Sold-Out: Implications for Non-Market Valuation*

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Abstract. The composition of alternatives in individual choice sets may change as popular alternatives sell out. In using aggregate choice data in the estimation of random utility models (RUM) and corresponding willingness to pay (WTP) measures, analysts may not observe individual choice sets and incorrectly conclude that sold-out alternatives were available to all consumers at the choice occasion. This misspecification may lead to biased parameter and corresponding WTP estimates. We develop a two-step approach which models the probability of sellouts to account for sell-out bias. We apply the approach to model angler choice of recreational fishing trips, and we find the two-step model provides significantly higher WTP measures for attributes associated with sold-out alternatives.

Keywords. fisheries, marketing, nonmarket valuation, random utility models

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Introduction

Consumers often face fewer choices when previous customers purchase and deplete the available stock of a preferred product. These "sellouts" can occur in many different markets, including markets for recreation such as a ticket for a play, a place to camp at a national park, or a spot on a sportfishing trip—the empirical focus of this study.

In the context of random utility models, failure to account for sellouts may lead to bias in the parameter estimates of choice attributes. While the aggregate choice-set is known, knowledge of the choice-set at the individual choice occasion is rarely available. In the absence of information on the actual choice set at the time of decision, the analyst may incorrectly interpret the observed choice as the preferred choice—and the characteristics of the observed choice as preferable to the characteristics of sold-out venues not chosen.

In the standard random utility model (RUM) framework, the consumer chooses between a static set of alternatives at each choice occasion. While early modeling efforts allowed consumers to face individual choice sets constructed of different alternatives—see Haab and Hicks (1999) for a survey of the literature—they did not account for the possibility that earlier arrivals to the market could impact the availability of alternatives for later arrivals. In contrast, following Conlon and Mortimer (2013), our application relaxes the assumption that the practitioner knows the composition of the choice set available to each individual at the time of the choice occasion. While the econometrician may know the aggregate choice set prior to selection, once alternatives are chosen and sell out, the choice set under consideration for future consumers are a subset of the initial choice set. If the econometrician does not observe who actually faced these sellouts, naïvely applying a static choice set onto a conditional logit model may lead to incorrect parameter estimates.

Beyond fishing, many other recreational activities, such as hunting and camping, are characterized by sellouts. In the recreational setting, sellouts can occur frequently because the market mechanism is constrained either by regulation, resources, or, as in our case, infrequent price changes. For instance, Boxall (1995) and Little et.al. (2006) exploit lotteries for hunting permits for econometric estimation.[1] As another example, national park campgrounds are notoriously sold out.[2] While sellouts in our setup are within a profit-driven market and occur due to relatively sticky prices announced far in advance, the natural resource literature is prone to this type of error because the distribution of goods is not often market-driven.

We proceed with an introduction to the literature and a description of our empirical application. We then describe the standard framework and our modified model. This is followed by a presentation of the estimation results for both the standard our modified model. We conclude with a discussion of the results.

Literature

A large body of literature has been produced advancing choice modeling. This literature spans subject areas such as recreational demand and marketing, and it addresses many technical issues ranging from preference heterogeneity to the formation of the choice set.

Notably, many applications other than sellouts offer similar modeling challenges. In the recreation literature, the closest paper to ours is Haab and Hicks (1997). The application of this paper was to evaluate the behavior of survey takers at two different beach locations (Chesapeake Bay's western shore and New Bedford, Mass.). The likelihood function combined a multinomial logit framework with a probability model for whether choices actually appeared in the consideration set for

[1] These papers are discussed in further detail in the literature section.
[2] The National Park Service (2015 and 2017) warns visitors that at the Grand Canyon, "…campgrounds hustle and bustle and are often filled to capacity," and at Yosemite National Park there is a warning: "Be aware that nearly all reservations for the months of May through September and for some other weekends are filled the first day they become available, usually within seconds or minutes after 7 am!"

any particular individual. Like our results, this paper found substantial differences between the traditional multinomial logit model and their alternative model.

