Jointly Estimating Site-Choice and Trip Length for Non-Market Valuation

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Abstract

Traditional site-choice demand models ignore or oversimplify the trip length decision made by consumers, thus limiting the scope of analysis that can be done by the researcher. Researchers that consider site choice and trip length can calculate additional non-welfare endpoints that can be used in dynamic simulations, providing more information to policymakers. We develop and estimate a joint site-choice, trip length, and on-site cost model that links site-choice and trip length decisions using a full-information maximum likelihood approach. We apply this model using data collected from non-resident anglers that participated in a recreational saltwater fishing trip in Alaska. Non-resident Alaskan anglers are individuals who live outside of Alaska, but who participate in a saltwater fishing trip via private or charter (guided) boat in Alaska. These anglers typically visit Alaska very infrequently but spend multiple days participating in a saltwater fishing trip while visiting. Thus, fishing trip length is an important margin of choice. Our findings suggest that increasing the harvest rate may reduce fishing time and a one-fish increase in the harvest rule may increase expected mortality at a slower rate than when on-site time is ignored. This result implies that researchers that ignore trip length may under- or overestimate the impact on non-welfare endpoints which may lead to unintended consequences.

1 INTRODUCTION

People routinely make decisions that have both space and time components. For example, when an individual is planning a beach trip, she selects both the beach to visit and the amount of time to spend at the beach that maximizes expected utility. Each site considered for outdoor recreation provides a set of amenities (presence of lifeguards, beach rentals, food availability, etc.) that can be expected to influence the location choice and the time spent enjoying various site-specific activities (Parsons et al., 1999; Alegre & Pou, 2006; Lew & Larson, 2008; Martínez-Espiñeira & Amoako-Tuffour, 2008; Voltaire et al., 2017). Other types of individual economic activity involving space and time components include tourism (Alegre & Pou, 2006; Barros & Machado, 2010; Grigolon et al., 2014), transportation (Haghani & Sarvi, 2016; Sharma et al., 2019), hunting (Hussain et al., 2016), fishing (Bell & Leeworthy, 1990; Berman & Kim, 1999), rock-climbing (Shaw & Jakus, 1996; Scarpa & Thiene, 2005), other recreational activities (Parsons & Kealy, 1992; Herriges & Phaneuf, 2002; Hynes et al., 2009) and hospital choice (Brown & Theoharides, 2009; Moscone et al., 2012). Empirical work in multiple subfields of economics explores the spatial element of individual choice, typically modeling the decision of where to go as selecting within a set of discrete locations. Relatively few empirical studies of spatial choice consider the temporal component of the same decision problem: how long to stay at the selected location (Shaw & Feather, 1999).

Empirical models of spatial choice are standard tools used by economists to value natural resources and environmental amenities, which are often non-market goods[1]. A typical application using revealed preference data involves collecting information on the sites visited by individuals to estimate preferences for site attributes, for example, water quality at different ocean beaches in a region. There are at least two categories of empirical results from this form of analysis that are of interest for both research and public policy. The usefulness of each type of result may be limited when the time component of spatial behavior is not modeled empirically. The first category comprises estimates of well-known welfare

[1] Non-market environmental goods are goods that are not sold in a traditional market but still have monetary value to consumers (e.g. clean air or water, etc.). The monetary value for non-market goods are not revealed through market prices so economist use non-market valuation methods to estimate the costs and benefits from changes in environmental quality

measures, including willingness-to-pay for marginal changes in site attributes (e.g., local water quality at the beach) and average compensating variation for non-marginal changes in the same attributes. These estimates are nearly always denominated in per-choice occasion units. Unless the activity is one where site visits are naturally constrained to last roughly the same amount of time, the analyst may need to make strong assumptions about the length of time per visit to assign welfare measures meaningful units of time. This limitation creates practical problems for applying welfare measures in environmental and resource policy analysis because other inputs to policy analysis–in particular costs increasing environmental quality–can be measured over intervals of time (e.g., a daily basis).

The second category of empirical results sought from models of spatial behavior related to resources and environmental quality are non-welfare endpoints of location visits. In addition to directional predictions of which site may receive more or less total visits due to a change in site attributes, other endpoints may include the impact of those visits on the sites themselves. A major use of empirical models of location choice in fisheries economics, for example, is to predict shifts in the spatial distribution of harvest when a subarea is closed to fishing[2] (Smith & Wilen, 2003). Lack of empirical information about time on site often presents an even more severe problem for predicting non-welfare endpoints, since they may not be possible to construct reliably due to a fundamental apples-and-oranges problem: location visits are denominated in per-trip units, while auxiliary information about the impacts of location visits are frequently denominated in per-day or similar units. Absent an accompanying empirical model of time-on-site, strong assumptions may be needed to connect predicted spatial behavior to endpoints of interest, particularly when significant heterogeneity in time-on-site exists. Important secondary effects of site visits, such as local economic impact, are also challenging to derive from spatial models without linked information on time-on-site.

In this paper, we develop a model of individual site-choice, trip length, and daily on-site costs. We estimate the model using data from surveys of non-resident anglers who

[2]Non-welfare endpoints are key outputs for related models in forestry (Hoganson & Rose, 1984; Hashida & Lewis, 2019), transportation (Horne et al., 2005), and agriculture (Lázár et al., 2015) simulations that are used by policymakers when making decisions

participated in a recreational saltwater sport angling trip in Alaska[3] (Lew et al., 2010; Lew & Larson, 2015). We use our model to estimate both the per trip and daily welfare effect for changes in harvest policies, the value per Alaskan fishing trip, and the change in expected mortality for changes in harvest policies. Our model extends a handful of past studies in the non-market valuation literature that consider both site choice and time spent on site, either using a nested logit framework that includes a level of choice between a single- or multi-day trip (Lupi et al., 2001; Yeh et al., 2006) or a sequential approach where the time spent on site is predicted and substituted into a site-choice model (Berman & Kim, 1999). We improve on these papers by carefully linking the time spent on site and on-site costs in a jointly-estimated empirical framework. To the best of our knowledge, our analysis is the first to use a site choice and time-on-site empirical model to predict expected harvest mortality caused by anglers. Fish mortality is a major ecological impact of recreational angling that is an increasing focus of fishery policy around the world (Arlinghaus et al., 2016; Punt et al., 2016). Fisheries policymakers are turning toward management strategy evaluations (MSE) to rank and compare harvest control rules based on the effectiveness of each outcome (Smith et al., 1999; Fulton et al., 2014; Punt et al., 2016). MSE is a simulation-based tool that uses interdisciplinary data to apply specific analyses and estimate the trade-offs of different harvest control rules such as the impact to fish mortality. MSE's are considered the most appropriate tool to evaluate fishery policies (Punt et al., 2016). But MSE's still ignore the on-site impact from changes in fishery policy that limits their effectiveness (Massey et al., 2006; Lee et al., 2017).

We estimate the model using two separate editions of the survey: one for non-resident anglers who visited Alaska in 2011, and another for those who visited in 2016. Matching our previous expectations, model estimates imply that an increase in the expected daily harvest rates will increase the trip length for most key Alaskan species. However, as the historical harvest rate for Pacific halibut increases, the estimated coefficients suggest that trip length may have a negative impact. Anglers may substitute fishing time with other non-fishing activities while in Alaska once they reach a satiation point. This implies that ignoring the

[3]We analyze model estimates for two separate but linked surveys of non-resident anglers: one conducted for anglers who went saltwater fishing in Alaska in 2011, and another for anglers who went in 2016.

on-site time component may bias MSE estimates causing unintended policy consequences. Increases in the historical harvest rate will have a significant impact on trip length, but the direction and magnitude are unknown when on-site time is ignored. We use the fitted model to calculate the change in expected recreational mortality from a one-fish increase in the bag limits for Pacific halibut (*Hippoglossus stenolepis*). A one-fish increase in the bag limit in southeast Alaska increases the expected mortality of 44.2% and 27.9% in 2011 and 2016 compared to a slightly smaller increase to expected mortality of 34.8% and 24.2% in 2011 and 2016, respectively. This suggests a non-uniform spatial change in expected harvest mortality that can impact fishery managers' strategies in changing harvest rules.

In the next section, we discuss relevant literature pertaining to jointly considering site choice and on-site time of individuals, followed by a theoretical model of utility maximizing behavior subject to dual monetary and time constraints in the site choice context. In Sections 4 and 5, we give a brief description of the recreational Alaskan fishery and describe the data used in the model. In Section 6, we describe the site choice and trip length specifications and how these models are linked. In Section 7 we present and discuss the results from the joint model. Using the estimated coefficients from the joint model, we estimate the welfare effect and change in trip length for a small increase in the historical harvest rate for each species, discussed in Section 8. Within this section, we also present a simple illustration of a policy-relevant non-welfare endpoint that can be calculated using this framework. The final section discusses the next steps of the model, including how we can use this model in a bioeconomic framework, and other limitations of the model.

2 RELEVANT LITERATURE

Researchers have developed theoretical models to analyze utility maximization problems where an individual chooses the site to visit and the amount of time to spend on site (Smith et al., 1983; Bell & Leeworthy, 1990; McConnell, 1992). In these theoretical models, the researcher must determine if on-site time is exogenously or endogenously determined before deciding how to include on-site time in the utility model. If on-site time is assumed to be exogenous, then the site-choice model can simply include on-site time as a right-hand side variable in the site-choice model. However, the researcher must decide how to include on-site time within the model. On-site time affects the utility function in two distinct ways. The first impact is through the on-site cost term via monetary cost spent and the opportunity cost of on-site time (Smith et al., 1983). The higher monetary cost could be associated with additional lodging fees, restaurant and food costs, and other on-site expenses. But individuals that have longer on-site time are also foregoing the value from other activities. Increases to total on-site cost will provide disutility to the individual. The second impact to utility is directly from the benefit of spending more time on site assuming an individual is gaining utility from participating in additional recreational activities. Due to the dual impact of on-site time, researchers may not know how changes to on-site time may impact an individual's net utility (McConnell, 1992).

Researchers in the recreational demand literature have developed empirical models that consider the site-choice and on-site time decisions for a given sample based on the theoretical models discussed above (Bell & Leeworthy, 1990; Berman & Kim, 1999; Lupi et al., 2001; Alegre & Pou, 2006; Yeh et al., 2006). Many of these studies use a nested logit framework to differentiate between single- and multi-day trips (Lupi et al., 2001; Yeh et al., 2006). Yeh et al. (2006) allows for different total expenditures based on trip length, allowing for additional costs, such as lodging, in the trip expenditure function for multi-day participants. Alegre and Pou (2006) estimates a trip length model for tourists using a binomial logit model (1 for trips under 7 days; 0 for trips over 7 days) as a function of demographics, number of trips, party size, daily on-site price, travel price, and other site-specific attributes. Berman and Kim (1999) discuss three methods (exogenous, reduced form, and structural) to account for on-site time when analyzing a site choice model based on the theoretical model developed by McConnell (1992). The structural model estimates on-site time as a function of the monetary trip expenditures, travel time, party size, other site-specific attributes and a constant using a censored normal regression model for on-site time predictions. On-site time predictions are used in a nested logit site choice model that is a function of travel costs, travel time, on-site time differentiated by employment type, and site-specific attributes. This method estimates the on-site time model first, then uses the predicted on-site time values in the site choice model. We use the Berman and Kim (1999) structural framework as a basis for our joint model described further in section 6. Our model improves upon the methods from Berman and Kim (1999) by considering on-site cost in the on-site time model based upon the work by Landry and McConnell (2007), considering the attribute-specific utility impact from increases to on-site time, and uses a full-information maximum likelihood framework to simultaneously estimate all coefficients instead of using predicted values in multiple stages. Jointly estimating all coefficients allow for correlated error terms between each model improving the efficiency of estimates (Enders & Bandalos, 2001).

3 THEORETICAL MODEL

In typical travel cost models, individuals are assumed to maximize their utility by choosing the number of trips to take subject to money and time constraints. Previous literature has extended this theoretical framework to allow for consideration of time spent on-site as a choice variable (Bockstael et al., 1987; Bell & Leeworthy, 1990; McConnell, 1992; Larson, 1993; Berman & Kim, 1999). These models have many similarities between the inclusion of on-site time and in the implications for measuring recreation demand. Below, we present a theoretical model similar to those in the literature and make slight modifications to the model based on empirical data that is commonly available for researchers today.

