Weighting and Imputation for Missing Data in Fisheries Economic and Social Surveys

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ABSTRACT

Surveys of fishery participants are often voluntary and, as a result, commonly have missing data associated with them. The two primary causes of missing data that generate concern are unit non-response and item non-response. Unit non-response occurs when a potential respondent does not complete and return a survey, resulting in a missing respondent from those who had been contacted to participate in the survey. Item non-response occurs in returned surveys when an individual question is unanswered. Both types of missing data may lead to issues with extrapolating results to the population. Numerous approaches have been developed to address both types of missing data, and two of the principal ones, weighting and data imputation, are discussed in this paper. We explain how to adjust data to estimate population parameters from surveys and illustrate the effects of different weighting and data imputation approaches on estimates of costs and earnings in the Alaska charter boat sector using data from a recent survey. The results suggest that ignoring missing data will lead to markedly different results than those estimated when controlling for the missing data.

Keywords: Alaska, charter boat fishing, data imputation, missing data, non-response bias, sample weighting, survey methods

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Surveys are commonly used in fisheries research to understand economic and social conditions of specific populations of fishery participants, such as anglers, fishing communities, commercial fishermen, and charter operators. To this end, surveys involve selecting a subset of the population of interest (the sample), gathering information from the sample about variables of importance, and generating estimates for the sample to make inferences about the characteristics of the population. Probability-based samples (e.g., simple random samples and stratified random samples) are generally used to ensure sample estimates have known statistical properties and avoid selection bias, which can lead to samples that are not representative of the population if not controlled for (e.g., Lohr 2010, Rea and Parker 2005).[1] Provided the sample is representative of the population and every element in the sample provides all the requested information, sample estimates are generally accepted as good estimates of population parameters.[2] However, in this context, missing data can be problematic, as the representativeness of the sample is brought into question, which undermines the ability of the survey results to be extrapolated to the population and thus the overall utility of the information.

Survey researchers are generally concerned with two types of non-response that result in missing data (e.g., Lohr 2010, Groves et al. 2004). The first type of non-response, *unit non-response,* refers to sampled individuals or entities (i.e., the targeted respondents contacted to participate) that do not respond to any component of the survey. In the case of mail surveys, for instance, this manifests as individuals, households, or businesses who receive the survey in the mail, but do not complete and return the survey questionnaire. For voluntary surveys, some level of unit non-response is expected, particularly in recent years as response rates in traditional survey modes (i.e., mail and telephone) have declined (Dillman, Smyth, and Christian 2009; Connelly, Brown, and Decker 2003; de Leeuw and de Heer 2002).

In fisheries-related economic and social surveys, it is common for researchers achieving "good" response rates to assume representativeness of random samples, or alternatively, the absence of non-response bias (i.e., the systematic difference between respondents and non-respondents). Several benchmark response rate levels have been put forth as sufficient, or "good." For example, the results of Dolsen and Machlis (1991) have often been used to justify ignoring potential non-response bias when response rates exceed 65% (e.g., Margenau and Petchenik 2004). However, in a meta-analysis of survey response rates, Groves (2006) found that response rates may not be a good predictor of the presence of non-response bias. This suggests that it is generally insufficient to rely solely on a "good" response rate to evaluate the potential presence of non-response bias.

In the broader survey literature, weighting methods have a long history of being used to adjust the influence of sample respondents for providing information about the population (Brick and Kalton 1996; Bethlehem 2002). Fisher (1996) appears to be the first to discuss the use of weighting methods in fisheries surveys with an application to an angler survey. Given this, it is surprising how few fisheries studies actually employ formal methods, such as weighting, to adjust for non-response bias when non-response occurs. Among fishery-related studies, those that use weighting methods to adjust for unit non-response have almost exclusively been in the domain of recreational fishing surveys (Fisher 1996; Hunt and Ditton 2002; Tseng, Huang, and Ditton 2012), although Knapp (1996; 1997) does apply non-response weighting for surveys of commercial fishery participants in the Pacific halibut fishery in Alaska.

A second type of non-response also common in voluntary surveys is item non-response. *Item non-response* refers to cases where individual questions in the survey are left unanswered. For survey types in which answering each question is not compulsory, and especially for questions that may be cognitively difficult to answer or viewed as too intrusive, item non-response tends to be pervasive. A variety of data imputation methods have been developed that allow the use of incomplete surveys by replacing the missing values with imputed values so that both item respondents and item non-respondents can be included in the analysis (Brick and Kalton 1996; Little and Rubin 1989; Durrant 2009). The use of data imputation methods to adjust for item non-response in fisheries studies is far less frequent than even the sparing number of cases where unit non-response is addressed. In fact, we were unable to find any study in the published literature that explicitly uses formal data imputation methods for dealing with item non-response. Instead, the most common strategy used in the fisheries literature appears to be to remove surveys with missing data for one or more variables—meaning that frequently only surveys with completed responses are used for the analysis (e.g., Fisher 1997; Beardmore et al. 2011; Bacalso, Juario, and Armada 2013). More striking is that a far greater number do not even acknowledge item non-response in their data.

Given the pervasiveness of unit and item non-response, it is surprising how little attention has been given to ways of handling both types of non-response in fisheries economic and social science surveys.[3] In this paper we illustrate the use of weighting and data imputation methods to adjust for missing data in an economic survey of charter boat fishing businesses in Alaska. We restrict our efforts to a few commonly employed adjustment methods and illustrate the difference between the methods in terms of the estimated population totals and associated standard errors.

To our knowledge, this is the first study to explicitly adjust for both unit and item non-response in a fisheries survey.

The remainder of the paper is organized as follows: We present an overview of the weighting and data imputation methods used to deal with missing data in the next section. This is followed by a description of the data used to illustrate the application of several of these methods and a presentation of the specific weighting and data imputation methods applied to the data. Next, we present the results as applied to a survey of the Alaskan charter fishing sector. The paper concludes with a discussion of the comparison of results across missing data methods and future directions for research.

Weighting and Data Imputation Methods

There are several common ways of dealing with missing data in surveys. In this paper, we focus on weighting methods typically used to adjust for representativeness of the sample due in part to unit non-response, and data imputation methods used to address item non-response among respondent data.