In addition to consideration sets, another related issue is crowding. McConnell (1977) discussed crowded beaches and used congestion as an explanatory variable in the main estimating equation. This solution for crowding does not translate well to sellouts, as sellouts are different than crowding, since crowded places are still available in the choice set. An example of congestion analysis in the recreational fishing literature, along with a literature review, is found in Schuhmann and Schwabe (2004). They add expected congestion into a random utility framework and carefully map out how the utility response to crowding may differ between catch-and-release anglers and catch-and-keep anglers. As in McConnell (1977), this paper models congestion as a characteristic that impacts utility; whereas if a site is sold out, the choice is eliminated from the choice set of some individuals.

Besides price, lotteries are another method to allocate scarce resources that would otherwise sell out. Several papers in the recreation literature look at recreation lotteries—Boxall (1995) [antelope hunting]; Little, et.al. (2006) [elk hunting]; and Yoder, Ohler, and Chouinard (2014) [whitewater rafting]. These three papers explore how to model lottery-allocated recreation goods. Lotteries add complexity to the decision-making process since consumption of the final good and who receives the supply is randomized. This contrasts to our setup, in which anglers enter the market with a 0-1 opportunity to purchase a ticket on a particular vessel, based on whether that vessel sells out.

Economists have also explored modifications to choice sets outside the resource economics context. Putler and Lele (2003) estimate demand for college theater, which occasionally, sells out, by specifying McFadden's (1974) multinomial logit model differently. First, they estimate aggregate shares of attendance. After specifying aggregate shares, the estimating equation specifies that if estimated aggregate attendance would exceed the capacity of the theater, sales would simply be the capacity of the theater. This analysis works in part because the supply of tickets is the same in every play and is fairly straightforward to model; our application involves variable supply of trips. DeShazo, Cameron, and Saenz (2009) modify the standard multinomial logit model to measure the impact of outside options for travel to Costa Rica. They are able to add an additional parameter to test whether relevant choices are being omitted from the model.

The mathematics of estimating a sellout have been explored in depth in the marketing literature on many product applications. Musalem, et.al. (2010) use Bayesian econometrics to simulate stock-outs of shampoo. The authors of this paper modify the multinomial logit model and implement MCMC methods to arrive at a Bayesian posterior distributions of model parameters. Conlon and Mortimer (2013) explores sellouts in the context of vending machines that sometimes run out of particular products. This paper uses a likelihood function which averages all possible combinations of potential choice sets. Both Musalem, et.al. (2010) and Conlon and Mortimer (2013) are focused on estimating lost revenues from stock-outs in addition to gathering parameters of their RUM. Conlon and Mortimer's method does have one disadvantage—it is extremely difficult to estimate. Each potential choice set enters as a factor in the likelihood, leading to 2^N factors, where N is the number of stock-outs. The numerical estimation is a discussion in their paper. Our application has an extremely large 2^N.[3]

Finally, it is possible to explore sellouts without the use of an underlying logit framework. Other alternatives to these methodologies include Fox (2007) and Gupta and Çakanyıldırım (2016). Fox suggests maximum score estimation, and Gupta and Çakanyıldırım compare the multinomial logit model to their proposed mathematical model that is robust to sellouts and has other desirable properties. Gupta and Çakanyıldırım also provide a review of recent marketing literature on the topic.

[3] Computationally complex methods are becoming more popular in the recreation literature as well. A working paper by Reeling, Verdier, and Lupi (presented 2016) is estimating willingness to pay for big bear hunting in Michigan. Their willingness to pay estimation required the use of 20 parallel processers. While not complex by today's standard, Carson, Haneman, and Wegge (2009) outlines use of a then (in the 1980s) computationally-complex nested logit framework used to predict salmon fishing demand in Alaska.