We assume that an individual's utility, $u(\mathbf{x}, \mathbf{t}, \mathbf{S}, z^M, z^T)$,), is a function of the number of trips taken to recreation sites (indexed from $j = 1, ..., J$) and represented by the vector x_i, the time spent on-site at each of the J sites, t_i, a (Q x J) matrix of Q quality characteristics of the J sites, S , a numeraire good that costs money but not time, z^M, and a numeraire good that costs time but not money, z^T. Individuals are assumed to maximize utility by choosing the number of trips and total time spent at each site subject to money and time budgets. The standard budget and time constraints are:

$$M = \sum_{j=1}^{J} x_j \cdot p_j + p_z \cdot z \tag{1}$$

$$T^{*} = \sum_{j=1}^{J} x_j \cdot (\gamma_j + t_j) + \theta \cdot q \tag{2}$$

where M is income, p_j is the round-trip travel cost to site j, p_z is the cost of the numeraire good z^M, T^* is the total time available for leisure consumption, γ_j is the round-trip travel cost to site j, and θ is the time spent consuming z_T. In many recreational demand studies, the total price of a trip is equal to the round-trip monetary travel cost. However, models that allow on-site time to be endogenous must also consider the on-site cost, which is the own-price of on-site time. Thus, we specify the total price of a trip as follows:

$$p_j = p_j^{tr} + p_j^{osc} \cdot t_j \tag{3}$$

where p_j^{tr} is the round-trip travel cost to reach the recreational site and p_j^{osc} is the daily on-site costs. The available time for leisure, T^*, is exogenously determined from working hours h where the total amount of leisure time is equal to $T^* = T - h$. Using this property, we can re-write the time constraint in monetary terms measured by angler i's wage rate w, shown below:

$$w \cdot h = w \cdot \left(T - \sum_{j}^{J} x_j \cdot (\gamma_j + t_j) - \theta \cdot q \right) \tag{4}$$

We can collapse the time and money budget constraints into a single one if an individual has a flexible work schedule by substituting the time constraint into the budget constraint (Bockstael et al., 1987; McConnell, 1992). This results in the following single constraint:

$$y = \sum_{j}^{J} x_j \cdot \left(p_j^{tr} + \gamma_j \cdot w + p_j^{OSC} \cdot t_j + w \cdot t_j \right) + p_z \cdot z \tag{5}$$

where $y = M_0 + w \cdot T^*$. The single budget constraint shows that exogenous money income plus the (monetary) opportunity cost of leisure time is equal to the sum of three things. The first is total round-trip travel cost which is equal to sum of the monetary cost of travel and the opportunity cost of travel time valued at the wage rate. The second is on-site costs. The total on-site cost is equal to the sum of total monetary on-site cost and the opportunity cost of on-site time, where the opportunity cost of on-site time is the trip length valued at the wage rate. The final term in the single budget constraint is the total cost for the numeraire good. Using the single constraint, an individual's utility maximization problem is as follows:

$$\max_{x,t,z} \; u(\mathbf{x}, \mathbf{t}, \mathbf{S}, z^M, z^T) - \lambda \left(y - x_j \cdot \sum_j^J \left(p_j^{tr} + \gamma_j \cdot w + p_j^{osc} \cdot t_j + w \cdot t_j \right) - p_z \cdot z \right) \tag{6}$$

The solution to this maximization problem for individuals with a flexible work schedule is $V_i(p_j^{tr} + p_j^{osc} \cdot t_j, t_j, s, z, q)$. Using the envelope theorem, we can show that the trip demand for site j, as shown in

$$x(p_j^{tr}, p_j^{OSC}, p_z, s_j, y) = -\frac{\partial V / \partial p_j^{tr}}{\partial V / \partial y} \tag{7}$$

This is the common finding that theoretically supports the use of the multi-site travel cost model. But this assumes that on-site time is exogenously determined by the individual when it is more likely that an individual chooses the site to be visited and the amount of on-site time. When on-site time is endogenous McConnell (1992) shows that the demand function can be estimated using the envelope theorem. The Marshallian demand for on-site time is shown below:

$$t(p_j^{tr}, p_j^{OSC}, p_z, s_j y) = -\frac{\partial V / \partial p_j^{osc}}{\partial V / \partial p_j^{tr}} \tag{8}$$

It is shown that on-site time is a function of not only on-site cost but round-trip travel cost too. Bell and Leeworthy (1990) develop a theoretical model for on-site time that compliments the finding by McConnell (1992) using on-site cost and travel cost in their on-site time demand model. Although this model cannot be used for welfare estimates (McConnell, 1992), it can be used to estimate a multi-site travel cost model with exogenous on-site time. In the empirical model, described further below, we estimate equation 8 to get exogenous estimates of on-site time that are used in the travel cost model. McConnell (1992) shows that if on-site time is exogenous, then the solution to the utility maximization problem where on-site cost is not chosen by the individual is the same as equation 7 but on-site time is simply a parameter, $x = f(p_j^{tr}, p_j^{OSC}, p_z, s_j, y, t_j)$. The effect of on-site time on utility remains unknown because of the dual nature of on-site time on costs and utility (McConnell, 1992). Since the empirical model estimates an exogenous on-site time for the trip demand model, the budget constraint remains linear and welfare calculations remain the unchanged.

4 EMPIRICAL SETTING

Alaska is a major tourism destination for saltwater recreational anglers. In 2016, approximately 300,000 non-resident sportfishing licenses were sold with about two-thirds participating in a guided or charter trip (McDowell Group, 2018). Anglers travel from all over the world for the chance to catch and harvest a large Pacific halibut or salmon (Lew & Larson, 2012). The long travel distance and opportunity to harvest prized species cause anglers to spend multiple days fishing in Alaska (McDowell Group, 2017). The multiple fishing destinations plus the varying fishing lengths make this an ideal setting to empirically examine the joint site-choice and trip length model. The two most common species of fish targeted by recreational anglers are Pacific halibut and salmon (Lew & Larson, 2015).

Silver salmon (*Oncorhynchus kisutch*) and king salmon (*Oncorhynchus tshawytscha*) are managed by the Alaska Board of Fisheries (BOF) and the ADF&G. BOF establishes the harvest regulations for silver and king salmon and the ADF&G implements and enforces the BOF regulations. Although the IPHC and BOF areas do not overlap perfectly, Area 2C is similar to the southeast region and Area 3A, excluding Kodiak, is similar to the southcentral region. The bag limit for silver salmon in southeast Alaska in 2016 was 6 fish longer than 16 inches or 10 fish less than 16 inches. The bag limit for king salmon in southeast Alaska in 2016 is one-fish longer than 28 inches. Additionally, non-residents must purchase a king salmon stamp each day that a fish is harvested, costing between $10 and $3.50 depending on the number of days spent fishing (Romberg, 2016).

Pacific halibut along the west coast of the United States (U.S.) and Canada, known as "Convention" waters, are managed by the International Pacific Halibut Commission (IPHC). Convention waters are broken down into unique areas that the IPHC uses during stock assessments. A map of the areas in the Convention waters are shown in Figure 1. The IPHC makes recommendations to the North Pacific Fishery Management Council (NPFMC) on the total allowable catch (TAC) for each area in Alaska. Areas 2C (southeast) and 3A (southcentral) have the highest harvest of Pacific halibut in Alaska. The IPHC and NPFMC recognize the impact of recreational anglers on Pacific halibut stocks and began regulating recreational charter harvest in Alaska since 2008 via bag limits and reverse slot limits (NMFS, 2008). A reverse slot limit states the lower and upper limit in which a fish can be harvested. A Pacific halibut that falls within the stated range must be discarded. In Area 2C in 2016, anglers could harvest a Pacific halibut if the length fell within the reverse slot limit (>43 inches and <80 inches). In Area 3A in 2016, anglers could harvest two fish where one fish could be any size and the second must be less than 28 inches in length (NMFS, 2016). Prior to the CSP, harvest regulations were less stringent. In 2011, the harvest regulation in Area 3A was two-fish of any size and in Area 2C was one fish with a maximum length of 37 inches (NMFS, 2011).

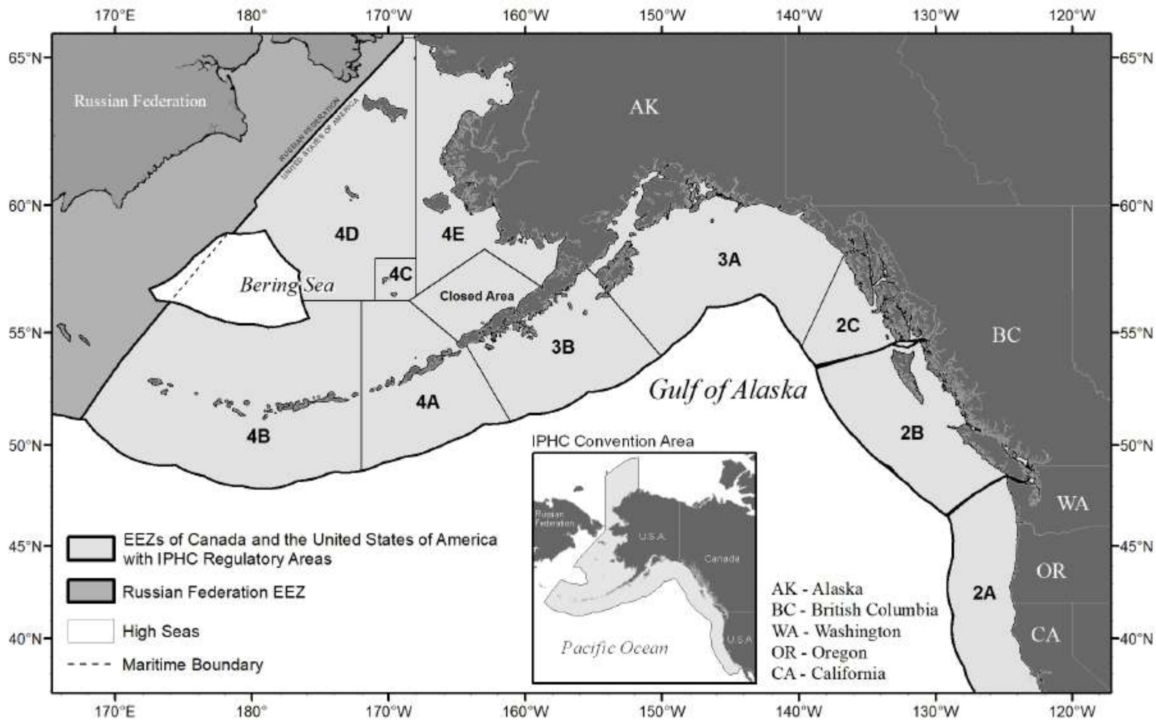

Figure 1: Map of the IPHC Areas along the west coast of the United States and Canada. This photo shows the three major regulatory areas managed by the IPHC. Photo taken from IPHC (IPHC, 2022)

5 DATA

We analyze data collected in the 2012 and 2017 Alaskan Saltwater Sport Fishing Surveys (Lew et al., 2010). In early 2012 and 2017, a random sample of 2,000 and 2,200, respectively, non-residents who purchased a 2011 and 2016 Alaska sport fishing license were sent the survey. We focus on non-resident anglers due to their likelihood to participate in multi-day trips and the variance of trip lengths among the sample. Of the 2,000 and 2,200 non-residents that received the survey, 475 and 463 respondents completed all the necessary questions for the site choice, trip length, and on-site cost model and visited a single-site. Table 1 reports the mean demographics of survey respondents and those of the U.S. populations in 2017. Survey respondents are typically older, have a higher annual income, and smaller household size than the U.S. population and are more likely to be Caucasian and male.

Table 1: Comparison of demographic information between the 2012 and 2017 survey samples and the 2017 U.S. Population

	2012 Non-Resident Survey	2017 Non-Resident Survey	2017 U.S. Population
Gender – % Male	76.2%	78.4%	49.2%
Age – Mean age in years	55.2	55.2	37.7
Ethnicity – % Sample Caucasian	93.1%	94.0%	73.3%
Household Size – Mean # of People Living in Household	2.18	2.06	2.64
Education – % Sample with 4-year college degree or higher	57.1%	60.0%	30.3%
Wage – Median Hourly Wage Rate	$30.00 $39.99	$30.00 $39.99	NA
Income	$80,000 $99,999	$100,000 $124,999	$69,717

Note: Demographic information for the U.S. Population uses data from the 2017 American Community Survey (ACS) database (USCB, 2016)

The survey focused on fishing behavior in Alaska during the prior year (e.g. respondents in the 2017 survey were asked about trips in 2016). It included questions about anglers' most recent Alaskan saltwater sport fishing trip including the site visited, the length of the fishing trip, which species were targeted, the purpose of the trip, and other trip-related information. The survey asked about fishing behavior to 22 saltwater fishing sites in Southeast Alaska (10 fishing sites) and Southcentral Alaska (12 fishing sites). The 2012 and 2017 Alaskan Saltwater Sport Fishing Survey bases the sites in each region off of the management used by the Alaska Department of Fish & Game (ADF&G) (Figure 1). The ADF&G regions are slightly different from IPHC areas. Respondents provided information on which of the fishing site(s) they visited during their most recent trip to Alaska and the number of days spent fishing at each site. Approximately 82% of respondents that participated in a saltwater fishing trip visited a single site and approximately 55% participated in a fishing trip that lasted multiple days. To avoid the potential bias caused by multiple sites being visited on the same trip, we limit the analysis to anglers that visited a single site (Yeh et al., 2006). When anglers visit more than one site on the same trip, the underlying assumption of the travel cost model that trip cost proxies for the price of the recreational fishing experience breaks down (Parsons, 2003). By considering only trips to single sites, we reduce the potential for multi-purpose bias.

Figure 2a: Southcentral Sites

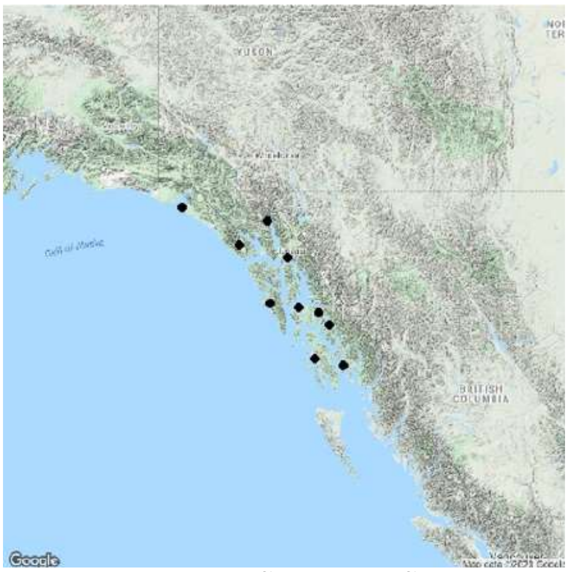

Figure 2b: Southeast Sites

Approximately 55.7% of the single-site trips were taken to three sites–Ketchikan (19.9%), Homer (19.9%), and Seward (15.8%). We group all sites visited for each non-resident into the 12 non-Southeast Alaska sites and 9 Southeast Alaska sites listed in Table

5. Respondents were asked to indicate the fishing mode (charter/guided fishing, private boat fishing, or shore fishing) used during their most recent Alaskan fishing trip. Approximately 83.4% of non-residents participated in a guided or charter fishing trip with the remaining respondents indicating having fished by private boat or from shore. Private boat fishing generally refers to any unguided/non-charter fishing. Anglers that participate in a charter fishing trip do so via a cruise ship or a fishing lodge. Approximately 10.1% and 13.0% of 2011 and 2016 anglers, respectively, participate in a saltwater fishing trip via a cruise excursion and approximately 30.7% and 30.9% of 2011 and 2016 anglers, respectively, participate in a saltwater fishing trip via a fishing lodge. Cruise excursions are commonly bound to single-day trips as the cruise makes routine stops along their route. Fishing lodges commonly offer multi-day fishing packages that allow anglers to target multiple species during their trip and are all-inclusive.