Weighting

Unit non-response is one of several types of missing data for which survey researchers often attempt to compensate, such that the sample data can be used in analyses without concerns over the missing data. The compensation mechanism often employed involves applying weights to individuals in the responding sample that adjust for missing data associated with unreturned questionnaires (Brick and Kalton 1996; Little and Rubin 1989). Weighting is also employed to adjust for other sources of non-representativeness of the sample relative to the population, such as when the sampling methods used result in unequal probabilities of any individual in the population being selected for the sample. In data analysis, responses by an individual with a weight greater than one will count more than those with a weight equal to or less than one. The individual weight given to the *i*th respondent in a sample is denoted w_i, which is commonly represented as the product of several potential weights (e.g., Brick and Kalton 1996):

$$\text{Individual weight for } i\ (w_i) = w_{i1} \cdot w_{i2} \cdot w_{i3}. \qquad (1)$$

In equation (1), there are three weights that make different kinds of adjustments.[4] In statistical sampling, adjustments are often made to samples to adjust, or correct, for departures from the sample selection procedure that may occur if the sampling procedure employed leaves out one or more population segments (Brick and Kalton 1996). We denote the weight that adjusts the sample for sample selection as w_1. This weight, often called the "base weight," is equal to the inverse of the probability of being selected for the sample (e.g., Little and Vartivarian 2003; Brick and Kalton 1996).[5] In a simple random sample of n respondents from a population of size N, the base weight is equal to N/n for everyone in the sample. In a population census, where the sample equals the population, w_1 equals 1 since $N = n$. For cluster samples, w_1 will be the same for each individual within a cluster, but different across clusters.

The second weight, denoted as w_2, represents the non-response adjustment weight. This weight is applied to account for the potential differences between those who responded and those who did not (from among all of the individuals contacted to participate). Generally, calculating this weight requires information about both respondents and non-respondents.[6] For example, the most common approach to calculate non-response weights is to select one or more variables from an external data source and calculate weighting classes, or adjustment cells (Brick and Kalton 1996; Little 1986). The weighting classes are discrete partitions of the data over one or more variables for which there is information on both respondents and non-respondents. Weights are calculated as the inverse of the frequency in each class. Alternatively, in cases in which there are multiple variables known about both respondents and non-respondents that are believed to influence the decision to respond or not respond, regression-based approaches can be employed that estimate the probability of responding to the survey explicitly (e.g., Iannacchione, Milne, and Folsom 1991; Micklewright, Schnepf, and Skinner 2012). To determine which variables may distinguish respondents from non-respondents, a logit or probit model regressing response or non-response on candidate variables with available data for both respondents and non-respondents may be used (e.g., Moore and Tarnai 2002).

The final weight, denoted as w_3, is the post-stratification weight. It represents a further adjustment of the respondent sample data to ensure that the sample conforms to one or more known *population* totals. Thus, post-stratification reduces the potential bias due to incomplete coverage of the population (Brick and Kalton 1996). It is important to note that calculations of w_2 and w_3 are distinguished by the information upon which they are based. The non-response adjustment weight (w_2) is based on differences in sample characteristics between respondents in the sample and non-respondents in the sample. The post-stratification weight (w_3) is based on differences in population characteristics from the respondent sample that are typically evaluated from external data sources (e.g., U.S. Census demographic data for general household surveys). In post-stratification, respondents in each class—with respect to a specific variable known about the population—is multiplied by a factor so that the weights for the class respondents sums to the population total for that class. More formally, suppose that for the variable of concern, the total size of the population is X and the totals for each class of respondents within the total population ($c = 1, 2, \ldots C$) are denoted X_c, such that $X_1 + X_2 + \ldots + X_C = X$. Furthermore, suppose that for the sample, the class totals are denoted X_c^s. Then the post-stratification weight, w_3, is (X_c/X_c^s).[7] See Holt and Smith (1979) for details.

As is clear from the discussion above, calculating w_2 and w_3 requires having at least some information about non-respondents and the population, respectively, that can be used to compare with the sample of respondents. In cases where there are no external sources of data on the sample of respondents and non-respondents, researchers sometimes conduct follow-up surveys of non-respondents to collect some basic information that can be used to generate the non-response adjustment weights, w_2 (e.g., Arlinghaus, Bork, and Fladung 2008; Sutton and Ditton 2005). For recreational angler survey samples drawn from fishing license registries, there is often some basic information, such as the location of residence, which may be utilized for comparing the sample to the total population and developing the post-stratification weights, w_3. For surveys of commercial fishermen, auxiliary information about the population is generally more abundant (though access varies), and often includes information about fishing vessels, licenses and permits issued, and other information collected by state and federal regulators. For more diffuse populations, such as stakeholder groups with indiscernible boundaries, information for calculating these weights is more challenging to procure.

Data Imputation

In order to address item non-response, data imputation methods are employed to fill in missing data with appropriate responses for specific questions that are not answered by respondents. Brick and Kalton (1996), Little and Rubin (1989), and Durrant (2009) provide useful summaries of several data imputation methods. Brick and Kalton (1996) note that imputation methods can generally be thought of within a multiple regression framework. Following this, suppose y is the variable of interest with item non-response. We let y_r be the value of y when reported and y_m the value when missing because a respondent chose not to provide an answer. In addition, suppose the vector **z** is a vector of auxiliary variables that are used to impute values for y. Thus, for the ith observation, the regression

$$y_{mi} = f(\mathbf{z}_{mi}) + \varepsilon_{mi} \tag{2}$$

can be used to explain the differences between imputation methods. From this perspective, imputation methods can be distinguished in two primary dimensions: (a) stochastic assumptions (ε_{mi}) and (b) the auxiliary variables used ($\mathbf{z}_{mi}$). The vector of auxiliary variables may include data external to the survey, other variables from within the survey, or item responses for the variable of interest (y_r). Data imputation methods that allow for stochasticity are called stochastic (or random) imputation methods. Those that do not are called deterministic imputation methods. When auxiliary variables are used to explain variation in responses, the approach is referred to as a regression imputation method. A special case occurs when all the auxiliary variables in the regression are categorical, which results in imputation class methods.

In a common approach, researchers assume that auxiliary variables do not have an effect and ignore potential effects of stochasticity. This results in a specific value being used to replace missing values, such as the mean or median of item responses. When stochasticity is accounted for in this approach, a residual term is added to the specified value. However, these simple, single-value imputation approaches are less desirable for imputation of variables when there are auxiliary variables available that are correlated with the variable and can better explain some of its variation.