This paper also contributes to the large literature in fisheries economics, particularly recreational fisheries. For a survey of different methodological approaches that have been taken in this literature, see Johnston, et.al. (2006), which does a meta-analysis of 48 studies. Papers that look at assumptions made in standard utility models for recreation demand include Hicks and Strand (2000); Kaoru, Smith, and Liu (1995); Parsons and Hauber (1998); Parsons, Plantinga, and Boyle (2000); Schuhmann (1998); and Scrogin, et.al. (2004). Hicks and Strand (2000) closely examine the list of alternative sites for their set of recreational anglers; these assumptions of what to include or exclude in the choice set ultimately may impact parameter estimates. Parsons and Hauber (1998) and Parsons, Plantinga, and Boyle (2000) similarly explore the expansion and contraction of choice sets, and how an econometrician's decision to include or exclude choices in the model impact parameter estimates for models of Maine fisheries. Kaoru, Smith, and Liu (1995) discuss the theoretical difficulties they faced in choosing an appropriate list of choices in their analysis of North Carolina fisheries. Schuhmann (1998) and Scrogin, et.al. (2004) integrate Poisson models of expected catch before they do willingness-to-pay assumptions.

Nested logit models are a generalization of multinomial logit models that allow for multi-step decision making. These are different than sellouts because sellouts are not decisions made by the angler. However, they can be of use in predicting angler response when a large set of decision are made to avoiding closed sites (Carson, Hanemann, and Wegge (2009))—or when there are multiple site areas and adequate data on non-participation (Greene, Moss, and Spreen (1997)).

One unique contribution this paper makes is it looks into a census of trips, which allows us to estimate model parameters without making assumptions about the representativeness of agents in the model. In contrast, much of the fisheries literature relies on angler or recreator surveys [Parsons and Kealy 1992 (general lake recreation); Jankus, Dadakas, and Fly 1998; Shaw and Ozog 1999; Hauber and Parsons 2000; Lew and Larson 2011; Larson and Lew 2013]. Kuriyama, Hilger, and Hanemann (2013) discuss the possibility of using Monte Carlo simulation methods and information on survey effort to correct for sampling done at particular recreation sites. In contrast to angler surveys, Carter and Liese (2010), use hedonic pricing and a survey of boat pricing. Surveys are also popular for other recreational activities. Dimara and Skuras (1998) explore caves—and mutlinomial logit models—through a survey on how cave admittance should work in Northwest Greece. Lanz and Provins (2013) use a RUM to analyze a survey for parameters for environmental improvement near Seaham, England. Rodrigues et.al. (2016) uses surveys and a random-parameter logit framework to determine losses associated with climate-change associated sea warming and acidification in the Mediterranean. Hynes, Hanley, and Garvey (2007) estimate separate models for different whitewater rafting skill sets and find that different skill sets have different parameter vectors after estimating a conditional logit RUM.

Empirical Application

Our empirical application focuses on the San Diego County, CA, based charter- and head-boat recreational fleet. The fleet offers trips targeting highly migratory species (HMS) sportfish, such as bluefin tuna (*Thunnus orientalis*), yellowfin tuna (*Thunnus albacares*), albacore tuna (*Thunnus alalunga*), dolphinfish (*Corypahaena hippurus*), and yellowtail amberjack (*Seriola lalandi dorsalis*) (the “five species of interest”).

Anglers travel nationally and internationally to fish for these species on vessels that offer specialized trips that range from a few hours to a week or even more. In 2012, the commercial passenger fishing vessel (CPFV) industry contributed to supporting 1,500 jobs in Southern California and added $1.0 billion of value to the economy as a whole (Hilger 2014; National Marine Fisheries Service 2014).

Trips are commonly classified into different trip types based on the length of the trip. Focusing on the five species of interest, our analysis uses aggregate passenger choice data for overnight, 1½ day, and 2 day[4] trips during the 2012 high season (July 2-September 30[5]), where the five species make up a majority of the catch. Table 1 reports species catch composition by trip length type. Trips less than one day are excluded as species of interest are not commonly caught. Trips longer than two days are not considered in the model as they often involve specialized itineraries and added amenities. Both the shorter and longer trips are considered to be parts of different markets.[6] Each weekend or set of connected weekdays is considered one choice occasion, with Friday considered part of the weekend.