In the RUM site choice model, individual-level and site-specific travel cost and time information are needed. In this study, travel costs and times are calculated for each respondent between each fishing site and where each individual began their fishing trip, which we call the "home base". Two candidates for the home base are available in the data, the individuals' residence (i.e., their home zip code) or where in Alaska they identified as their home base for their Alaska activities (asked in the survey). Which of these home base options to use is determined by responses to a question that identifies whether fishing was a primary purpose of the Alaska trip or not. The question asked respondents to categorize their trip into one of three types. The first indicates the trip was one where fishing was planned for most, or all, of the time spent in Alaska, which indicates "avid anglers." The second type is a trip where saltwater fishing was planned, but other activities were also important. These individuals are termed "purposeful anglers." The final type of trip is one where there were no plans made prior to the trip to saltwater fish, but fishing was done opportunistically. These individuals are called "incidental anglers." Approximately 19.9% are incidental anglers, 47.6% are purposeful, and 30.2% are avid, and 2.2% of anglers did not select a category. We assume that the home base for incidental and purposeful anglers or the anglers who did not select a category is the home base in Alaska that they identified in the survey. Avid anglers are assumed to start their fishing trip at their residence (outside

Alaska), with the home-address zip-code being used.

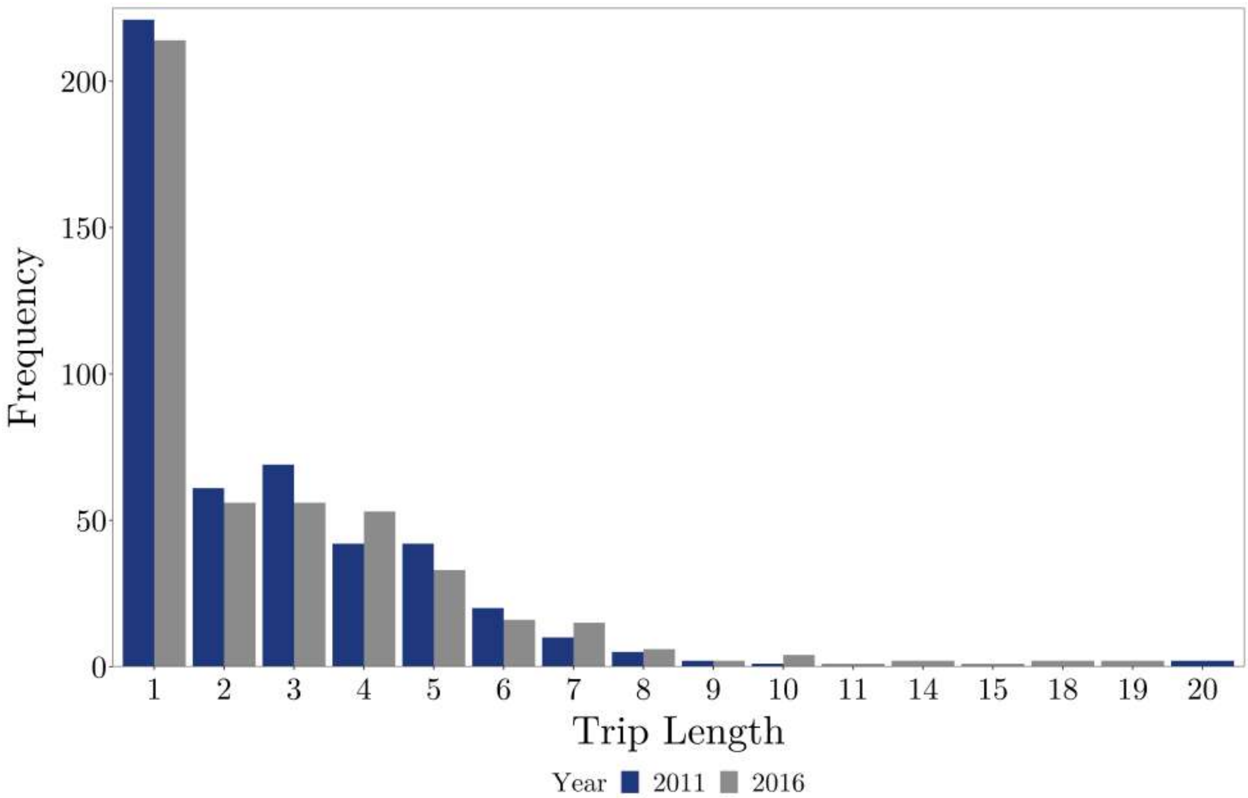

Figure 3: Frequency of reported fishing trip lengths from the 2012 and 2017 surveys. The distribution of trip lengths are similar among samples although there are more trips lasting longer than 10 days in the 2012 survey compared to the 2016 survey.

Site-specific historical harvest rates are used to understand how site choices are influenced by expected harvest rates. Site-level estimates of annual catch, harvest, and trips collected by the ADF&G for the period 1996 to 2016 were used to construct the daily historical harvest rates used in the analysis (Romberg, 2017). These historical harvest rates consider harvest from guided and unguided trips[4] where charter specific harvest data was available. We proxy for anglers' expected harvest rates by considering the three-year mean harvest rate prior to the year they participated in a trip (e.g. historical harvest rates between 2013 and 2015 are used for 2017 survey respondents). Table 5 in the Appendix reports the three-year average daily harvest rates for key Alaskan species by site used by respondents in 2011 and 2016.

[4]Except for sites (Anchor Point, Clam Gulch, Ninilchik and Deep Creek, Kenai, and Seldovia)

6 METHODS

This section introduces an econometric model of joint site choice and trip length. The trip length model estimates the probability that angler i's fishing trip will last l_i days based on the monetary travel cost to the site visited, logged daily on-site costs, historical harvest rates of Pacific halibut, king salmon, silvers salmon, and other fish, and site- and regional-specific fixed effects. On-site cost and trip length may be endogenous due to reverse causality and simultaneity. We account for this relationship by considering daily on-site cost as opposed to total on-site cost and substituting a daily on-site cost function into the trip length model (Landry & McConnell, 2007). The daily on-site cost model is a function of a constant, trip characteristics, and angler-specific demographics. The site choice model is linked to the trip length model via the expected trip length. The site choice model represents the indirect utility of angler i choosing site j as a function of the full-trip travel costs, round-trip travel cost and on-site cost, the per-trip historical harvest rates of Pacific halibut, king salmon, silver salmon, and other fish, and site- and regional-specific fixed effects. Site choice, trip length, and daily on-site cost are estimated by maximizing the joint log-likelihood using a full-information maximum likelihood framework.

As mentioned in Section 5, we use two surveys of different individuals that participated in an Alaskan fishing trip in 2011 and 2016. Using two identical surveys lends to the possibility of pooling the data. Pooling the data implicitly assumes that the preferences and standard deviations, or scales, are constant among surveys. But it may be unlikely that preferences do not change over time and are different between samples. Swait and Louviere (1993) suggest four different cases to test before a researcher pools data. The first case assumes equal parameters and scales among the two samples. The second case allows for scale differences but continues to assume equal parameters. Cases three and four assume different parameters between the two surveys implying a change in preferences over time. Case three assumes no scale differences while case four assumes differences in scale, similar to cases one and two. The researcher should estimate each case and conduct a log-likelihood test to determine the appropriate case (Swait & Louviere, 1993).

6.1 Trip Length Model

Trip length is a strictly positive integer that measures the days spent fishing during an angler's most recent 2016 Alaskan trip. The trip frequency or length literature commonly estimates a count data model, frequently a Poisson (Creel & Loomis, 1992; Alegre et al., 2011; Pokki et al., 2018; Buason et al., 2021) or negative binomial model (Hussain et al., 2016; Boto-García et al., 2019) when this type of data is available. The Poisson distribution imposes a strong assumption that the mean and variance of the distribution are equal, known as equidispersion (Martínez-Espiñeira & Amoako-Tuffour, 2008). This assumption typically does not hold with trip length data because the mean is typically smaller than the variance. The negative binomial distribution is more flexible than the Poisson model because it considers an overdispersion parameter allowing the researcher to test for equidispersion (Martínez-Espiñeira & Amoako-Tuffour, 2008). An additional feature of the trip length data is that trip length is always greater than or equal to a single day. The zero-truncated negative binomial distribution is a special case of the negative binomial model that tests for overdispersion while assuming no values can take a value of zero.

Within select data sets, such as fishery bycatch, cigarette consumption, and trip frequency, it may be common to see a large observation of zeros within the data (Sheu et al., 2004; Minami et al., 2007; Kim et al., 2021). Researchers account for the high probability of zero observations using a zero-inflated negative binomial (ZINB) distribution where the probability of equaling zero is a function of select variables. We observe a similar characteristic in our trip length data, but instead of a large observation of zeros, approximately 46 percent of all trip lengths last a single-day. The zero-inflation property of the ZINB distribution can be adjusted to account for one-inflation or the additional probability that an angler will always participate in a single-day trip. For example, some anglers participate on a fishing trip via a fishing excursion from a cruise ship. Despite changes in site-specific attributes, anglers fishing from a cruise ship are bound to a single-day trip because of the strict itinerary of cruise excursions. Since there is a high probability of an angler participating in a single-day trip in addition to the non-zero property, we assume that the trip length model follows a one-inflated zero-truncated negative binomial (OIZTNB) distribution. The probability density function (PDF) for the OIZTNB distribution is shown below where the probability of trip length l_i:

$$\pi_i^l(l_i) = \begin{cases} \omega_i + (1-\omega_i)\cdot p_+(1,\alpha) & l_i = 1 \\ \\ (1-\omega_i)\cdot p_{++}(l_i,\alpha) & l_i > 1 \end{cases} \tag{9}$$

where ω_i is the probability of angler i participating in a single-day trip, $p_+(1,\alpha)$ is the probability of observing a one for the zero-truncated negative binomial distribution, $p_{++}(l_i,\alpha)$ is a zero-one-truncated distribution, and α is the overdispersion parameter. The probability of angler i participating in a single-day trip is estimated as a binary logit model that is a function of a constant, a cruise dummy variable, and a lodge dummy variable. The cruise dummy variable is equal to 1 if angler i participated in a fishing trip via a cruise excursion. The lodge dummy is equal to 1 if angler i participated in a fishing trip from a fishing lodge. If $\omega_i = 0$, then the probability function in equation 9 collapses to a zero-truncated negative binomial distribution. The negative binomial distribution is estimated using an exponential function, shown below:

$$\begin{aligned} \lambda_{i,j} = exp\Bigg(& \theta_1 \cdot ln\left(OSC_{i,j}\right) + \theta_2 \cdot TC_{i,j}^{tr} + \theta_3 \cdot PH_j + \theta_4 \cdot KS_j + \theta_5 \cdot SS_j + \theta_6 \cdot OF_j + \\ & \theta_7 \cdot RSC_{SE} + \delta \cdot SSC \Bigg) \end{aligned} \tag{10}$$

where OSC_i are the daily total on-site costs, $TC_{i,j}^{tr}$ is angler i's round-trip monetary cost to site j, PH_j, KS_j, SS_j, and OF_j are the daily historical harvest rates for Pacific halibut, king salmon, silver salmon, and other species at site j, and RSC and SSC are regional- and site-specific constants, respectively. The expected trip length for angler i visiting site j, $E[l_{i,j}]$, is shown below:

$$E[l_{i,j}] = \omega_i + (1+\omega_i)\cdot \lambda_i \cdot \left(1 - (1+\alpha\cdot\lambda)^{-\alpha^{-1}}\right)^{-1} \tag{11}$$

where the first term is the probability of participating in a single-day trip despite changes to variables in equation 9 and the second term is zero-truncated negative binomial weighted by the probability of participating in a multi-day trip. This is one piece that is needed to link the trip length model with the site choice model. But to estimate the total on-site fishing cost, we also need to estimate a exogenous daily on-site cost.