In imputation class approaches, a small number of auxiliary variables are used to classify respondents. Simple imputation methods (assigning the mean of a class, for example) or regression-based methods can then be used to assign values within each class of respondents. Hot deck imputation is one type of imputation class approach (Andridge and Little 2010). In hot deck imputation, the value from an item respondent (the donor) is assigned to a non-respondent. The donor is generally selected from the group of item respondents that are most similar to the respondent with the missing value. As Brick and Kalton (1996) note, the number of imputation classes must be selected carefully since there needs to be at least one donor in each class. Another hot deck method uses a distance function-based approach (Chen and Shao 2000). In this approach, a distance function is minimized to identify the "nearest neighbor" from the set of item respondents. That is, for the jth item non-respondent, the researcher finds the item respondent that minimizes the distance function (D_j) across all item respondents (N^r):

$$D_j = \sum_{i=1}^{N^r} \left| \mathbf{x}_i - \mathbf{x}_j \right| , \tag{3}$$

defined for a set of auxiliary variables ($\mathbf{x}$) assumed to be related to the variable of interest. The "nearest neighbor" provides the donor value for the missing value.

Regression-based imputation models involve estimating equation (2) for the item responses, then using the estimated function to predict the missing values (Durrant 2009). In deterministic regression imputation, the predicted values are used as the imputed values. In stochastic regression imputation, an error residual is added to the predicted values to allow for randomization and uncertainty. The residual term can be drawn from a standard zero-centered distribution (e.g., the normal distribution) with the appropriate standard deviation from the model, or by drawing from computed residuals from the fitted values for the item responses, either randomly or for a respondent with similar characteristics. Regardless of the method used to select residuals, the stochastic approach is generally seen as preferred to the deterministic one since it maintains the distribution of y. However, this parametric approach is susceptible to misspecification issues and goodness-of-fit issues.

For this reason, in this paper we focus instead on two simple data imputation methods and three imputation class approaches. The two simple data imputation approaches involve replacing missing values with either zero or the mean of item responses (*zero imputation* and *mean imputation*); stochasticity is ignored. These simple approaches are likely to be the most commonly used in filling in missing data from incomplete questionnaires, and population estimates with imputed values from these approaches will be compared against those that use each of three different hot deck imputation approaches. The first hot deck imputation approach considered uses a small number of auxiliary variables to define respondent classes from which random donor values are taken to replace those in the same class. We refer to this approach as the *random hot deck imputation*. The two other hot deck imputation approaches described use a nearest neighbor approach. In the *deterministic nearest neighbor imputation*, the item respondent corresponding to the minimum value of the distance function associated with a set of auxiliary variables (i.e., the nearest neighbor) provides the donor value. In the *K-nearest neighbor imputation*, a donor value is randomly selected from among the top K nearest neighbors.

An important consideration in adopting an imputation approach is variance estimation (e.g., Lohr 2010).[8] It is well known that standard variance estimation procedures (e.g., Taylor-series approximation, jackknife, and simulation methods) of imputed data will generally underestimate the true variance. For example, Rao and Shao (1992) discuss how the jackknife resampling approach to estimating variance leads to a naïve estimator when applied to data imputation due to the fact that the standard (delete-1) jackknife method does not account for the variance due to the imputation itself. To remedy this shortcoming, they propose a general approach for adjusting the jackknife variance estimator so that it does incorporate the imputation method in the variance calculation. The procedure involves replicating the imputation of values in each jackknife-replicated dataset. Shao (2002) discusses how the procedure can be extended to any imputation method. We employ this approach to estimate the variance in this study.

An Empirical Application

To illustrate weighting and data imputation methods, we generate estimates of population-level totals and means for costs and earnings from data collected in a survey of saltwater sport fishing charter businesses in Alaska. The Alaska charter boat sector has undergone significant change in recent years due, at least in part, to regulatory changes in the management of the Pacific halibut (*Hippoglossus stenolepis*) sport fishery. To control growth of the charter sector in the primary recreational charter boat fishing areas off Alaska, a limited entry program was implemented in 2010 (75 Federal Register 554). In addition, in the past several years, charter vessel operators in Southeast Alaska (International Pacific Halibut Commission [IPHC] Area 2C) have been subject to harvest controls that impose both size and bag limits on the catch of Pacific halibut on guided fishing trips, with these limits being more restrictive than the regulations for non-guided trips (e.g., 78 Federal Register 16425).[9] Moreover, a Catch Sharing Plan (CSP) will be implemented during 2014 that formalizes the process of allocating catch between the commercial and charter sector and for evaluating changes to harvest restrictions (78 FR 75843). The CSP allows leasing of commercial halibut individual fishing quota (IFQ) by eligible charter businesses. Leased halibut IFQ could then be used by charter businesses to relax harvest restrictions for their angler clients, since the fish caught under the leased IFQ would not be subject to the charter sector-specific size and bag limits that may be imposed—though the non-charter sector size and bag limit restrictions (currently two fish of any size per day) would still apply to charter anglers individually.

The Alaska Saltwater Sport Fishing Charter Business Survey was developed by the U.S. National Marine Fisheries Service (NMFS) to collect baseline economic information about the charter sector for use in evaluating the effects of the changing management landscape on the charter sector and economy. It was developed after extensive input from numerous charter boat business operators (the target population) in focus groups, in-depth interviews, and meetings with charter boat associations. The 12-page survey included questions about employment, services offered to clients, revenues, costs, types of clients served, and other information useful for classifying responses.

The survey was administered in the first half of 2012 as a repeated mail survey to the entire population of saltwater sport fishing charter boat businesses actively offering charter fishing experiences in Alaska during 2011 (650 businesses).[10] Thus, statistical sampling methods were not employed to determine the businesses that would receive the survey—a complete census was conducted whereby all eligible businesses were contacted to participate; in this case, the eligible population consisted of 650 saltwater sport fishing charter businesses.[11]

Like many voluntary cost and earning surveys conducted in the fishing sector, this survey is a good candidate for adjusting for missing data. Despite following a Dillman tailored design survey administration approach (Dillman, Smyth, and Christian 2009) involving multiple contacts by mail and telephone, the survey achieved a low overall response rate of approximately 27 percent, or 174 respondents. Thus, 73 percent of the population did not respond to the survey. The low unit response rate is not a rare outcome among voluntary cost and earnings commercial fishery surveys (e.g., Fisheries and Oceans Canada 2007; Holland et al. 2012), and is low enough to trigger concerns about non-response bias. In addition, there were numerous questions with low item-response rates, with an average item non-response rate of 32 percent across all questions. That is, the average question in the survey had about 32 percent of respondents leave the question blank. The low unit response rate and the pervasive item non-response rate suggest that adjustments must be made for missing data for population-level estimates to be considered valid.[12] Moreover, there was a rich set of auxiliary information available about all charter businesses in the population that could be utilized to construct weights and impute data.