Data for model estimation comes from several data sources. Skippers are required to enter species caught, number of anglers (passengers), and additional trip characteristics, into the *Skipper's Log Book*, forms from which are subsequently submitted to the California Department of Fish and Wildlife (CDFW). This database forms a census of CPFV vessel trips. Log book records were analyzed to classify logbook entries into trip types (Hilger and Sweeney 2013). Vessel characteristic data is provided by the U.S. Coast Guard and the California Department of Fish and Wildlife vessel registration data. To determine price information, we build a dataset from internet archives and other provided information.[7]

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[4] In equations, we will refer to "i day," with "1 day," "1½ day," and "2 day" referring to "overnight," "1½ day," and "2 day," respectively. In Table 1, there is a trip called "full day." "Full day" is different than "overnight" in that full day typically fishes for one fisherman's work day, while overnight trips typically last around 24 hours.

[5] July 1 was excluded since it would be the only day in one particular weekend in July.

[6] Regarding shorter trips, there was also very little variation in the price of shorter trips, which made increased willingness to pay for better amenities either zero or unidentified. Regarding longer trips, in the beach recreation context, Yeh, Haab, and Sohngen (2006) is an excellent overview of the challenges of including the correct basket of recreational goods when trips could be a classified as what they call "multiple-objective trips." In an extremely long trip, this would include recreation on the water, fishing, food, and lodging.

[7] For the purposes of choice-set building, for 2-day trips, the weekday or weekend status is based off of the first day fished. For purposes of prices, the price is a combination of fishing days. The Internet Archive's Wayback Machine is a large database that crawls and stores websites as they appear during the crawl (archive.org). Most vessels in 2012 booked through websites. We attempted to use 2012 data to the extent possible; in some cases, we imputed 2012 prices from inflation-adjusted 2013 or 2014 prices. Actual price paid is not observed, so we assume that anglers paid the posted price. In some cases, there was low price variability on a vessel—in this case, we averaged the prices for each vessel-trip combination. In other cases, vessels employed more nuanced pricing schemes, in which case we brought this temporal scheme into the data. For charter trips, the price per angler was calculated by dividing the vessel's charter rate by the number of passengers aboard the trip. For a small number of trips, no price information was available, and these were dropped from the analysis.

As the *Skipper's Log Book* only provides aggregate passenger data at the trip level, we do not have complete data on the anglers themselves.[8]

In our application, 59.4% of non-chartered trips in the sample sell out, suggesting that estimation of a standard RUM could result in biased parameter and welfare estimates. In this setting, boats advertise trip prices well in advance—before realizing actual demand. Thus, they are unable to clear the market through the typical price mechanism.

Our parameter of interest is the proportion of species caught that are in the five species of interest. This will focus attention on the primary species targeted and landed by the skipper. The Southern California CPFV fishery differs from most other charter and head boat fisheries because vessels are opportunistic in which species they target. The five species of interest are difficult to target; while local availability of HMS species is exogenous to skipper decisions, skippers can increase the odds of catching HMS species through knowledge, skill, capital (vessel characteristics and electronic technology), and increased search (burning fuel and increasing costs). On specific trips, vessels that are unable to catch HMS commonly will switch to secondary species groups, such as rockfish and bass. The objective of this study is to provide an estimate of the willingness to pay of consumers for increases in the expectation of catching primary target species relative to secondary target species.