6.1.1 On-Site Cost Model

On-site costs may be endogenously determined with trip length. We would expect on-site cost to increase with trip length but trip length to decreases with rising on-site costs. Landry and McConnell (2007) introduce a logged daily on-site cost hedonic model and use the exogenous predictions in the trip length model to break this endogeneity. Our model estimates the daily monetary cost spent on fishing-related days and activities by an angler using observed on-site cost data. Total on-site fishing cost is the sum of lodging and food/restaurant costs during fishing days, charter and licensing fees, and other fishing related costs such as ice and gear. The logged daily on-site cost model is shown below:

$$ln(OSC_i) = \phi_0 + \phi_1 \cdot q_i + \phi_2 \cdot s_i + \phi_3 \cdot D_i^c + \epsilon_i^{os} \tag{12}$$

where q_i is a vector of angler-specific demographics, s_i is the number of anglers that were paid for in the on-site cost calculations, D_i^c is a dummy variable equal to 1 if angler i participated in a charter fishing trip and ϵ_i^{os} is the stochastic disturbance term. We find that logging daily on-site costs provides a good statistical fit compared to the linear counterpart. By logging daily on-site cost, we are changing the stochastic disturbance term from a Gaussian distribution to a log-normal distribution. The PDF for the log-normal distribution is:

$$\pi_i^{osc}(ln(OSC_{ij})|\theta) = \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma_{os}^2}} \cdot exp\left(-\frac{ln(OSC_i) - \theta_0 - \theta_1 \cdot q_i - \theta_2 \cdot s_i - \theta_3 \cdot D_i^c - \theta_4 \cdot rp_i)^2}{2\sigma_{os}^2}\right) \tag{13}$$

where σ_{os} is the standard deviation of the log-normal distribution. Using the PDF in equation 13, we can write the log-likelihood function as:

$$LL_1(\theta, \sigma) = -\frac{I}{2} ln(2\pi) - \frac{I}{2} ln(\sigma_{os}^2) - \frac{1}{2\sigma_{os}^2} \sum_{i=1}^{I} (ln(OSC_i) - \theta_0 - \theta_1 \cdot q_i - \theta_2 \cdot s_i - \theta_3 \cdot D_i^c - \theta_4 \cdot rp_i)^2 \tag{14}$$

where I is the total number of respondents. The trip length model is conditional on the realized standard deviation of the stochastic disturbance term from the on-site cost model. Instead of using the exogenous predictions from the daily on-site cost model, we substitute the daily on-site cost model from equation 12 into the daily on-site cost term in the trip length model shown in equation 10. This allows us to take advantage of the simultaneous decision of trip length and on-site cost and the stochastic error term in the on-site cost model. Substituting equation 12 into equation 10, the trip length model becomes:

$$\begin{aligned} \lambda_i = \exp \Bigg(& \theta_1 \cdot (\phi_0 + \phi_1 \cdot q_i + \phi_2 \cdot s_i + \phi_3 \cdot D_i^c + v_i \epsilon_i^{os}) + \theta_2 \cdot TC_{i,j}^{tr} + \theta_3 \cdot PH_j + \\ & \theta_4 \cdot KS_j + \theta_5 \cdot SS_j + \theta_6 \cdot OF_j + \theta_7 \cdot RSC + \delta \cdot SSC \Bigg) \end{aligned} \tag{15}$$

where σ_i^{os} is distributed normally with a mean 0 and standard deviation 1. By considering the stochastic disturbance term in 15, the trip length model is modeled using a random parameter one-inflated zero-truncated negative binomial (RPOIZTNB) model. The RPOIZTNB allows for preference heterogeneity by estimating the standard deviation associated with the given randomly-distributed coefficient (Hynes & Greene, 2016; Whitehead et al., 2018). In equation 15, we assume heterogeneous preferences for the logged daily on-site cost by considering the stochastic disturbance term. The probability for trip length shown in equation 9 must now be evaluated over the distribution of stochastic disturbance term, shown below:

$$\pi_i^{tl} = \int_0^1 \omega_i + (1 - \omega_i) \cdot p_+ (1, \alpha) f(\sigma_{os}) \cdot d\sigma_{os} \int_1^{\inf} (1 - \omega_i) \cdot p_{++} (l_i, \alpha) f(\sigma_{os}) \cdot d\sigma_{os} \tag{16}$$

We use simulation methods to numerically solve for equation 16 since this function does not have a closed form solution. The simulated probability is based on the simulated mean of the negative binomial distribution, shown below:

$$\pi_i^{tl} = \frac{1}{R}\sum_{r=1}^{R}\frac{\Gamma\left(l_i+\alpha^{-1}\right)}{\Gamma\left(l_i+1\right)\left(\alpha^{-1}\right)}\cdot\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_i^r}\right)^{\alpha^{-1}}\cdot\left(\frac{\lambda_i^r}{\alpha^{-1}+\lambda_i^r}\right)^{l^i}\cdot\left(1-\left(1+\alpha\cdot\lambda_i^r\right)^{-\alpha^{-1}}\right)^{-1} \quad (17)$$

where $r = [1, \cdots, R]$ is the number of quasi-random Halton draws taken from a normal distribution. The expected trip length and daily on-site cost are used when calculating the full-cost term that links the trip length model to the site choice model.

6.2 Site Choice Model

We estimate a site-choice model to elicit preferences for site-specific attributes and use the estimates to calculate the welfare effect from changes in attribute levels. A standard approach is to formulate the angler's site choice problem as a RUM model (Morey et al., 1993; Alvarez et al., 2014). RUM models approach the conditional indirect utility of angler i visiting site j as $U_{i,j} = V_{i,j} + \epsilon_{i,j}$ where $V_{i,j}$ represents the deterministic portion of utility, as observed by the researcher, and $\epsilon_{i,j}$ represents the stochastic error, the component of utility known to the individual but not to the researcher. In the RUM model, angler i is assumed to choose the site that has the highest utility out of the J choices in the individual's choice set in a speecific choice occassion. Thus, the probability angler i visits site j is $Prob[V_{i,j} + \epsilon_{i,j}^{sc} \geq V_{i,k} + \epsilon_{i,k}^{sc} \forall k \neq j]$ Different assumptions about $\epsilon_{i,j}^{sc}$ lead to different types of RUM models. Here, we assume that the error follows a generalized extreme value (GEV) distribution, which results in the nested logit (NL) model.The nested logit model weakens the IIA property by placing site alternatives in relevant nests where the IIA property holds within the nest but not between other nests. Each nest constains a dissimilarity parameter, also called the inclusive value, that measures the correlation between alternatives within the same nest (Morey 1999). If the dissimilarity parameter is equal to 1, then the nested logit model collapses back into the conventional multinomial logit model, shown below. As long as the dissimilarity parameter is not equal to 1, then breaking the IIA property between alternatives is valid. But, for a nested logit model to be consistent with utility maximization theory, the dissimilarity parameter must be between 0 and 1.

We assume a two-level nested logit model where the angler decides on the fishing mode (charter v. non-charter) before site choice. Under this stochastic assumption, the probability of angler i visiting site j is:

$$\pi_{i,j} = \pi_{i,j|m} \cdot \pi_{i,m} \tag{18}$$

where $\pi_{i,j|m}$ is the probability angler i visits site j conditional on fishing mode m and $\pi_{i,m}$ is the probability of angler i choosing fishing mode m. Additional details for the probability of angler i visiting site j conditional on fishing mode m and the probability of angler i choosing fishing mode m can be found in the Appendix. The deterministic portion of utility, $V_{i,j}$ is shown below:

$$\begin{aligned} V_{i,j} = &- exp\left(\gamma\right) \cdot Z_{i,j} + \beta_1 \cdot (PH_j \cdot E[l_{i,j}]) + \beta_2 \cdot (KS_j \cdot E[l_{i,j}]) + \\ &\beta_3 \cdot (SS_j \cdot E\left[l_{i,j}\right]) + \beta_4 \cdot (OF_j \cdot E[l_{i,j}]) + \delta \cdot RSC + \eta \cdot SSC \end{aligned} \tag{19}$$

where $Z_{i,j}$ are the full-cost for angler i visiting site j described further in equation 20, PH_j, KS_j, SS_j, OF_j are the daily historical harvest rates for Pacific halibut, king salmon, silver salmon, and other fish, $E[l_{i,j}]$ is the expected trip length (in days) angler i spends fishing at site j, and RSC and SSC are regional- and site-specific constants. Multiplying the daily historical harvest rate by the expected trip length controls for higher expected harvest with long expected trip lengths. Following recommendations from Carson and Czajkowski (2019), we assume that the marginal utility of money, γ, is strictly negative by specifying the cost term to be the negative exponential of the full-cost coefficient. The full-cost term is the sum of round-trip travel cost and on-site fishing cost. Round-trip travel cost is commonly calculated as the sum of round-trip monetary cost and the monetized cost of travel time (Haab et al., 2012; Alvarez et al., 2014; English et al., 2018). This travel cost calculation is due to the time and money-constrained consumer choice theory that states that an individual making a labor-leisure decision maximize their utility subject to a monetary and time budget constraint (Becker, 1965). Monetary travel cost is the amount of money spent during travel, while the opportunity cost of travel time is time spent in travel converted to a monetary value. The opportunity cost of travel time is the shadow value of travel time (SVTT) multiplied by the travel time to site j. It is common to assume that the SVTT is a proportion of an individual's exogenous income or wage rate (Cesario & Knetsch, 1970; Cesario, 1976). But the exact proportion is unknown forcing economists to make assumptions about the proportion when calculating travel costs. Researchers commonly assume that the proportion is between one-third and the whole wage rate (Cesario, 1976; McConnell & Strand, 1981; Train, 1998; Landry et al., 2012; English et al., 2018). The SVTT can also be jointly estimated with site choice model (Bockstael et al., 1987; Feather & Shaw, 1999; Shaw & Feather, 1999; Lew & Larson, 2005, 2008, 2014). These latter studies find a better statistical fit for models that estimate a proportion of the wage rate to be used in the SVTT calculations rather than assume a constant proportion (Lew & Larson, 2005, 2008). It is likely that the employment status of angler's has an effect on the SVTT as employed angler's are trading a observed wage rate for travel where unemployed anglers are trading a shadow wage for travel. For this reason, we differentiate the SVTT based on employed, E and unemployed, U, anglers when calculating travel costs (Bockstael et al., 1987).

The full-cost term also considers the monetary on-site fishing cost and the shadow value of on-site time. Monetary on-site cost are calculated as the product of the expected trip length multiplied by 8, representing the average hourly time spent fishing per day, shown in equation 11, and the exponential of the logged daily on-site cost estimated in equation 12. We assume that the shadow values of time are the same for travel and time spent on-site (Larson & Shaikh, 2001). The full-cost calculation is shown below:

$$Z_{i,j} = 2 \cdot p_{i,j} + \eta \cdot m_{i,j} + (\kappa_E \cdot w_i \cdot D_E + \rho_U \cdot (1 - d_E)) \cdot (2 \cdot t_{i,j} + 8 \cdot E[l_{i,j}]) \tag{20}$$

where $p_{i,j}$ is the monetary travel cost of angler i visiting site j, $m_{i,j}$ is the monetary on-site cost per fishing day, $\kappa_E \cdot w_i \cdot D_E$ is the proportion of the wage rate used in the SVTT calculations for employed anglers where w_i is angler i's wage rate and D_E is a dummy variable equal to 1 for employed anlgers and 0 for non-employed anglers, ρ_U is the monetary SVTT for unemployed anglers, $t_{i,j}$ is the travel time for angler i visiting site j, and $E[l_{i,j}]$ is the expected fishing trip length measured in days. The log-likelihood function for the site choice model is:

$$LL_2 = \sum_{i=1}^{I} \sum_{j=1}^{J} d_{i,j} ln(\pi_{i,j}) \tag{21}$$

where $d_{i,j} = 1$ if angler i visited site j and 0 otherwise. The joint site-choice, trip length, and on-site cost model are estimated using a full-information maximum likelihood (FIML) function. Appendix A contains the FIML function and additional information about the RPOIZTNB distribution.

7 RESULTS

We use the bbmle package in RStudio to maximize the joint site-choice, trip length, and on-site cost log-likelihood function listed in Equation 39 in the Appendix (Bolker & Bolker, 2017). We first test for equal parameters and scale between the two surveys (Swait & Louviere, 1993). The estimated coefficients and goodness-of-fit parameters for the joint models using the 2012 and 2017 data separately and for cases 1, 2, and 4 are found in section A.4 in the Appendix. We use a log-likelihood ratio test to test the hypothesis of equal parameters and scales between the 2012 and 2017 survey data. Based on the results from the log-likelihood ratio tests, we reject the hypothesis of equal parameters at the 99% confidence level and fail to reject the hypothesis of equal scales at the 99% confidence level. These results suggest the use of case 3 which allows for different preferences between each survey but equal scales for the behavioral models.

7.1 Trip Length Model Results

The selected results for the trip length model can be found in Table 2 and the full results with the on-site cost coefficients and regional- and site-specific constants can be found in section A.4 in the Appendix. The trip length model has two components. The first is the probability that an angler will participate in a single-day trip despite changes in site-specific attributes. We find that the decision to participate in a fishing trip via a cruise excursion or a fishing lodge has a significant influence on the probability of a single-day trip. The results suggest that an angler that participated in a fishing trip from a cruise excursion in 2011 had a 94.3% likelihood of participating in a single-day trip compared to 92.6% likelihood in 2016. However, if an individual participated in a fishing trip from a fishing lodge, there was a 19.4% likelihood of participating in a single-day trip in 2011 and a 17.7% likelihood in 2016.

Table 2: Estimated fishing trip-length coefficients for a one-inflated zero-truncated negative binomial (OIZTNB) model

	Survey Version	
	2012	2017
Probability of Single-Day Trip:		
Constant	0.068	0.221*
	(0.118)	(0.124)
Cruise Dummy	2.733***	2.301***
	(0.718)	(0.513)
Lodge Dummy	-1.492***	-1.761***
	(0.019)	(0.238)
Trip Duration Model:		
Daily On-Site Cost	-0.142***	-0.154***
	(0.048)	(0.037)
Logged Monetary Travel Cost	0.143***	0.088***
	(0.019)	(0.020)
Pacific Halibut	0.225	-0.829**
	(0.158)	(0.408)
King Salmon	17.201***	17.258***
	(2.997)	(4.438)
Silver Salmon	0.392	0.693
	(0.853)	(1.099)
Other Fish	1.899***	2.082***
	(0.605)	(0.634)
Overdispersion Parameter (α)	0.045**	
	(0.018)	
N	475	463
Log-Likelihood	-784.707	-773.019
AIC	1,617.413	1,594.037
BIC	1,717.332	1,693.343

Note: Other Fish includes the historical harvest rates for rockfish, lingcod, "other" salmon, and "other" species

The second component of the trip length model estimates the number of days an individual may spend fishing. We find that travel cost, on-site cost, and select historical harvest rate have a significant impact on trip length. Also, we find that the overdispersion parameter is significantly different from 0 suggesting overdispersion is present in the data and the use of a Poisson distribution would be limiting.