Our focus here is on the revenue and cost information collected in the survey. Respondents were asked to provide information on the total revenue earned during the 2011 fishing season across all sources, including direct payments from client fishing trips, payments received from a booking agent or other service (i.e., broker) for client fishing trips, payments for non-fishing activities (such as transportation, eco-tours, etc.), and commissions from referrals. In addition, respondents were asked for the revenue they received from leasing or selling a charter halibut permit (CHP), which is a federal permit issued to charter businesses required for Pacific halibut fishing under the limited entry program (75 *Federal Register* 554). For these revenue categories, the number of item respondents and descriptive statistics are presented in Table 1.

The survey also included several questions that collected detailed information about annual expenditures incurred during 2011, including those associated with providing charter boat services (charter trip operating expenses, such as vessel fuel, fish processing and shipping, broker fees, vessel cleaning, and supplies); general overhead expenses (non-wage payroll costs, utilities, repair and maintenance, business insurance, office supplies, etc.); expenses incurred for vehicles, machinery, and equipment; and payments for buildings, land, and other real estate. Table 2 presents the descriptive statistics for these expenditure categories for the item respondents.

This survey was conducted as a census and did not exclude any eligible member of the population; as such, the base weight (w_1) for all individuals in the sample is 1. Importantly, since the survey in this study is a census of the population, the two other weights considered in this study are both based on population-level data. Fortunately, in this case a wealth of external auxiliary information about respondents and non-respondents (and generally the population of charter boat operators targeted in the survey) is available in the form of saltwater charter logbook data mandated by the Alaska Department of Fish and Game (ADF&G).[13] These data include information on when, where, and how much charter boat fishing occurred during the year, including details on the number of clients and trips, fish targeted and harvested, and the residency of charter clients. The availability of these effort data and the likelihood that they are correlated to costs and revenues allows us to explore the effects of different weighting and data imputation methods on population-level estimates of total costs and total revenues.

For this paper, we construct weights to account for non-representativeness of the unit respondents, then apply the five different data imputation methods discussed above to evaluate differences in population-level total cost and total revenue estimates. Total cost and total revenue are calculated by summing over the weighted cost and revenue categories, respectively, after missing data have been imputed.

Results

Table 3 presents a comparison of responding and non-responding charter businesses with respect to several variables created from the charter logbook data. These auxiliary variables were selected to capture characteristics of charter businesses in Alaska that varied across the sector, mainly related to when fishing occurred, the size of the operations, the fish targeted, and the types of clients. Across the variables, respondents and non-respondents appear fairly similar, with minor discrepancies in several instances. However, given the number of variables available for comparing respondents and non-respondents, and to conduct a more in-depth evaluation, we took an approach similar to Moore and Tarnai (2002) and estimated a logit model to formally assess differences between respondents and non-respondents. Variables from Table 3 formed the independent variables, and an alternative-specific constant (ASC) associated with respondents[14] was added to capture unmodeled respondent effects. Table 4 presents the model results, which indicate that the only two variables for which there is a significant difference between respondents and non-respondents, when holding all else constant, are dummy variables indicating no fishing was done in the late season (mid-Aug – September) and no fishing was done in the off-season (October – March): more non-respondents tended to fish in the late and off-seasons than respondents. Otherwise, there were no statistically significant effects from other variables that may represent differences between respondents and non-respondents. These results are robust to a variety of specifications tried. Consequently, these two dummy variables formed the basis for calculating w_2, the non-response adjustment weights. Cross-tab frequency tables for the respondents and for the total sample (respondents and non-respondents) were constructed. From these, weights were constructed as the ratio of the number of total population elements to the number of response sample elements in each cell (Table 5).[15] The non-response adjustment weights range from 0.53 to 2.30. The responses provided by those with a weight of 2.30 (businesses not fishing in the late shoulder season, but fishing in the off-season) have over four times as much weight in the calculation of population estimates as the responses assigned 0.53 (businesses fishing in both the late shoulder and off-season) since the latter group was overrepresented in the responding sample relative to the former.

The post-stratification weight (w_3) addresses non-coverage bias in the sample that may result because the sample does not include a sufficient representation of the population in relation to one or more key variables. In this case, the principal dimension to control for in post-stratification is the size of the charter business, which we defined as the number of client fishing trips reported. Another potential post-stratification dimension would be the region in which charter-based fishing for halibut occurred (IPHC Area 2C or Area 3A). In Table 6, w_3 is calculated as a simple post-stratification weight based on client-only trips (denoted *weight A*), and, alternatively, on both the fishing region and client-only trips (denoted *weight B*). Note that the range of post-stratification weights, regardless of the assumption, is much smaller than for the non-response adjustment weight, with weights ranging from 0.78 to 1.20 for weight A, and 0.73 to 1.45 for weight B. This suggests that, at most, some observations will contribute about twice as much weight as others. The total weight for each respondent was determined using equation (1).

For the hot deck imputation methods, we again rely on the charter logbook data to provide the auxiliary information necessary for these imputation approaches. In the random hot deck imputation, we set up three respondent classes based on the size of the charter business (which is likely linked closely to the revenues and costs), proxied by the total number of client trips in 2011. The respondent classes were (a) fewer than 200 trips, (b) between 201 and 400 trips, and (c) more than 400 trips.[16] Within these classes, donor values were randomly selected from among the item respondents. For the two nearest neighbor hot deck imputations, eight variables from the charter logbook data were used in equation (3) to evaluate the closeness of item respondents to each item non-respondent to determine the best candidate to provide the donor value. These eight variables were the following: a dummy variable indicating whether fishing occurred in Southcentral Alaska (IPHC Area 3A), the number of guides used, the number of calendar days fished, the total client fishing trips, a dummy variable indicating crew fishing trips were taken, a dummy variable indicating some unpaid fishing trips were taken during the season, the number of hours spent fishing for Pacific salmon, and the number of hours spent fishing for bottomfish (including Pacific halibut).[17] The K-nearest neighbor algorithm we use assumes K = 3.

