that triggers more restrictive regulations on charter anglers and businesses, charter businesses may have heterogeneous responses, with some shifting effort away from Pacific halibut to focus on other species, changing the length or type of fishing trips they offer, or exiting the sector altogether. The economic impacts can then be measured to the extent these effects can be translated into shocks used in the Southern Alaska SAM model. Some research to understand the role fishing regulations have on anglers' valuation of saltwater charter fishing trips has been done that found recreational fishing values are sensitive to harvest regulations (Lew and Larson, 2015), but additional research is needed to be able to forecast changes in charter fishing trip demand and the consequent effects on the charter industry.

The approach followed in this study for estimating standard errors of the economic contributions differed from existing studies (English, 2000; Seung and Lew, 2013; Lew and Seung, 2014) by utilizing a jackknife resampling approach to account for the input variance rather than bootstrapping. This was simple and straightforward to apply, begging the question why more economic impact and economic contribution studies do not apply similar methods to generate estimates of the variance of their estimates. Estimating the variance of economic impacts or contributions allows for statistical testing of hypotheses central to policy decisions, such as whether an economic impact associated with a policy intervention is statistically significant or not, whether the economic impact of one policy intervention exceeds that of another, or whether the economic contribution of one industry is statistically greater than another. Relying on point estimates of economic impacts and contributions in policy analyses runs the risk of arriving at the wrong conclusions because the analyses are made with incomplete information. Thus, in cases where there are known sources of variation in the inputs to economic impact models, measuring the variance of impact measures should be of central importance; the jackknife approach presented here provides a feasible way to procure this information.

One caveat related to the specific approach presented here is worth noting—even though the jackknife approach is computationally less intensive than the bootstrap, it may lead to inconsistent estimates in cases where the input data are not "smooth" (Efron and Tibshirani, 1994). In this case, the jackknife was convenient because of its consistency with how standard errors of population-level inputs (costs and revenues) were generated with the underlying data imputation (*K*-nearest neighbour) approach. However, the large number of expenditure categories and presence of item non-response indicate there could be gains from bootstrapping standard errors. Future research could examine how to apply a bootstrapping-based approach in both the data imputation process and regional economic modelling.

And finally, this study used a single-region model—a SAM model for the Southern Alaska economy. However, several recent studies (Kim *et al.*, 2017; Seung and Lew, 2017) have shown the importance of accounting for linkages between multiple regional economies when modelling economic impacts and contributions from recreational fishing activities, particularly for regions that are closely linked economically. The economic contribution of the charter sector is likely not limited to Southern Alaska because the Alaska economy is strongly interconnected with the economies of other US regions, importing large amounts of goods and services and factors of production from these regions. Thus, a multi-regional SAM modelling framework is likely to capture the full economic contribution of the Alaska charter sector transpiring in other US regions, and thus represents a useful direction for further extensions of this work.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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