Model development

We start by following a standard random utility model (McFadden 1974). Denote U_{ir} to be the utility of angler $i = 1,\ldots,I$ and trip r. There are T choice occasions, $t = 1,\ldots,T$. In our case, the choice occasion is a set of connected weekdays or the connected weekend, with Friday being considered the weekend. The set of choices available during time occasion t is $\boldsymbol{\rho}_t$, with $r \in \boldsymbol{\rho}_t$. In this setup, $U_{ir} = v_{ir} + \varepsilon_{ir}$, where v_{ir} is the

[8] Occasionally, online portal information provided information on the total size of the trip. For many trips, we also do not know the total number of tickets available; this has to be inferred for many trips based on historical sales. While capacity of the vessel may be available, it is apt to change based on the trip type.

deterministic component, and ε_{ir} is random, Type I Extreme Value, error. The probability of selecting trip $r \in \boldsymbol{\rho}_t$ is:

$$\frac{\exp(v_{ir})}{\sum_{\hat{r}\in\boldsymbol{\rho}_t}\exp(v_{i\hat{r}})} \tag{1}$$

The deterministic component, $v_{ir} = \mathbf{x}_{ir}'\boldsymbol{\beta}$, includes price and fish catch variables. The willingness to pay (WTP) for a particular trip attribute, j, is given by $-\beta_j/\beta_{\text{price}}$. Equation (1) is estimated using maximum likelihood.

Let Ξ_r equal (fish that are in the five species) ÷ (total fish caught) for the vessel-trip type combination from the previous year.[9] Since there are new entrants, we also estimate a parameter for missing Ξ_r. Denote prop_r:

$$\text{prop}_r = \begin{cases} \Xi_r & \text{not missing } \Xi_r \\ \bar{\Xi}_r & \text{missing } \Xi_r \end{cases} \tag{2}$$

Here, we take average Ξ_r ($\bar{\Xi}_r$) and use this for vessels without a Ξ_r. Our estimating equation is:

$$\begin{aligned} v_{ir} = \sum_{\iota\in\{1,1½,2\}} \tau_\iota \times \text{prop}_r \times 1\{r \text{ is trip type } \iota\} + \left[\sum_{\iota\in\{1½,2\}} \phi_\iota \times 1\{r \text{ is trip type } \iota\}\right] + \beta_{\text{price}}\text{price}_r \\ + \beta_\Xi \times 1\{\text{missing } \Xi_r\} + \beta_s \times (\text{vessel length}_r \times \text{vessel beam size}_r) + \beta_{a(1)} \times \text{vessel age}_r \\ + \beta_{a(2)} \times (\text{vessel age}_r)^2 \end{aligned} \tag{3}$$

Here, $\varphi_{1½}$ and φ_2 represent coefficients on dummies for whether the trip was 1½ day or 2 days (with 1 as the base). We estimate with and without this term $\left[\sum_{\iota\in\{1½,2\}} \phi_\iota \times 1\{r \text{ is trip type } \iota\}\right]$: These are the "long" and "short" models. Results for this setup without accounting for sellouts are presented in Table 2.

[9] We analyzed pure fish counts, and we found prop_r was the most appropriate variable for our context. Pure fish counts take into account angler skill, which we considered given. Pure fish counts also take into account potentially reduced catches from vessel crowding. Although some information may be available on vessel websites, the final angler count is ultimately realized at trip departure. In this market, vessels are awarded for being able to target fish species that are highly valued, so prop_r is a good indicator or the vessel's ability to find species of interest without implicating angler skill, which the vessel doesn't directly control.

Sell-out model

The sell-out model proceeds in the following way:

1. Estimate a probability model to assign a probability of the vessel being sold out.
2. Assign a queue spot and subsequent probability of the vessels being sold out for each passenger-trip combination. Simulate whether these sellouts are realized.
3. Run the WTP model based on the final choice sets.

Steps (2) and (3) are run 1000 times over possible choice sets.