We find that travel cost has a positive and significant correlation with the number of days spent fishing at a given site. This result is consistent with findings in the transportation literature that suggests more expensive travel costs lead to longer trip lengths (Alegre & Pou, 2006). But daily on-site cost has a negative and significant correlation with trip length suggesting that increases in the daily on-site will reduce trip length. This result matches previous expectations as daily on-site cost acts as the own price for trip length and follows the law of demand. We also assume that the daily historical harvest rates for key Alaskan species impact the trip length for anglers in 2011 and 2016. We find that angler preferences for the historical harvest rates for king salmon and "other" species are positive and significant in both surveys. Angler preferences are also positive for silver salmon in 2011 and 2016 but are not statistically significant. The coefficient for Pacific halibut is positive and insignificant in 2011 but negative and significant in 2016. It is possible that the negative coefficient may reflect that once an angler reaches their expected harvest rate of Pacific halibut, they would rather substitute their time spent fishing with a non-fishing activity. Recreational anglers participating in an Alaska saltwater fishing trip commonly ship their harvest to their home address. Shipping fresh fish requires special packaging that can be exponentially expensive as the weight of a fish increases. Since Pacific halibut is a relatively large fish, harvesting an additional Pacific halibut may increase the shipping cost substantially.

The trip length model is linked to the site-choice model via the predicted trip length. The figure below compares the actual trip length to the predicted trip length for anglers in 2011 and 2016. The x-axis represents the actual trip length angler i took to site j and the y-axis represents the predicted trip length from the trip length model. The black line is a 45 degree line from the origin. If the model perfectly predicted trip length, then all observations would fall on the black line. The whiskers of the box-plot represents the 2.5% and 97.5% quantiles. The trip length model over predicts trip lengths for anglers that participated in a single-day trip despite the one-inflation component of the OIZTNB distribution. The model also under predicts trip lengths for anglers that participated in a trip greater than 5 days. However, the trip length model predicts 56.4% of the sample within a single-day and 84.0% within two-days. We do find that the OIZTNB distribution provides better predictions than the traditional ZTNB distribution but methods that attempt to improve the trip length fit are discussed further in section 8.

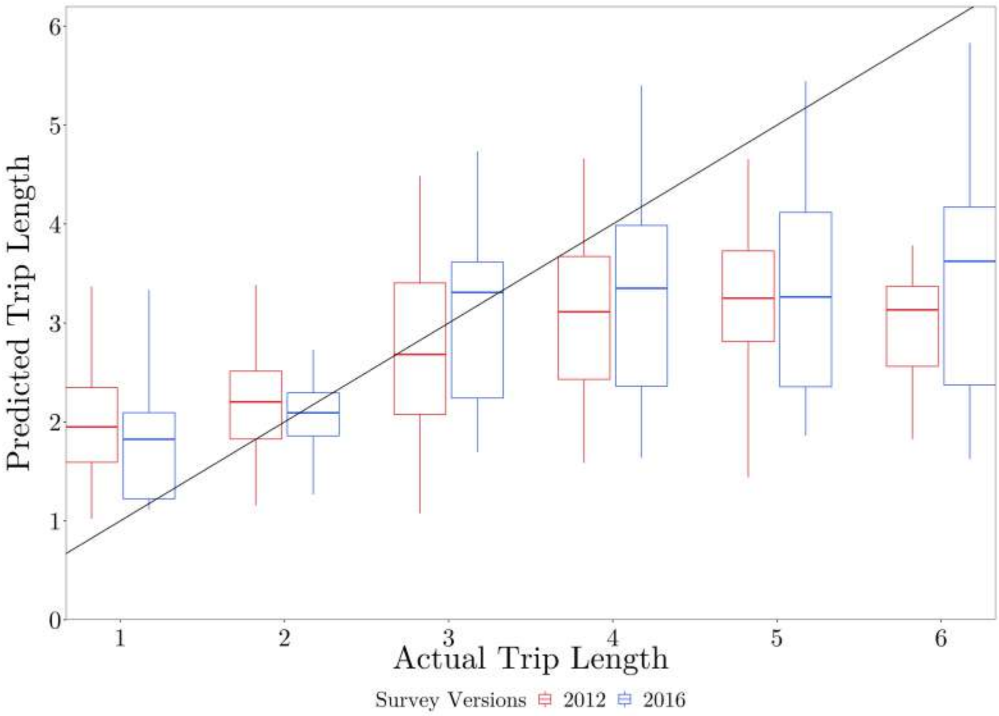

Figure 4: Predicted trip length compared to the length of the actual trip taken by the angler. This graph shows that the OIZTNB distribution slightly over predicts single-day trips and under predicts trips lasting longer than 5 days.

7.2 Site-Choice Model Results

The site choice model is estimated as a two-stage nested logit model where the first decision is mode choice (charter vs. non-charter) followed by site choice. The inclusive value for the first level of the nested logit model, mode choice, is significantly different from 1 in 2011 at the 99% level but is not significantly different from 1 in 2016 at the 10% level suggesting that the IIA property is overly restrictive in 2011 but is not in 2016. The full-cost coefficient is negative and significant matching a priori expectations. This suggests that an angler is less likely to visit a site as it becomes more expensive relative to all other sites in

Table 3: Estimated site-choice coefficients for a jointly estimated site-choice and trip length model

	Survey Version	
	2011	2016
Travel Cost (γ)	-5.290***	-5.584***
	(0.134)	(0.112)
κ_E	0.727***	0.793***
	(0.160)	(0.157)
ρ_U	31.315***	38.843***
	(7.761)	(8.176)
On-Site Cost (δ)	-0.056***	-0.098***
	(0.021)	(0.030)
Pacific Halibut	0.044	0.084
	(0.102)	(0.179)
King Salmon	0.285	-0.569
	(0.858)	(0.689)
Silver Salmon	0.512***	1.001***
	(0.183)	(0.184)
Other Fish	-0.052	0.177
	(0.260)	(0.242)
$IV_{Charter}$	0.940***	0.981***
	(0.067)	(0.072)
N	475	463
Log-Likelihood	-1,105.405	-1,150.360
AIC	2,246.81	2,336.72
BIC	2,321.75	2,411.199

Note: Other Fish includes the historical harvest rates for rockfish, lingcod, "other" salmon, and "other" species

the choice set. The full-cost calculation considers the monetary value of travel and on-site cost and the opportunity cost of time for employed and unemployed anglers. Economists commonly assume that the shadow value of travel time (SVTT) is equal to a proportion of the wage rate where the proportion is assumed to be between 0.25 and 1 (Cesario & Knetsch, 1970; Cesario, 1976). The results suggest that the proportion of the wage rate used in SVTT calculations is near 0.75 for non-resident Alaskan anglers in 2011 and 2016. We estimate the actual SVTT in dollar units for unemployed anglers since they do not have an observable wage rate. The results suggest that the SVTT for unemployed anglers is \$30.82 and \$39.53 in 2011 and 2016. The additional component of the full cost calculation is the monetary value of on-site cost. We find that the monetary on-site cost coefficient is negative and significant suggesting that the cross-price parameter between monetary on-site cost and monetary travel cost is the opposite. This suggests that monetary travel cost may be substituted for monetary on-site cost. In other words, anglers may choose a site that is relatively cheaper to visit and substitute the remaining travel cost with increased on-site costs.

Site choice is also a function of the three-year average daily historical harvest rates of Pacific halibut, king salmon, silver salmon, and "other" fish which consists of lingcod, rockfish, "other' salmon, and "other" species. The daily historical harvest rates are interacted with the expected trip length to illustrate higher expected harvest from longer fishing trips. In 2011 and 2016, the preferences for the historical harvest rates of all species, but king salmon in 2016, are positive. However, only silver salmon is statistically significant in both years. Positive preference coefficients suggest that higher expected harvest rates relative to all other sites will increase the likelihood of angler i choosing site j. Similarly, since the daily expected harvest rates are interacted with the expected trip length, the preference coefficients suggest that longer trips will result in positive utility from increased harvest. Although we do find evidence of differences in the parameters between surveys, it is interesting to note that the coefficients are similar between years for most terms. The full results of the joint model, including the estimated coefficients for the regional- and site-specific constants, the on-site cost model, and goodness-of-fit parameters, are listed in section A.4 in the Appendix.

8 WELFARE ANALYSIS

RUM models are consistent with utility theory which allows for researchers to calculate the compensating variation (CV) for changes in site-specific attributes, excluding travel cost, and site closures (McFadden et al., 1973). The additional trip length decision in our joint model does not change per-trip welfare calculations for the site-choice model. But we do have to consider how changes in site-specific attributes impact trip length since the site-choice model is linked via the expected trip length. Therefore, a change in the historical harvest rate will cause an increase in utility from more catch but disutility from an increase in on-site cost from a longer fishing trip. The sign of the CV estimate largely depends on the relationship between these two opposing effects. The CV calculation for a nested logit model is shown below:

$$CV_i = \frac{log\left(\sum_j^J exp\left(V_{i,j}^1/\lambda_c\right)^{\lambda_c}\right) - log\left(\sum_j^J exp\left(V_{i,j}^0/\lambda_c\right)^{\lambda_c}\right)}{exp\left(\gamma\right)} \tag{22}$$

where γ is the travel cost coefficient, the superscript 0 and 1 indicates calculations using the observed site-specific attributes and hypothetical site-specific attributes, respectively, and λ_c represents the dissimilarity coefficient for the charter nest relative to the non-charter nest. The expected trip length for OIZTNB distribution is shown in equation 11. Since the trip length model considers the stochastic error component from the on-site cost model, we must simulate the expected trip length, as we did during the estimation of the trip length model, to account for potential heterogeneity among anglers. The simulated expected trip length is shown below:

$$\hat{E}\left(L = l_i | \, L > 0\right) = \sum_{r=1}^{R} \omega_i + (1 + \omega_i) \cdot \lambda_i^r \cdot \left(1 - (1 + \alpha \cdot \lambda_i^r)^{\alpha^{-1}}\right)^{-1} \tag{23}$$

where $r = [1, ..., R]$ for R Halton draws.

We simulate a statewide 10% increase in the historical harvest rates of Pacific halibut, king salmon, and silver salmon. We present the mean welfare effect, the mean change in the expected trip length, and 95% confidence intervals for each species using the Krinsky-Robb simulation approach presented in Table 8 (Krinsky & Robb, 1986). This approach is common in the recreational demand literature to provide additional information from welfare estimates. The welfare results are calculated using 5,000 Krinsky-Robb draws.

Table 4: Welfare effect for a 10% statewide increase in the historical harvest rates of Pacific halibut, king salmon, and silver salmon

	Compensating Variation		Change in Expected Trip Length	
	2011	2016	2011	2016
Pacific Halibut				
10%	-\$2.03	\$6.61	0.037	-0.076
	(-\$8.65, \$3.12)	(-\$1.69, \$18.37)	(-0.013, 0.091)	(-0.149, -0.003)
King Salmon				
10%	-\$30.16	-\$12.16	0.404	0.324
	(-\$57.37, -\$5.97)	(-\$56.68, \$36.02)	(0.262, 0.557)	(0.165, 0.522)
Silver Salmon				
10%	\$8.00	\$34.70	0.030	0.052
	(-\$9.54, \$25.17)	(\$18.60, \$59.23)	(-0.107, 0.178)	(-0.113, 0.227)

An increase in the statewide historical harvest rates by 10% yielded a positive CV for Pacific halibut in 2016 and silver salmon in 2011 and 2016. When we increase the statewide historical harvest rate for Pacific halibut in 2016, trip length decreases causing disutility from a shorter fishing trip but utility from a reduction in on-site cost. The reduction in on-site cost outweighs the disutility from a shorter fishing trip causing a positive CV. But in 2011, the opposite occurs. A statewide increase in the historical harvest rate of Pacific halibut causes utility from a longer fishing trip but greater disutility from higher on-site cost leading to a negative CV. In 2011 and 2016, a 10% statewide increase in the historical harvest rate for king salmon causes a large increase in trip length. This causes a large increase in disutility from on-site costs leading to a negative CV. Silver salmon is the only species that has a greater utility from increased catch relative to the disutility of increased on-site time in 2011 and 2016. We do find temporal differences between surveys for each species as preferences for each species and the marginal utility of money change over time and between samples.

We can also calculate the value per-trip using traditional welfare measures. The value per-trip is calculated by artificially closing all sites in the choice set. In other words, the new indirect utility is equal to zero. The per-trip value calculation is shown below:

$$\hat{CV_i} = \frac{log\left(\sum_j^J exp\left(V_{i,j}^0/\lambda_c\right)^{\lambda_c}\right)}{exp(\gamma)} + 0.5572 \tag{24}$$

where 0.5572 is Euler's constant. The mean per-trip values in 2011 and 2016 are \$606.40 (\$465.67, \$762.68) and \$645.10 (\$526.86, \$787.53) in 2016 dollars, respectively, with 95% confidence intervals in the parentheses. A histogram of the Krinsky-Robb per-trip value simulations is found in Figure 6. The per-trip values are similar between surveys and do not show as much temporal change as the welfare estimates.

8.1 Change in Expected Recreational Mortality

Considering trip length allows the researcher to estimate additional endpoints other than the traditional welfare calculations described above. We use the site choice and trip length parameters to calculate the percentage change in the expected recreational mortality for non-resident anglers from statewide and regional changes in bag limits for Pacific halibut from the guidelines set in 2011 and 2016. To calculate the change in expected mortality, we first need to know how harvest may change based on changes in the bag limit. We use a simplified approach to estimate the change in the harvest rate for a one-fish increase in the bag limit. We assume that the expected harvest rate is proportional to the bag limit, shown below:

$$HarvestRatio_j = \frac{E[Harvest_j^0]}{BagLimit_j} \tag{25}$$

This formula implicitly assumes that an increase in the bag limit has no impact on the age distribution from the stock and selectivity of recreational anglers. These are oversimplifying assumptions for many Alaskan species, including Pacific halibut, and a more complex bioeconomic model would be needed to correctly assess how changes in the bag limit may affect the harvest rates as discussed further in Section 8. The purpose of this simplified exercise is to illustrate additional endpoints that can be calculated by considering trip length. We use the expected harvest ratio to calculate the percentage increase to the original historical harvest rate from increasing the bag limit by one fish, shown below:

$$E[Harvest_j^1] = HarvestRatio_j \cdot BagLimit^1 \tag{26}$$

where $BagLimit^1$ is the new bag limit with a one-fish increase. The new and original harvest rates are used to calculate the percentage change in the expected mortality. Expected mortality is calculated as the daily expected harvest rate multiplied by the expected trip length for each site. Since we want to account for substitution effects between sites, we multiply the expected mortality for each site by the probability of visiting that site shown below:

$$E[Mortality_{i,j}] = \pi_{i,j} \cdot E[Harvest_j] \cdot E[l_i, j] \tag{27}$$

where $\pi_{i,j}$ is the joint probability of angler i visiting site j. The percentage change in mortality presented below is calculated as the change between the expected mortality function with the original daily historical harvest and the new historical harvest rates. We simulate the percentage change in mortality using 5,000 Krinsky-Robb simulations.