For each weighting assumption (no weighting, weight A, and weight B) and data imputation method (zero imputation, mean imputation, random hot deck imputation, deterministic nearest neighbor imputation, and K-nearest neighbor imputation), the population-level total expenditures and total revenues are calculated. These estimates are the weighted sum over all the expenditure and revenue categories, respectively, and are presented in Table 7.

Standard errors of these totals are calculated according to the adjusted jackknife variance estimation procedure (Rao and Shao 1992).

The results indicate that regardless of the weighting approach used, the zero imputation method always led to the lowest estimates and the mean imputation method always resulted in the highest estimates across the imputation methods. When no weighting is applied to adjust for non-response and post-stratification, total revenues range from a low of $101 million (s.e. = $1.93 million) with the zero imputation method to a high of $155 million (s.e. = $2.62 million) with the mean imputed values, while the total costs had a low of $118 million (s.e. = $1.79 million) and a high of $194 million (s.e. = $3.00 million), again associated with the zero and mean imputation methods, respectively. Weighting only by where fishing was done (weight A) led to a lower estimates of total revenue, $90 million (s.e. = $1.71 million) for zero imputation and $144 million (s.e. = $2.39 million) for mean imputation, compared to the estimates with no weighting. Similarly, total expenditures estimates of $110 million (s.e. = $1.62 million) under zero imputation and $186 million (s.e. = $2.84 million) for mean imputation are smaller than the corresponding no weighting estimates. When weighting by both the region where fishing occurred and by the amount of fishing done (weight B), the estimates for the zero and mean imputation approaches are, somewhat surprisingly, almost identical to those for the case without weights.

Among the hot deck imputation method results, the random hot deck imputation estimates are always lower than the nearest neighbor-based estimates. When no weighting is applied, the total revenue estimate using the random hot deck imputation approach is $127 million (s.e. = $8.27 million) and the total expenditure estimate is $169 million (s.e. = $5.90 million). When weighting by weight A, the estimates are lower, with a total revenue estimate of

$114 million (s.e. = $7.05 million) and a total expenditure estimate of $155 million (s.e. = $5.16 million). Again, the total revenue and expenditure estimates under the weight B assumption are very similar to the unweighted estimates.

The deterministic nearest neighbor and K-nearest neighbor imputation estimates are similar to one another, regardless of the weighting assumption. With no weighting, the deterministic revenue and expenditure estimates are $143 million (s.e. = $0.2.65 million) and $174 million (s.e. = $2.58 million), while the stochastic (K-nearest neighbor) estimates are almost identical, differing primarily in the standard error estimates, which are larger due to the randomness incorporated into the procedure ($4.31 million and $6.93 million, respectively). Under the weight A assumption, the total revenue and expenditure estimates from both are slightly higher than the random hot deck imputation estimates (about $127 million and $162 million, respectively). Under the weight B assumption, total revenue and expenditure estimates are $139 million and $174 million, respectively, with standard errors that follow the same pattern as noted above.

Discussion

To formally assess differences between the estimates calculated under the different weighting and data imputation methods, we calculate the 90% confidence intervals for the difference in estimates using the method of convolutions approach (Poe, Giraud, and Loomis 2005), a computationally-intensive approach that gives precise estimates for estimating the difference between two independent empirical distributions. In our case, we use the jackknife replications from the adjusted jackknife variance estimation to generate the empirical distribution of pairwise differences. Confidence intervals containing zero suggest no statistical difference between the totals. Comparing the estimates across data imputation methods, but holding the weighting method constant, the results indicate that across all weighting assumptions, the zero imputation estimates are statistically lower than all other estimates and the mean imputation estimates are statistically larger than the other estimates (Table 8). Additionally, there is no statistical difference between the random hot deck and nearest neighbor imputation estimates. These patterns were consistent between the total revenue and total expenditure estimates.[18]

The first finding that the zero imputed values are lowest and mean imputed values are largest is unsurprising given that the simple imputation methods do not use additional information to determine the best value to replace missing values and instead assign the same value to all missing values. Therefore, zero imputation will always lead to the lowest estimates (assuming values cannot be negative) since the other methods will assign at least some non-zero values to item non-respondents. And, if the distribution of item responses is not fairly uniform and the mean is influenced by several large values, we would expect the mean imputation-based estimates to be larger than the other methods.

The data imputation alternatives used in this application, namely the random hot deck, deterministic nearest neighbor, and K-nearest neighbor methods, yield statistically similar estimates. This in itself does not provide clear guidance on the best data imputation to use for these data. However, we argue that in this case, the K-nearest neighbor approach is the preferred one. This is largely due to two factors, one endemic to this application, and another more general reason. First, in this application, there is a wealth of auxiliary data likely to shed light on several important characteristics of each charter business, both for the item respondents and non-respondents. Since all variables of interest are likely to be correlated to some degree with the size of the operation, where and when the business operates, and other information available in the charter logbook data, we are able to draw from a number of candidate variables in identifying good donor values from among item respondents for a given item non-respondent.

Given that the random hot deck imputation approach does not use the full set of auxiliary information (due to the need to keep dimensionality low so imputation classes containing a minimum number of donor values can be identified), the nearest neighbor imputation approaches stand to identify better donor values since they use more auxiliary data in the imputation process. In comparing the nearest neighbor imputation approaches, a second factor comes into play. Recall that the difference between the two nearest neighbor methods used in this paper is that one selects the donor value associated with the one item respondent that is closest to the one with the missing value based on criteria embodied in the distance function in equation (3), and the other randomly selects from the top K (in this case three) nearest neighbors. Selecting randomly from among several different nearest neighbors will minimize the potential impact of outliers being used as donors. As a result, stochastic imputation methods, such as the K-nearest neighbor imputation approach, are generally preferred over deterministic ones. For these reasons, the total revenue and total expenditure estimates that used the K-nearest neighbor imputation to deal with item non-response are likely to be the most appropriate estimates for use by policymakers.