Step one

First, we run a linear probability model for Step One.[10] Denote N_t as the number of anglers during timeframe t, and denote **v** to be a vector of vessel fixed effects for vessels $v = 1,\dots,V$.

$$1\{r \in \boldsymbol{\rho}_t \text{ is soldout}\}$$

$$= \alpha_0 + \delta_1 N_t + (\delta_2 N_t^2) + \sum_{v=1}^{V} \mathbf{v}' 1\{r \text{ on vessel } v\} + \sum_{m \in \{\text{July,Aug}\}} \eta_m 1\{r \text{ is during } m\}$$

$$+ \sum_{\iota \in \{1½,2\}} \theta_\iota \times 1\{r \text{ is } \iota\text{-day}\} + \sum_{\iota \in \{1,1½,2\}} \mu_\iota \,\text{price}_r 1\{r\ is\ \iota\text{-day}\} + \varepsilon_r \tag{4}$$

We do not use the $\delta_2 N_t^2$ term because the AIC is higher without it. We also retrieve the standard error of the forecast for this equation, which we denote $\hat{\sigma}_{lr}$. Results for equation (4) are presented in Table 3.

Step two

For angler i, draw parameter:

$$\hat{g}_i \sim U(0,1) \tag{5}$$

[10] Sellouts are inferred. Charter boats are not considered sold-out; we assume that a similar charter boat would have been available. They are not included in (4), but they are included in the second stage if they were boarded to account for those who boarded charter boats instead of head boats.

This parameter simulates the queue of anglers, and we use $\hat{\delta}$ from (4) to subtract out a proportion of the sellout probability based on simulated arrival time. The probability of sellout will be $\hat{\delta}\hat{g}_i N_t$ lower if the angler arrives earlier. Define p_{ir} as:

$$p_{ir} \coloneqq \widehat{\text{soldout}}_{rt} - \hat{\delta}\hat{g}_i N_t \quad (r \in \boldsymbol{\rho}_t) \tag{6}$$

We draw $q_{1ir} \sim U(0,1)$ and $q_{2ir} \sim N(0,1)$. Trip r is eliminated from the choice set for angler i if (a) it is sold out, (b) it is a headboat, and (c) the following holds:

$$q_{1ir} \leq p_{ir} + \hat{\sigma}_{Ir} q_{2ir} \tag{7}$$

Here, q_{1ir} is a weighted coinflip to determine if the vessel is sold out in this instance.

Step three

We run equation (1) on the set of vessels in the choice set.

Alternative logit model

We also run Step One with a logit model.

$$\begin{aligned} &P(r \in \boldsymbol{\rho}_t \text{ is soldout}) \\ &= F\Bigg(\alpha_0 + \delta_1 N_t + (\delta_2 N_t^2) + \sum_{v=1}^{V} \mathbf{v}' 1\{r \text{ on vessel } v\} + \sum_{m \in \{\text{July,Aug}\}} \eta_m 1\{r \text{ is during } m\} \\ &+ \sum_{\iota \in \{1½,2\}} \theta_\iota \times 1\{r \text{ is } \iota\text{-day}\} + \sum_{\iota \in \{1,1½,2\}} \mu_\iota \, \text{price}_r 1\{r \; is \; \iota\text{-day}\}\Bigg) \end{aligned} \tag{8}$$

With $F()$ denoting the cumulative logistic distribution. We then draw $\hat{\lambda}_i \sim U(0,1)$ to simulate the queue. The probability of being sold out is estimated using a market of $\widehat{N}_{it} = \hat{\lambda}_i N_t$. The probability of being sold out for (i,r), given fitted values denoted with hats, is $\pi_{ir} = P(r \in \boldsymbol{\rho}_t \text{ is soldout} \mid \hat{\alpha}_0, \hat{\boldsymbol{\delta}}, \hat{\mathbf{v}}, \hat{\boldsymbol{\eta}}, \hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\mu}}, \widehat{N}_{it})$. Draw $q_{ir} \sim U(0,1)$. The trip is eliminated if (a) it is sold out, (b) it is a headboat, and (c) the following holds:

$$q_{ir} \leq \pi_{ir} \tag{9}$$

One disadvantage of this method is that if a vessel-trip type combination is imputed as always or never sold out, it cannot enter this estimation, and is not adequately modeled. For the second stage, vessel-trip type combinations that are always sold out are considered to have modeled probability of sellout equal to 1, which we adjust downward by $\hat{\delta}\hat{g}_i N_t$, where $\hat{\delta}$ is the estimate from the *linear* first-stage model, equation (4). Vessels that were never sold out will always be in the choice set.