The Pacific halibut bag limit in 2011 and 2016 for guided recreational anglers was one-fish and two-fish in Areas 2C (southeast Alaska) and 3A (southcentral Alaska), respectively. We consider a statewide increase in the bag limit in 2011 and 2016 by one fish. A statewide increase in the bag limit results in an increase in the historical harvest rate of Pacific halibut by 72.1% in 2011 and 2016. Using the calculations above, we estimate that recreational mortality from non-resident anglers will increase by 75.2% (53.9%, 110.3%) in 2011 and 51.1% (25.2%, 90.9%) in 2016. The increase in recreational mortality is greater than the expected increase in the historical harvest rate because anglers are participating in longer trips in 2011. But in 2016, the opposite occurs. A one-fish increase causes a relatively smaller increase in expected mortality compared to the expected harvest because anglers are participating in a shorter trip. We find similar results for regional changes in Area 2C and Area 3A. The average increase in historical harvest rates for a one-fish increase in the bag limit in Area 2C and Area 3A is 44.2% and 27.9%, respectively. The box plot below illustrates the change in expected mortality compared to the change in harvest rates, illustrated by the red dotted line.

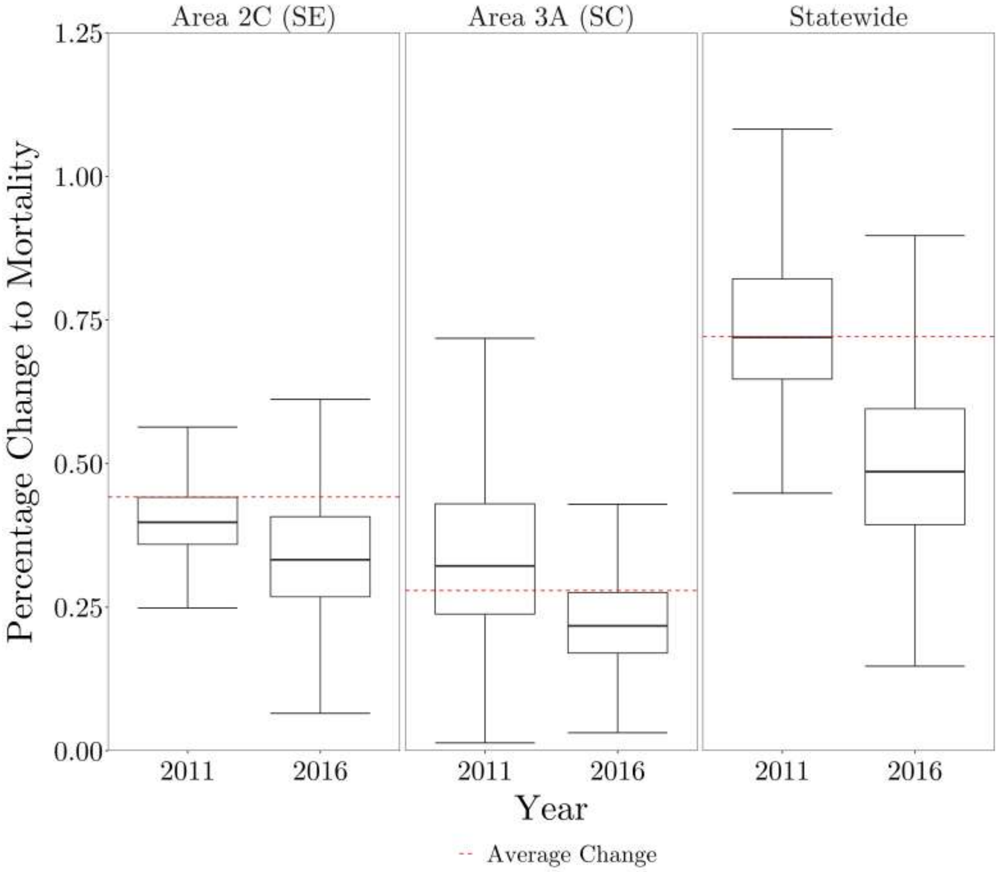

Figure 5: Change in expected mortality from a change in the bag limit in Area 2C, Area 3A, and Statewide (Areas 2C and 3A). The dotted-red line indicates the change in the historical harvest rate.

In the histogram above, we see that regional and statewide increases in the bag limit in 2016 causes an increase in recreational mortality but at a slower rate than the average increase in statewide harvest rates. This is due to the negative coefficient in the trip length model that suggests higher harvest rates shorten fishing times discussed in more detail above. But in 2012, a change in the bag limit in Area 3A increases the expected mortality at a faster rate than the percentage change in the expected historical harvest rate due to the positive coefficient in the trip length model. But in Area 2C, the percentage change in the expected mortality increases at a slower rate than an increase in the historical harvest rate. In Area 2C, a one-fish increase in the bag limit would allow anglers to harvest 2 fish which is the same as the original bag limit in Area 3A. But as we increase the bag limit in Area 2C, there is a substitution effect away from sites in Area 3A and into sites in Area 2C. This causes the expected mortality in Area 3A to decrease as the probability of visiting a site in Area 3A decreases. But the increase in the expected historical harvest rate in Area 2C is less than a one-fish increase in the bag limit. This results in a net decrease from a one-fish increase in Area 2C as the decrease in expected mortality in Area 3A is greater than the increase in expected mortality in Area 2C.

9 CONCLUSION

We develop a linked site-choice, trip length, and daily on-site cost model. This model framework can be applied to various recreational activities where the researcher is interested in the impact a policy change may have on site choice and trip length components. If a researcher is only interested in per-trip welfare effects, then linking site-choice and trip length is not necessary and one can simply estimate a site-choice model (McConnell, 1992). But researchers interested in the on-site time impact, daily welfare effects, or the change in non-welfare endpoints should consider the on-site time and site-choice decisions. Incorporating the site-choice and on-site time components can increase the realism and applicability of MSE models in policy decision making. This model can be improved upon but provides a step forward to incorporate the site-choice and trip length decision in a recreational demand model.

We apply the linked model to two surveys of recreational non-resident anglers that participated in an Alaskan saltwater angling trip in 2011 and 2016. In the trip length model, we find that the historical harvest rates for most key Alaskan species are positively correlated with trip length, matching previous expectations. However, increasing the Pacific halibut harvest rule may shorten trip length as the expected harvest rate is reached more quickly causing a reduction in fishing trip length. We estimate how a change in the bag limit for Pacific halibut will impact the expected non-resident recreational mortality. We find that expected mortality increases with an increase in the bag limit, but at a slower rate than expected due to the shortened trip length. Additionally, spatial changes in the bag limit do not cause uniform spatial changes in the expected harvest mortality as anglers may substitute between sites with different harvest restrictions. We made some simplifying assumptions about the biology of the Pacific halibut stock, angler selectivity, and the change in expected harvest rates from a one-fish increase to the bag limit. Future work will relax these assumptions by introducing additional biological data and models to simulate a recreational bioeconomic model. The simple calculation is meant to illustrate how researchers could utilize changes in trip length to calculate additional endpoints.

This model framework does contain areas that can be addressed in future research. The first is related to the specification of the full-cost term. We currently assume that the marginal utility of money is the same between total travel cost and on-site cost allowing for a simplified welfare calculation. The marginal utility of money may be separated into the marginal utility of money for travel and the marginal utility of money for on-site time. But separating these terms brings additional complications into the welfare calculation that have not yet been addressed. Similarly, we currently assume that the shadow value of time is the same between travel and on-site time but past research suggests that the shadow value of travel time may differ among leisure activities (DeSerpa, 1971; Palmquist et al., 2010). Future work will attempt to disentangle the marginal value of money and the shadow value of time between travel and on-site time improving the realism of the model.

The second area for future research is improving trip length predictions. Predicted trip length is the link between the trip length and site-choice model. Having accurate predictions is crucial for the applicability of this model. We currently use a OIZTNB distribution that weighs predicted trip lengths by the probability of an angler being bound to a single-day trip. But the predicted values in our empirical model tend to under predict single-day trips and over predict trips longer than 5 days. Future work will explore other trip length specifications of the trip length model, such as a hurdle or latent class model, to provide better predictions and potentially the non-participation decision.

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A APPENDIX

A.1 TRIP COST CALCULATIONS

We calculate the travel cost from each respondent's home-base to each fishing site in their choice site. Detailed driving, airfare, and ferry trip costs and travel time data were collected by the Pacific States Marine Fisheries Commission (PSMFC). Commercial airfare and air-time data were collected from the U.S. Department of Transportation's' (USDOT) Bureau of Transportation Statistics based on 2012 and 2016 data (USDOT 2012; USDOT 2017). This data list the average one-way fare and flight time between all airports in 2012 and 2016. Non-commercial (seaplane) airfare and flight time was calculated using the average fare and flight time between locations based on data from Alaska Seaplanes (Alaska Seaplanes 2020). All driving cost to the airport, marine port, and fishing location are computed using the 2012 and 2016 AAA average cost-per-mile of \$0. and \$0.5645, respectively. The AAA average cost-per-mile considers average annual fuel expenditures for a medium-sized sedan with depreciation that travels an average of 15,000 miles per year. This does not include other vehicle costs such as insurance, maintenance, or registration. Maritime costs and times were calculated using the average 2012 and 2016 one-way ferry fare between ports from the Alaskan Maritime Highway System. We assume that non-resident's with a home base outside of Alaska choose the trip with the lowest total travel cost and non-resident's with a home base within Alaska choose the trip with lowest travel time. Since the primary purpose of the fishing trip for anglers with a home base within Alaska was not fishing, they most likely had additional Alaskan activities planned where total trip time had a higher constraint.

A.1.1 Airfare

The initial cost for each respondent is the driving cost from the respondent's home-base to the nearest airport. All driving costs in the model are calculated by multiplying the total distance (in miles) by the 2012 and 2016 AAA average cost-per-mile of \$0. and \$0.5645. Non-residents whose home-base is in Alaska can travel to Juneau, AK or Anchorage, AK from their nearest airport then to the fishing location nearest each fishing site. Juneau and Anchorage are the two largest airports in Alaska and act as a hub for all other Alaskan regional airports. In other words, from Juneau or Anchorage, all other airports can be reached but our data does not allow for direct travel between regional Alaskan airports. The airfare is the average ticket price between each location during 2012 and 2016 based on data from the U.S. Department of Transportation's (USDOT) Bureau of Transportation Statistics (USDOT 2012; USDOT 2017). Respondent's drive the remaining distance from the fishing sites nearest airport to the actual fishing site. If maritime travel is required then we use the driving cost from the airport to the nearest ferry location and the average ferry cost to the port nearest the fishing site plus the driving cost from the ferry port to the fishing site.

Calculating air-travel for non-residents whose home-base is outside of the Alaska is more complicated. Identical to the Alaskan non-residents beginning inside Alaska, the initial driving cost from the address to the nearest airport is calculated for each respondent. However, non-residents beginning outside of Alaska must travel to one of four major airports that made trips to Alaska in 2012 and 2016, Chicago, Honolulu, Portland, or Seattle, before flying to Alaska. Then, from each of these airports, the respondent can fly to Juneau, Anchorage, or, directly to the fishing site if air travel is available. Once the respondent arrives at the nearest airport to each fishing site, the driving cost or ferry cost is calculated from the airport to the actual fishing site mirroring the final step for the Alaskan non-residents. We also allow respondents to travel to Juneau or Anchorage from Chicago, Honolulu, Portland, or Seattle before travelling to the fishing site. The flowchart below illustrates all possible air-travel combinations to reach the same fishing site. This results in 12 possible airfare combinations for each non-resident. Airfare and driving costs are summed together for each possible combination.

A.1.2 Driving

Non-residents whose home-base is within Alaska have the option of driving directly from their home-base to each fishing site in their choice set. If a road is available, then the road distance is used to calculate total driving costs using the AAA average cost-per-mile. But, if no road distance is available, then the straight-line distance is used to calculate the driving costs. This is typically the minimum cost option of travel for non-respondents beginning within Alaska. Non-Alaskan residents whose home-base begins outside of Alaska do not have the option of driving directly from their address to a fishing site.

A.1.3 Maritime

Non-residents beginning within Alaska have the option of taking a ferry to each fishing site in Southeast or Southcentral Alaska. Similar to calculating total airfare, we calculate the driving cost from the resident's home-base to the nearest ferry port. Once at the ferry port nearest the home base, the average cost between each fishing port is the assumed costs of maritime travel to each fishing site if a route is available. From the port nearest the fishing site, we calculate the driving cost from the ferry port to each fishing site. The ferry method with the minimum total time is the assumed maritime route taken that is compared with all other travel methods above. Most respondents whose home base began within Alaska choose to drive directly to the Alaskan site or take ferry.