The method of convolutions comparisons also were used to evaluate the effect of weighting for a given data imputation approach (Table 9). Even though estimates of total revenues and expenditures are similar between the unweighted and weight B estimates in our empirical application across all data imputation methods, this is coincidental. The weight B assumption is based on post-stratifying on both the region in which fishing occurred and the number of client fishing trips during 2011 (and embodies the non-response adjustment weights as well). The range of the post-stratification weights suggests post-stratification weighting has a moderate marginal effect since the range of the weights is not large, yet they are different from one. Statistically significant differences between total estimates under the no weighting and weight A assumptions (except in the case of random hot deck imputation) provide further evidence that weighting assumptions affect estimates. Similar differences were found between estimates assuming weight A and those assuming weight B across the data imputation methods. Thus, it is clear that weighting matters, and an argument can certainly be made for the weight B estimates to be preferred over the other estimates due to those estimates ensuring the sample matches with several key population-level variables.

In our application, the survey was conducted as a census of the population, where each member of the population was included. This negated any need to adjust the sample for the sampling methods used, thus removing one of the several factors that are often adjusted for with weighting. As a result, the weighting in our application was perhaps not as pronounced as it would be when individual weights are also adjusted for sampling methods in other cases.

In general, the selection of the weighting and data imputation methods used to adjust for missing data in a given survey will depend upon the availability, quality, and completeness of auxiliary data. In this application, we had a large amount of auxiliary information about the survey population that enabled us to employ a variety of weighting and data imputation approaches to deal with both unit and item non-response since the data reflected key characteristics of the population that could be related to the variables in the survey with missing data. This is not always the case. However, even for populations with no external sources of information collected about them, follow-up surveys that gather information on a few key characteristics (e.g., Arlinghaus, Bork, and Fladung 2008; Sutton and Ditton 2005) can be used to assess non-response bias and developing adjustment weights, if necessary.[19] Moreover, although not done in this paper, data imputation methods can utilize data from other questions in the survey itself as auxiliary data instead of, or in addition to, auxiliary data from an external source, provided there are questions in the survey that are likely related to the variable of interest with missing data. In this case, the survey data used may itself have missing values, which raises questions about how to utilize it in the data imputation procedure. One possible way to address this problem is presented by Brick and Kalton (1996) who discuss multivariate imputation, an iterative procedure of repeated data imputation across multiple questions with item non-response that continues until a convergence criterion is met.

We have discussed the use of weighting and data imputation methods in the context of a cost and earnings survey, but the methods are applicable to other types of economic and social science surveys, including surveys of anglers, stakeholders, communities, and other fishery participants, as well as the general public. It is important to stress that the methods are only useful for surveys that are censuses of populations or utilize probability samples, samples drawn from the population in which the sampled elements have a known probability of being selected. These types of surveys, with appropriate adjustments when necessary to address missing data or sampling issues, can be used to draw inferences about the population. Convenience samples are not uncommon among fisheries surveys, but by construction are not representative of the population. As a result, the methods described in this paper cannot be employed with those surveys to adjust the sample so that it is more representative of the population and capable of drawing population inferences.

Finally, from a policy perspective, our empirical results suggest that as a whole, the Alaska charter sector operated at a net loss during 2011. This is consistent with anecdotal evidence from charter boat operators and is supported by the fact that fewer charter businesses were in operation during 2012 than in 2011.[20] Since survey-based cost and revenue estimates such as these are used as inputs in fishery regional economic impact models (e.g., Lew and Seung 2010) and policy decisions, improving the accuracy of these estimates is important since any biases they embody may be amplified in subsequent analyses.

Conclusion

Missing data are persistent in economic and social surveys in fisheries, but are rarely accounted for when analyzing and presenting the results from these studies. From a methodological perspective it is clear that when auxiliary data are available, ignoring missing data in fisheries surveys is unlikely to be an optimal strategy, and will often lead to results that are biased. As shown in this paper, there are several straightforward methods researchers can apply in the analysis of survey data that will correct for these missing data and lead to improved population estimates. We have described and illustrated the application of weighting to adjust a sample of respondents to better reflect the population, and several data imputation approaches to deal with missing data in individual questions, in a survey of charter fishing businesses in Alaska. The use of these methods in fisheries research enables survey researchers to provide useful information from surveys for which unit and item non-response are issues, as well as to improve estimates based on these data that can be used by fishery managers.

Research on dealing with missing data continues to be an active area, and several other recent methods that were not covered here have been proposed that may prove useful for addressing missing data in fisheries survey. For example, Rubin (1996) advocates multiple imputation, a Bayesian approach that uses repeated trials of the imputation process as a way of estimating population mean and variance estimates that minimize mean-squared error. A comparison of this and other recent methods to the comparatively simpler approaches presented here are left for future research.

The focus of this paper has been on presenting several ways of dealing with missing data. However, in closing, it should be emphasized that the best situation is one in which there are no missing data, or at least there are minimal missing data. To this end, it is worth emphasizing that survey researchers should endeavor to minimize the potential for missing data by maximizing response rates through best practices in survey design, sampling, and implementation (e.g., Dillman, Smyth, and Christian 2009). In this way, the need to employ the methods described in this paper may be minimized, though researchers should nevertheless endeavor to assess the need to employ these types of methods with their survey data whenever response rates fall below 100%.

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Table 1.

2011 Annual Revenues ($)– Survey statistics for item respondents

Categories	Mean	Median	Std Dev	Item respondents
Charter fishing trips – direct payments from clients	162,601	46,900	570,974	133
Charter fishing trips – payments from booking agent or service	24,141	5,800	36,934	78
Non-fishing charter trips	26,500	2,000	68,521	83
Client referrals/booking commissions	7,796	0	24,637	61
Federal charter halibut permit sales income	16,541	0	99,059	58