A.1.4 Travel Time

We then compute the travel time for each step of the trip based on the travel method with the minimum cost for each site. Driving times from the respondents' are recorded using Google Maps and CDX ZipStream (CDXZipStream 2017). Flight times are provided by the USDOT Bureau of Transportation Statistics (USDOT 2013; USDOT 2017). Flight time is the in-air flight time between destinations. Ferry time is the time from departing the port to arriving at the destination port. If commercial airfare is used within the travel route, then an additional 2-hours is added in accordance with the Transportation Security Administration (TSA) recommendations for security, boarding, and other potential delays (TSA 2020). Similarly, if a ferry or seaplane is used within the travel route, then an additional hour is added in accordance with travel recommendations (Alaska Seaplanes 2021; AMHS 2021).

A.2 HISTORICAL HARVEST RATES

Table 5: Expected harvest rates for each site and species by year

	Pacific Halibut		King Salmon		Silver Salmon	
	2011	2016	2011	2016	2011	2016
Southeast Alaska						
Glacier Bay (Gustavus)	0.663	0.551	0.067	0.121	0.348	0.488
Haines (and Skagway)	0.064	0.117	0.072	0.033	0.027	0.027
Juneau	0.249	0.158	0.112	0.079	0.255	0.390
Kake	0.684	0.502	0.024	0.011	0.378	0.299
Ketchikan	0.220	0.177	0.152	0.114	0.634	0.593
Petersburg	0.495	0.411	0.082	0.054	0.152	0.225
Prince of Wales (Klawock)	0.523	0.350	0.109	0.172	1.008	1.113
Sitka	0.394	0.326	0.317	0.401	0.733	0.806
Wrangell	0.261	0.372	0.157	0.099	0.127	0.272
Yakutat	0.721	0.588	0.090	0.080	0.672	0.899
Southcentral Alaska						
Alaska Peninsula (Bristol Bay)	0.594	0.255	0.028	0.013	0.116	0.116
Anchor Point	0.943	0.789	0.055	0.091	0.064	0.074
Anchor Point	1.585	1.442	0.050	0.094	0.103	0.122
Clam Gulch	1.137	0.995	0.041	0.043	0.035	0.042
Clam Gulch	1.668	1.464	0.035	0.060	0.033	0.093
Cordova	0.320	0.371	0.020	0.064	0.421	0.350
Homer	0.943	0.789	0.055	0.091	0.064	0.074
Homer	1.585	1.442	0.050	0.094	0.103	0.122
Kenai	1.137	0.995	0.041	0.043	0.035	0.042
Kenai	1.668	1.464	0.035	0.060	0.033	0.093
Kodiak	0.689	0.547	0.179	0.177	0.378	0.312
Ninilchik (and Deep Creek)	1.137	0.995	0.041	0.043	0.035	0.042
Ninilchik (and Deep Creek)	1.668	1.464	0.035	0.060	0.033	0.093
Seldovia	0.943	0.789	0.055	0.091	0.064	0.074
Seldovia	1.585	1.442	0.050	0.094	0.103	0.122
Seward	0.624	0.572	0.024	0.032	0.917	0.928
Valdez	0.276	0.229	0.028	0.010	1.005	0.737
Whittier	0.286	0.244	0.020	0.019	0.236	0.207

Note: Italicized sites represent historical harvest rates for charter specific trips and the corresponding non-italicized sites represent historical harvest rates for non-charter specific trips

A.3 ADDITIONAL FUNCTIONS FOR THE JOINT SITE CHOICE, TRIP LENGTH, AND ON-SITE COST MODEL

A.3.1 Probability Function for Nested Logit Model

We assume a two level nesting structure where angler i can choose between charter or non-charter modes of fishing before choosing the site. There are 21 sites within the charter nest and 20 within the non-charter nest as Kake was only visited by charter anglers. The probability function for angler i choosing site j can be found in equation 18. The first term in equation 18 is the probability of choosing site j conditional on fishing mode m, shown below:

$$\pi_{i,j|m} = \frac{exp\left(V_{i,j}\right)/\lambda_m}{\sum_{j=1}^{J} exp\left(V_{i,j}\right)/\lambda_m} \tag{28}$$

where λ_m is the dissimilarity coefficient of all charter sites. We constrain the dissimilarity coefficient to be between 0 and 1 to remain consistent with RUM theory by setting λ_m equal to:

$$\lambda_m = \frac{exp\left(\lambda_m\right)}{1 + exp\left(\lambda_m\right)} \tag{29}$$

We cannot estimate a dissimilarity coefficient for each nest. So we constrain the dissimilarity coefficient for non-charter sites equal to 1 and estimate the dissimilarity coefficient related to the charter sites. The second term in equation 18 is the probability of choosing fishing mode m shown below:

$$\pi_{i,m} = \frac{exp\left(\lambda_m \cdot IV_{i,m}\right)}{\sum_{m=1}^{2} exp\left(\lambda_m \cdot IV_{i,m}\right)} \tag{30}$$

where $IV_{i,m}$ is the inclusive value, also known as the log-sum, calculated as:

$$IV_{i,m} = ln \sum_{j \in B_m}^{J} exp\left(V_{i,j}/\lambda_m\right) \tag{31}$$

The probability of choosing fishing mode m is a function of only the inclusive value as most demographics are used in the on-site cost model.

A.3.2 Detailed Probability Function for OIZTNB Distribution

The probability function for the OIZTNB distribution has two components. The first is the probability an angler will participate in only a single-day trip and the second is the probability an angler will participate in a trip of length l if they participate in a multi-day trip. These probabilities can be found in equation 9. The likelihood that angler i will participate in a single-day trip is based on the logit probability of below:

$$\omega = \frac{exp\left(\theta_0 + \theta_1 \cdot D_i^{Cruise} + \theta_2 \cdot D_i^{Lodge}\right)}{1 + exp\left(\theta_0 + \theta_1 \cdot D_i^{Cruise} + \theta_2 \cdot D_i^{Lodge}\right)} \tag{32}$$

where D_i^{Cruise} and D_i^{Lodge} are dummy variable equal to 1 if angler i participated in a fishing trip from a cruise ship and 0 otherwise or if angler i participated in a fishing trip from a fishing lodge and 0 otherwise. To calculate the log-likelihood function for the trip length model, we use the following relationship for the gamma function as shown in Cameron and Trivedi (2013) When determining the probability of a single day trip we add the logit model that determines the likelihood that an individual will participate in only a single-day trip and the probability that the zero-truncated negative binomial distribution is equal to 1 if they participate in a non-single day trip. The probability of 1 for a zero-truncated negative binoimal distribution is:

$$p_+(1, \alpha) = \alpha \cdot \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda}\right)^{\alpha^{-1}} \cdot \frac{\lambda}{\alpha^{-1} + \lambda} \cdot \frac{1}{1 - (1 + \alpha \cdot \lambda)^{\alpha^{-1}}} \tag{33}$$

The second step is estimating the probability an angler will particiapte in a trip of length l if they do participate in a multi-day trip. In other words, the probability they will participate in a trip greater than or equal to 2 days. For this, we need to know the probability of a zero-one-truncated negative binomial distribution. The probability function of a zero-one-truncated negative binomial distribution is:

$$
\begin{aligned}
p_{+}\left(l_i,\alpha\right) =& \frac{\Gamma\left(l_i+\alpha^{-1}\right)}{\Gamma\left(l_i+1\right)\Gamma\left(\alpha^{-1}\right)}\cdot\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda}\right)^{\alpha^{-1}}\cdot\left(\frac{\lambda}{\alpha^{-1}+\lambda}\right)_i^{l}\cdot \\
&\left[1-\left(1+\alpha\cdot\lambda\right)^{-1}-\frac{\Gamma\left(\alpha^{-1}+1\right)}{\Gamma\left(\alpha^{-1}\right)}\cdot\left(1+\alpha\cdot\lambda\right)^{\alpha^{-1}}\cdot\frac{\lambda}{\left(\alpha^{-1}+\lambda\right)}\right]^{-1}
\end{aligned}
\tag{34}
$$

We calculate the log-likelhiood for the OIZTNB distribution using the following shortcut:

$$
ln\left(\frac{\Gamma\left(l_i+\alpha^{-1}\right)}{\Gamma\left(\alpha^{-1}\right)}\right)=\sum_{c=0}^{l_i-1} ln(c+\alpha^{-1}) \tag{35}
$$

where c are discrete integers. Substituting this relationship into equation 38 yields the following log-likelihood function for a single-day trip:

$$
log\left(\pi_i^{TL}(l_i=1)\right) = log\left(\omega+(1+\omega)\cdot\alpha\cdot\left(1+\alpha\cdot\lambda\right)^{\alpha^{-1}}\cdot\frac{\lambda}{\left(1-\left(1+\alpha\cdot\lambda\right)^{-\alpha^{-1}}\right)}\right) \tag{36}
$$

and for a multi-day trip:

$$
\begin{aligned}
\log\left(\pi_i^{TL}(l_i>1)\right) =& log\left(1-\omega\right)+\sum_{c=0}^{l_i-1} log\left(c-\alpha^{-1}\right)-log\left(l_i!\right)-\left(l_i+\alpha^{-1}\right)log\left(1+\alpha\cdot\lambda\right)+l_i log\left(\alpha\right)+ \\
& l_i log\left(\lambda\right)-log\left(1-\left(1+\alpha\cdot\lambda\right)^{\alpha^{-1}}-\alpha\cdot\left(1+\alpha\cdot\lambda\right)^{-\alpha^{-1}}\cdot\left(\frac{\lambda}{\alpha^{-1}+\lambda}\right)\right)
\end{aligned}
\tag{37}
$$

The log-likelihood for the trip length model is simply the sum of these two function multiplied by indicator variables signaling if angler i participated in a single-day or multi-day trip, shown below.

$$
SLL_3=\sum_{i}^{I} d_i^{Multi}\cdot log\left(\pi_i^{TL}\left(l_i>1\right)\right)+d_i^{Single}\cdot log\left(\pi_i^{TL}\left(l_i=1\right)\right) \tag{38}
$$

A.3.3 JOINT LOG-LIKELIHOOD FUNCTION

We maximize the joint log-likelihood function using a full-information maximum likelihood framework. The joint log-likelihood function is the sum of the log-likelihood functions for the on-site cost model and the site-choice model and the simulated log-likelihood for the trip length model, shown below:

$$LL = LL_1 + LL_2 + SLL_3 \tag{39}$$

where LL_1 is the log-likelihood function for the on-site cost model, LL_2 is the log-likelihood function for the site-choice model, and SLL_3 is the simulated log-likelihood function for the trip length model.

A.4 RESULTS FOR A JOINTLY ESTIMATED MODEL FOR CASES 1 THROUGH 3 AND SEPARATELY ESTIMATED JOINT MODELS FOR 2012 AND 2017

Below are estimated coefficients for two independently estimated linked site choice, trip length, and on-site cost models for the 2012 and 2017 survey and the full results for the joint model (Case 3) presented in section 7. These models have identical specifications as described in section 6. We use the log-likelihood values from these models to test the hypothesis of equal parameters between survey versions. We find statistically significant differences between the estimated parameters between the 2012 and 2017 surveys.

Table 6: Estimated site-choice coefficients for a jointly estimated site-choice and trip length model

	Separately Estimated		Jointly Estimated	
	2012	2017	2012	2017
Site Choice Model:				
Travel Cost (γ)	-5.298***	-5.589***	-5.290***	-5.584***
	(0.1289)	(0.1143)	(0.134)	(0.112)
κ_E	0.74***	0.803***	0.727***	0.793***
	(0.1618)	(0.1627)	(0.160)	(0.157)
ρ_U	31.282***	39.324***	31.315***	38.843***
	(7.7443)	(8.4686)	(7.761)	(8.176)
On-Site Cost (δ)	-0.062***	-0.098***	-0.056***	-0.098***
	(0.0221)	(0.0306)	(0.021)	(0.030)
Pacific Halibut	0.044	0.08	0.044	0.084
	(0.0954)	(0.1816)	(0.102)	(0.179)
King Salmon	0.74	-0.544	0.285	-0.569
	(0.7918)	(0.6949)	(0.858)	(0.689)
Silver Salmon	0.498***	1.007***	0.512***	1.001***
	(0.1754)	(0.1857)	(0.182)	(0.184)
Other Fish	0.024	0.162	-0.0523	0.177
	(0.2513)	(0.2485)	(0.260)	(0.242)
Southeast Constant	-0.081	1.366***	0.046	1.351***
	(0.4106)	(0.3588)	(0.416)	(0.354)
η_{Homer}	1.819***	3.558***	2.000***	3.542***
	(0.2756)	(0.414)	(0.304)	(0.405)

η_{Juneau}	1.094*** (0.3875)	0.771** (0.3286)	1.116*** (0.402)	0.765** (0.325)
$\eta_{Ketchikan}$	2.845*** (0.3472)	0.892*** (0.3173)	2.892*** (0.371)	0.901*** (0.316)
η_{Kodiak}	0.258 (0.1801)	2.876*** (0.5969)	1.318** (0.627)	2.851*** (0.589)
$\eta_{DeepCreek}$	0.531*** (0.1153)	0.672 (0.4497)	1.498*** (0.347)	0.677 (0.444)
$\eta_{PrinceofWales}$	0.653 (0.4037)	0.233 (0.453)	0.680* (1.153)	0.236 (0.452)
η_{Seward}	1.079*** (0.278)	1.542*** (0.2364)	1.153*** (0.291)	1.540*** (0.235)
η_{Sitka}	0.5 (0.6591)	0.444 (0.5766)	0.782 (0.670)	0.451 (0.574)
IV - Charter	2.978** (1.471)	0.981*** (0.0723)	0.940*** (0.067)	0.981*** (0.072)
Probability of Single-Day Trip:				
Constant	0.073 (0.1175)	0.219* (0.1239)	0.068 (0.118)	0.221* (0.124)
Cruise Dummy	2.757*** (0.7195)	2.294*** (0.5131)	2.733*** (0.718)	2.301*** (0.513)
Lodge Dummy	-1.507*** (0.2237)	-1.756*** (0.2376)	-1.492*** (0.223)	-1.761*** (0.237)
Trip Duration Model:				
Logged Monetary Travel Cost	0.131*** (0.019)	0.09*** (0.0202)	0.143*** (0.019)	0.089*** (0.020)
Daily On-Site Cost	-0.152*** (0.0479)	-0.152*** (0.0381)	-0.142*** (0.048)	-0.154*** (0.037)
Pacific Halibut	0.286* (0.1614)	-0.813* (0.4153)	0.225 (0.158)	-0.829** (0.408)
King Salmon	18.046*** (2.8318)	17.285*** (4.4602)	17.201*** (2.997)	17.258*** (4.438)
Silver Salmon	0.404 (0.8788)	0.62 (1.111)	0.392 (0.853)	0.693 (1.099)
Other Fish	2.061*** (0.6064)	2.047*** (0.6561)	1.899*** (0.605)	2.082*** (0.634)
Southeast Constant	-1.973*** (0.3985)	0.906*** (0.228)	-1.930*** (0.404)	0.909*** (0.224)