Table 2.
2011 Annual expenditures ($) – Survey statistics for item respondents

Categories	Mean	Median	Std Dev	Item respondents
Vessel fuel	21,791	10,000	33,641	146
Fish processing and shipping	4,592	200	16,193	100
Referral fees	5,145	0	13,334	89
Vessel cleaning	15,012	125	112,034	99
Supplies (e.g, ice, bait)	13,123	3,000	75,153	139
Other vessel or trip operating expenses	7,122	2,160	18,689	84
Non-wage payroll costs (e.g., health insurance)	10,207	0	44,799	94
Utilities (e.g., telephone, internet)	4,383	2,000	6,623	132
Repair and maintenance expenses	11,677	4,650	23,655	136
Insurance (vessel, property & indemnity, liability)	8,078	2,950	15,602	144
Travel, meals, and entertainment	5,642	2,005	13,206	109
Office and general supplies	2,503	692	5,784	126
Legal and professional services, accounting, and advertising	5,974	1,190	22,683	126
Financial service fees and mortgage interest payments	15,445	2,200	46,634	109
Taxes and licensing fees	3,613	1,014	5,952	137
Vehicle fuel costs	3,089	1,079	8,519	120
Other general overhead expenses	20,715	2,483	62,889	92
Vessel(s) and vessel-related equipment	23,888	5,000	60,347	88
Vehicles (car/truck)	2,635	0	6,709	62
Fishing gear, tackle, safety equipment	3,267	1,200	5,797	97
Other machinery and equipment	2,107	300	4,731	66
Moorage/slip, boatyard and equipment storage space	2,971	1,500	4,291	111
Office space, lodging, and other shore-side facilities	13,942	614	49,967	68
Transferable fishing permits and licenses	3,545	0	13,157	68
Other business-related property and assets	32,952	0	144,061	60

Table 3.
Comparison of Respondents to Non-respondents

Variable	All	Respondents	Non-respondents
Did not fish in Southeast Alaska	50.2%	51.7%	49.7%
Only used a single guide	58.9%	59.2%	58.8%
Only used a single vessel	75.0%	71.8%	76.1%
Took 50 trips or less	55.1%	51.1%	56.4%
Fished 50 calendar days or less	58.3%	55.7%	59.2%
Did not fish in early shoulder season (April to mid-June)	27.3%	25.3%	28.0%
Did not fish in late shoulder season (mid-August through September)	21.9%	16.1%	23.9%
Did not fish in the off-season (October through March)	93.8%	90.2%	95.1%
Did not report any crew fishing trips	42.6%	37.9%	44.2%
Reported no Alaska resident clients	22.0%	19.0%	23.1%
Proportion of clients that are Alaska residents	13.9%	14.5%	13.7%
250 or fewer clients	58.9%	57.5%	59.4%
1,000 or more clients	5.7%	6.3%	5.5%
Did not report any non-paid trips	47.4%	43.1%	48.9%
Did not report fishing for salmon	7.9%	7.5%	8.1%
Did not report fishing for bottomfish (incl. Pacific halibut)	10.3%	8.6%	10.8%

Table 4.
Logit Model Results to Evaluate Factors Affecting Response Propensity

Variable	Estimate	Asymptotic t-value
Alternative specific constant (respondent)	-0.1476	-0.3450
Dummy: No fishing was done in SE Alaska	-0.1901	-0.7466
Dummy: One guide only	0.2637	1.1011
Dummy: One vessel only	-0.3034	-1.0871
Dummy: Total trips fished 50 or less	-0.6132	-1.1821
Dummy: Total days fished 50 or less	0.4158	0.8049
Dummy: No trips in early season (April - mid-June)	0.0000	0.0000
Dummy: No trips in late season (mid-Aug - September)	-0.5124*	-1.8574
Dummy: No trips in off-season (October - March)	-0.7710**	-2.1189
Dummy: No crew fishing trips taken	-0.1900	-0.8679
Dummy: no resident clients	-0.0822	-0.2932
Percent of clients that are Alaska residents	0.4003	0.5724
Dummy: Total clients 250 or less	0.4052	1.1594
Dummy: Total clients 1000 or more	-0.0196	-0.0465
Dummy: No non-paid trips	-0.1127	-0.4959
Dummy: No salmon fishing	0.1934	0.5356
Dummy: No bottomfishing	-0.0778	-0.2347
Mean log-likelihood value	-0.5567	
Likelihood ratio index	0.1969	
Akaike's information criterion (corrected)	793.1019	
Bayes information criterion	869.0794	

*= Statistically different from zero at the 10% level
**= Statistically different from zero at the 5% level

Table 5.

Non-response adjustment weights (w_2)

No late/off season fishing	**Weight (w_2)**
No late shoulder season or off-season fishing	1.3248
No late shoulder season fishing, but some off-season fishing	2.2996
Late shoulder season fishing, but no off-season fishing	0.9808
Both late shoulder season and off-season fishing	0.5270

Table 6.
Post-stratification weights (w_3)

Total client trips	Weight A Any area	Weight B Fish in Southcentral Alaska (Area 3A)	Fish in Southeast Alaska (Area 2C)
100 or less	1.0859	1.0977	1.0749
101-200	1.1958	1.1400	1.2562
201-300	0.7756	0.7836	0.7665
301-400	0.9238	1.2009	0.7506
401-500	0.9756	0.7985	1.4479
501-1000	0.9920	0.7410	1.3505
1001-7000	0.9059	0.7300	1.2137

Table 7.

Population Estimates of Total Annual Revenue and Expenditure (in $million)

	No weighting			
	Total revenue		Total expenditure	
Imputation method	**Total**	**Std Err**	**Total**	**Std Err**
Zero imputation	101.47	1.93	118.30	1.79
Mean imputation	154.64	2.62	193.94	3.00
Random class hot deck imputation	126.67	8.27	168.77	5.90
Deterministic nearest neighbor imputation	142.66	2.65	174.16	2.58
K-nearest neighbor hot deck imputation	142.81	4.31	176.64	6.93
	Weight A			
	Total revenue		**Total expenditure**	
Imputation method	**Total**	**Std Err**	**Total**	**Std Err**
Zero imputation	90.17	1.71	109.87	1.62
Mean imputation	144.19	2.39	186.11	2.84
Random class hot deck imputation	113.87	7.05	154.59	5.16
Deterministic nearest neighbor imputation	126.91	2.21	162.33	2.29
K-nearest neighbor imputation	128.32	3.96	162.60	6.03
	Weight B			
	Total revenue		**Total expenditure**	
Imputation method	**Total**	**Std Err**	**Total**	**Std Err**
Zero imputation	101.27	2.26	119.76	2.05
Mean imputation	155.86	2.92	196.71	3.26
Random class hot deck imputation	124.95	8.00	165.64	5.74
Deterministic nearest neighbor imputation	139.28	2.71	174.44	2.75
K-nearest neighbor imputation	139.33	4.22	174.66	6.87

Table 8.
90% Confidence Intervals for Difference in Totals (Value 1 – Value 2) for Weight B Estimates (in $million)

Value 1	Value 2	Total Revenue		Total Expenditure	
Imputation Method	**Imputation Method**	**Lower Bound**	**Upper Bound**	**Lower Bound**	**Upper Bound**
Zero imputation	Mean imputation	-56.20	-52.18	-80.00	-73.42
Zero imputation	Random hot deck	-45.83	-23.05	-57.01	-38.52
Zero imputation	Nearest neighbor	-40.09	-33.65	-58.46	-49.49
Zero imputation	K-nearest neighbor	-40.73	-26.57	-65.04	-43.67
Mean imputation	Random hot deck	8.09	31.67	19.16	38.87
Mean imputation	Nearest neighbor	13.49	20.91	17.26	27.63
Mean imputation	K-nearest neighbor	13.64	27.85	11.33	33.44
Random hot deck	Nearest neighbor	-15.19	8.60	-16.88	3.18
Random hot deck	K-nearest neighbor	-14.03	13.56	-20.59	7.06
Nearest neighbor	K-nearest neighbor	-3.21	11.49	-10.88	11.38

Table 9.

90% Confidence Intervals for Difference in Totals (Value 1 – Value 2) Under Different Weighting Assumptions (in $million)

Imputation Method	Value 1 Weighting Assumption	Value 2 Weighting Assumption	Total Revenue Lower Bound	Total Revenue Upper Bound	Total Expenditure Lower Bound	Total Expenditure Upper Bound
Zero imputation	None	Weight A	9.71	12.74	5.68	11.07
Zero imputation	None	Weight B	-1.46	1.36	-4.25	1.16
Zero imputation	Weight A	Weight B	-12.54	-10.01	-12.57	-7.29
Mean imputation	None	Weight A	8.07	12.71	4.11	11.57
Mean imputation	None	Weight B	-3.69	1.21	-6.58	1.12
Mean imputation	Weight A	Weight B	-14.00	-9.30	-14.39	-6.75
Random hot deck	None	Weight A	-4.14	33.81	-0.38	25.50
Random hot deck	None	Weight B	-16.40	22.34	-12.49	14.48
Random hot deck	Weight A	Weight B	-29.60	5.84	-24.25	1.02
Nearest neighbor	None	Weight A	12.04	19.44	6.31	17.34
Nearest neighbor	None	Weight B	-0.44	7.83	-5.87	6.12
Nearest neighbor	Weight A	Weight B	-16.07	-8.01	-17.62	-5.85
K-nearest neighbor	None	Weight A	4.65	23.44	-0.35	27.82
K-nearest neighbor	None	Weight B	-7.05	11.95	-14.45	15.09
K-nearest neighbor	Weight A	Weight B	-20.83	-2.37	-27.23	0.32

Footnotes

[1] Other potential biases may also occur in the selection of the sample, such as coverage bias.

[2] For this paper, we set aside the bias that may arise from poor survey design, which may lead to measurement bias.

[3] In the broader economics literature, many economic surveys selectively address missing data, particularly with respect to key economic variables such as income or wages, which are frequently skipped questions by respondents. See Little (1988) for an exception.

[4] Other adjustment weights may be possible, but the three discussed here are most common.

[5] A related weight sometimes seen in the recreational fishing literature corrects for avidity bias, the propensity to get a disproportionate number of avid anglers in the sample when using intercept sampling methods (Thomson 1991). Hindsley, Landry, and Gentner (2011) discuss weighting for avidity bias and for endogenous stratification associated with the non-random on-site sampling employed with the NMFS Marine Recreational Fisheries Statistics Survey.

[6] As an example of an alternative approach that does not use information about non-respondents, see Filion (1976) who assesses non-response by analyzing early and late responders.

[7] When multiple variables are important, post-stratification weighting may not be desirable. An alternative method, called raking (Battaglia, Hoagland, and Frankel 2009), or sample balancing, can be used. However, in our case, post-stratification is sufficient given that only one primary variable is selected for adjusting the sample.

[8] See also Lee, Rancourt, and Sarndal (2002) and Chen and Shao (2000).

[9] The other main area of Alaska in which saltwater fishing for Pacific halibut occurs is Southcentral Alaska (IPHC Area 3A), an area that includes the Cook Inlet region, Kodiak Island,

and the Prince William Sound. Harvest restrictions have not been imposed on charter fishing in this area to date.

[10] The original population frame included 17 businesses that did not engage in any client-based fishing during 2011 and were subsequently excluded from the analysis.

[11] NMFS plans to re-administer the survey to collect data for additional fishing seasons, which will enable an evaluation of changes in the charter sector over time.

[12] To our knowledge, there appears to be no consensus on a specific item or unit non-response rate that would trigger the need for weighting or imputation-based adjustments. Thus, it is the responsibility of individual researchers to assess the extent of missing data in survey studies and document the extent to which non-response bias may be a concern. In our empirical case, the low item and unit response rates suggested further investigation and adjustment.

[13] Details about the program can be found at http://www.adfg.alaska.gov/index.cfm?adfg=prolicenses.logbook.

[14] The ASC is a dummy variable assigned to respondents only.

[15] Note that it is possible to estimate predicted probabilities of responding from the logit model to generate weights for w_2. However, since the logit model with the two variables found to influence response propensity did not have a high likelihood ratio index (a pseudo-R^2 measure), using predicted values for the Pr(response) does not seem warranted. However, if there had been a large number of significant variables that differed between respondents and non-respondents, using the logit model to predict non-response adjustments weights would have been appropriate.

[16] Respondent classes were selected to ensure a sufficient number of donor values were contained in each class across revenue and cost categories.

[17] The non-dummy variables were normalized by the maximum values observed in the data.

[18] Since these results are qualitatively invariant across weighting assumptions, Table 8 presents only the 90% method of convolutions-based confidence intervals for the difference in total revenues and total expenditures for each data imputation method using the weight B assumption.

[19] As an example of an alternative approach that does not use information about non-respondents, see Filion (1976) who assesses non-response by analyzing early and late responders.

[20] ADF&G charter logbook data indicates activity by 627 businesses in 2012, suggesting some businesses active in 2011 were inactive or exited the fishery in 2012.