$\eta_{AnchorPoint}$	-0.744*** (0.1693)	-0.164 (0.3943)	-0.697*** (0.168)	-0.142 (0.387)
$\eta_{GlacierBay}$	1.231*** (0.2802)	-2.512*** (0.4247)	1.238*** (0.272)	-2.545*** (0.411)
η_{Homer}	-0.409** (0.1641)	-0.052 (0.3407)	-0.310* (0.166)	-0.045 (0.336)
η_{Juneau}	1.087*** (0.2495)	-1.144*** (0.3539)	1.082*** (0.249)	-1.179*** (0.339)
$\eta_{Ketchikan}$	-0.697** (0.3388)	-2.462*** (0.4763)	-0.609* (0.328)	-2.514*** (0.456)
η_{Kodiak}	-3.904*** (0.6204)	-3.663*** (0.7766)	-3.689*** (0.648)	-3.693*** (0.764)
$\eta_{DeepCreek}$	0.099 (0.1656)	1.015 (0.6649)	0.075 (0.160)	1.048 (0.648)
$\eta_{PrinceofWales}$	-1.642*** (0.5725)	-3.971*** (0.8069)	-1.542*** (0.553)	-4.050*** (0.784)
η_{Seward}	-1.009* (0.5817)	-0.993 (0.8801)	-0.948* (0.561)	-1.072 (0.861)
η_{Sitka}	-4.852*** (0.7712)	-8.816*** (1.5205)	-4.589*** (0.800)	-8.890*** (1.499)
η_{Valdez}	-0.398 (0.7477)	1.148 (0.7494)	-0.395 (0.721)	1.105 (0.742)
$\eta_{Whittier}$	-0.665** (0.2674)	-0.25 (0.3364)	-0.633** (0.263)	-0.259 (0.332)
$\eta_{Yakutat}$	0.81** (0.3845)	-1.776** (0.7189)	0.834** (0.369)	-1.850*** (0.693)
Overdispersion Parameter	0.027 (0.0234)	0.056** (0.0254)	0.045** (0.018)	
On-Site Cost Model:				
Charter Dummy	1.122*** (0.1008)	1.593*** (0.1116)	1.126*** (0.102)	1.594*** (0.111)
Party Size	0.309*** (0.0732)	0.275*** (0.056)	0.309*** (0.073)	0.274*** (0.056)
Party Size^2	-0.026*** (0.007)	-0.021*** (0.0044)	-0.026*** (0.007)	-0.021*** (0.004)
Male	-0.169 (0.1161)	0.005 (0.1188)	-0.169 (0.117)	0.005 (0.119)
	0.637***	0.508***	0.626***	0.513***

Graduate Dummy	(0.1546)	(0.16)	(0.155)	(0.160)
Undergraduate Dummy	0.574*** (0.1453)	0.674*** (0.1492)	0.552*** (0.145)	0.678*** (0.149)
Household Size	-0.04** (0.0202)	0.076** (0.033)	-0.037* (0.020)	0.076** (0.033)
Logged-Age	1.207*** (0.0531)	1.038*** (0.0511)	1.208*** (0.053)	1.038*** (0.051)
Standard Deviation (s)	1.087*** (0.0357)	1.107*** (0.0365)	1.087*** (0.036)	1.107*** (0.036)
N	475	463	475	463
Log-Likelihood	-2,605.868	-2,627.488	-5,231.099	
AIC	5,313.735	5,356.977	10,664.20	
BIC	5,526.064	5,524.759	11,153.42	

Next, we estimate four "cases" when combing the 2012 and 2017 survey versions (Swait & Louviere, 1993). The first case suggest that there exist equal parameters between both survey versions, including the scale coefficient. Case 2 improves the flexibility of the model slightly by allowing for scale differences between the two surveys while maintaining the assumption of equal parameters between the survey versions. A scale coefficient different from zero suggest scale differences between survey versions. We test the presence of scale differences by jointly testing if the scale coefficient in the utility model and the trip length model are significantly different from zero. We fail to reject the null hypothesis that both terms are jointly equal to zero. Finally, we test for parameter differences between the surveys using a log-likelihood test between the independently estimated models and case 2. We reject the null hypothesis of equal parameters between survey versions. The next 2 cases allow for differences between coefficients. Case 3 is slightly more limited than case 4 due to the assumption of equal scales among survey versions. The results suggest that there are not scale differences between the two surveys matching the findings from cases 1 and 2. Case 4 allows for parameter and scale differences. The results for case 3 are presented in table A.4. These are the main results presented in the paper.

Table 7: Estimated coefficients for cases 1, 2, and 4 for a joint site-choice, trip length, and daily on-site cost model

	Case 1		Case 2		Case 4	
	2012	2017	2012	2017	2012	2017
Site Choice Model:						
Travel Cost (γ)	-5.404***		-5.472***		-5.333***	-5.589***
	(0.0695)		(0.0713)		(0.152)	(0.1142)
κ_E	0.414***		0.36***		0.717***	0.802***
	(0.0757)		(0.0697)		(0.158)	(0.1625)
ρ_U	21.036***		18.482***		30.817***	39.304***
	(4.0259)		(3.793)		(7.676)	(8.4613)
On-Site (δ)	-0.105***		-0.104***		-0.056***	-0.098***
	(0.022)		(0.0229)		(0.0207)	(0.0306)
Pacific Halibut	0.275***		0.264***		0.046	0.079
	(0.0722)		(0.0663)		(0.096)	(0.1817)
King Salmon	1.954***		2.119***		0.302	-0.544
	(0.5283)		(0.5021)		(0.821)	(0.6946)
Silver Salmon	0.718***		0.604***		0.493***	1.006***
	(0.112)		(0.1107)		(0.176)	(0.1856)
Other Fish	0.190		0.242*		-0.055	0.162
	(0.1295)		(0.133)		(0.244)	(0.2483)
Southeast Constant	-0.335		-0.479**		0.042	1.365***
	(0.2341)		(0.2163)		(0.394)	(0.3587)
η_{Homer}	2.209***		1.843***		1.890***	3.558***
	(0.1566)		(0.1748)		(0.273)	(0.4140)
η_{Juneau}	1.441***		1.348***		1.062***	0.771**
	(0.2117)		(0.2026)		(0.335)	(0.3286)
$\eta_{Ketchikan}$	2.266***		2.1***		2.751***	0.892***
	(0.2024)		(0.1939)		(0.224)	(0.3173)
η_{Kodiak}	0.945**		0.519		1.250**	2.876***
	(0.3669)		(0.3617)		(0.518)	(0.5969)
$\eta_{DeepCreek}$	0.834***		0.695***		1.427***	0.673
	(0.2495)		(0.2308)		(0.316)	(0.4497)
$\eta_{PrinceofWales}$	-0.406		-0.518		0.662*	0.233
	(0.380)		(0.3547)		(0.347)	(0.4530)
η_{Seward}	1.506***		1.287***		1.104***	1.542***
	(0.1863)		(0.1844)		(0.263)	(0.2364)
η_{Sitka}	-0.094		-0.27		0.742	0.444
	(0.4076)		(0.3805)		(0.579)	(0.5766)

IV - Non-charter	0.911***	0.889***	0.960***	0.981***
	(0.0483)	(0.0465)	(0.067)	(0.0723)
Scale Coefficient		0.215***	0.048	
		(0.0646)	(0.112)	
Probability of Single-Day Trip:				
Constant	0.272***	0.28***	0.070	0.219*
	(0.0839)	(0.0824)	(0.1177)	(0.1239)
Cruise Dummy	2.527***	2.486***	2.730***	2.294***
	(0.4136)	(0.4127)	(0.7180)	(0.5132)
Lodge Dummy	-1.814***	-1.827***	-1.494***	-1.757***
	(0.1546)	(0.1524)	(0.2232)	(0.2376)
Trip Duration Model:				
Logged Monetary Travel Cost	0.089***	0.077***	0.141***	0.090***
	0.0166	(0.0178)	(0.0189)	(0.0202)
Daily On-Site Cost	0.044	0.065*	-0.145***	-0.152***
	0.0364	(0.0373)	(0.0476)	(0.0381)
Pacific Halibut	0.134	0.105	0.240	-0.815**
	0.1565	(0.1493)	(0.1595)	(0.4153)
King Salmon	-0.338	-0.59	17.319***	17.294***
	1.1915	(1.0952)	(2.9428)	(4.4613)
Silver Salmon	0.539	0.558*	0.366	0.622
	0.3408	(0.3307)	(0.949)	(1.1110)
Other Fish	0.004	-0.095	1.949***	2.048***
	0.1632	(0.16)	(0.6031)	(0.6559)
Southeast Constant	0.749***	0.788***	-1.921***	0.906***
	0.1549	(0.1537)	(0.3999)	(0.2279)
$\eta_{AnchorPoint}$	0.412**	0.431***	-0.707***	-0.164
	0.1911	(0.1653)	(0.1677)	(0.3943)
$\eta_{GlacierBay}$	-0.302	-0.372**	1.224***	-2.514***
	0.1858	(0.1777)	(0.2720)	(0.4245)
η_{Homer}	0.067	0.081	-0.325*	-0.052
	0.1669	(0.1606)	(0.1665)	(0.33407)
η_{Juneau}	-0.092	-0.18	1.083***	-1.145***
	0.1592	(0.1547)	(0.2475)	(0.3538)
$\eta_{Ketchikan}$	-0.552***	-0.563***	-0.627*	-2.464***
	0.1848	(0.1786)	(0.3286)	(0.4761)
η_{Kodiak}	0.331	0.398**	-3.720***	-3.665***
	0.2276	(0.202)	(0.6368)	(0.7766)

$\eta_{DeepCreek}$	0.518***		0.548***		0.081	1.017
	0.201		(0.181)		(0.1594)	(0.6646)
$\eta_{PrinceofWales}$	-0.395		-0.391		-1.552***	-3.974***
	0.3106		(0.2961)		(0.5537)	(0.8067)
η_{Seward}	-0.339		-0.279		-0.937*	-0.995
	0.3149		(0.3049)		(0.9368)	(0.8800)
η_{Sitka}	-0.637*		-0.55*		-4.633***	-8.822***
	0.3548		(0.3013)		(0.7887)	(1.5205)
η_{Valdez}	0.199		0.146		-0.368	1.147
	0.3262		(0.3167)		(0.7243)	(0.7494)
$\eta_{Whittier}$	0.275		0.331		-0.648**	-0.250
	0.2362		(0.2316)		(0.2627)	(0.3364)
$\eta_{Yakutat}$	-0.358		-0.386		0.826**	-1.777**
	0.2527		(0.2365)		(0.3705)	(0.7187)
Overdispersion	0.098***		0.044*	0.171***	0.032	0.055**
Parameter (α)	0.0236		(0.025)	(0.0497)	(0.0245)	(0.0254)
On-Site Cost Model:						
Charter Dummy	0.996***	1.504***	0.946***	1.518***	1.128***	1.593***
	0.0966	0.1194	(0.0976)	(0.1165)	(0.1014)	(0.1116)
Party Size	0.252***	0.23***	0.238***	0.233***	0.308***	0.275***
	0.0703	0.0536	(0.0693)	(0.0535)	(0.0732)	(0.0560)
Party Size^2	-0.023****	-0.017***	-0.022***	-0.018***	-0.026***	-0.021***
	0.0069	0.0045	(0.0069)	(0.0045)	(0.0071)	(0.0044)
Male	-0.148	0.029	-0.143	0.029	-0.169	0.005
	0.1101	0.1149	(0.1086)	(0.1154)	(0.1164)	(0.1188)
Graduate Dummy	0.518***	0.467***	0.495***	0.448***	0.631***	0.508***
	0.1532	0.1613	(0.152)	(0.161)	(0.1548)	(0.1600)
Undergraduate Dummy	0.439***	0.546***	0.421***	0.541***	0.558***	0.674***
	0.1423	0.1508	(0.1413)	(0.1502)	(0.1448)	(0.1492)
Household Size	-0.005	0.077**	-0.001	0.076**	-0.039*	0.076**
	0.0169	0.0309	(0.0159)	(0.0308)	(0.0204)	(0.0330)
Logged-Age	1.256***	1.092***	1.27***	1.092***	1.208***	1.038***
	0.0513	0.0522	(0.0512)	(0.0515)	(0.0532)	(0.0511)
Standard Deviation (s)	1.084***	1.11***	1.085***	1.11***	1.087***	1.107***
	0.0354	0.0367	(0.0354)	(0.0367)	(0.0357)	(0.0365)
N	475	463	475	463	475	463
Log-Likelihood	-5,354.823		-5,346.249		-5,230.958	
AIC	10,829.65		10,816.50		10,667.92	

BIC	11,120.27	11,116.81	11,166.82

A.5 ADDITIONAL RESULTS

The figure below is depicts Krinsky-Robb simulations of the value per trip anglers in 2011 and 2016. The simulations suggest that anglers in 2016 valued an Alaskan fishing trip more than in 2011. There is some overlap in the tails of each distribution but the medians are significantly different.

Figure 6: Frequency of per-trip values among the 2011 and 2016 surveys