Table 3 shows the result of both the linear and logit first stage.

Results

Results for the standard model are presented in Table 2. For the short version of the standard model, with the restriction that $\varphi_{1½} = \varphi_2 = 0$, WTP for trips that solely catch fish in the five species of interest are \$37, \$82, and \$232 for overnight, 1½ day, and 2 day trips, respectively. This result suggests that a ten-percentage point increase in the proportion of five-species fish caught on an overnight trip would be valued at \$3.71, or 10% of \$37.13. The unrestricted model shows there is no additional WTP for fish in the five species for 1½ or 2 day trips beyond what is already implied by taking such a trip. The WTP for the 1½ and 2 day trips over the overnight trip are $\varphi_{1½}$ = \$122 and φ_2 = \$252, respectively.

To view how the model may change by chance with different parameter draws, we run Steps 2 and 3 for the sell-out model again 1000 times using both the linear and logit corrections. Table 5 shows the median point estimates for each of these WTP calculations recovered from these draws, with all 1000 draws plotted in an online appendix. Values increase, with the exception of φ_2. As an example in Table 4, we present the results of the first draw of the sell-out model using both linear and logit first stages. The medians for the runs of the restricted linear sell-out model are \$161, \$209, and \$434, for WTP for overnight, 1½ day, and 2 day trips, respectively, and \$191, \$209, and \$527 for the logit sell-out model (Table 5).

Test of the Model

To test the difference between the standard and sell-out models, we calculate delta-method confidence intervals around $[\beta_{ij}/\beta_{\text{price}} - \alpha_j/\alpha_{\text{price}}]$, where $\boldsymbol{\beta}_i$ represents the j coefficients for the i = 1,…,1000 draws of the sell-out model, and $\boldsymbol{\alpha}$ represents the coefficients in the standard model. If $\beta_{ij}/\beta_{\text{price}} - \alpha_j/\alpha_{\text{price}} = 0$, then $\beta_{ij}/\beta_{\text{price}} = \alpha_j/\alpha_{\text{price}}$, and thus that individual pull of WTP for j in the sell-out model ($\beta_{ij}/\beta_{\text{price}}$) equals the WTP value in the standard model ($\alpha_j/\alpha_{\text{price}}$). In the online appendix, for various characteristics are plotted 1000 times, and we find that $\beta_{ij}/\beta_{\text{price}} \neq \alpha_j/\alpha_{\text{price}}$ for every individual pull on all characteristics tested for both the logit and linear models.

Conclusions

We have presented a methodological approach to account for sellouts in the context of discrete choice RUMs. We utilized a two-stage model which estimates the probability of sellouts in the first stage, and we used recovered estimates to inform the creation of individual choice sets in the second stage RUM estimation. The methodology is applied to a sportfishing dataset where the variable of interest is the relative proportion of catch of high value sportfish. Empirical estimation results indicate that the proposed model accounts for sell-out bias and produces statistically significant, larger welfare estimates for desirable attributes that are associated with sold-out alternatives.

While many activities experience frequent sellouts, these sellouts have not been accounted for in empirical models used to estimate WTP. While recent advances have been made in the marketing literature, these advances are currently computationally burdensome for large choice sets with large numbers of sellouts. With no information on sellouts, the analyst may incorrectly assume that the consumer has chosen their utility maximizing choice, when, in fact, they may be choosing from a less-preferred subset of the choice set. As resource managers frequently utilize welfare measure estimates as a component of cost-benefit or damage analysis, it is important to get them correct.

This particular model has a few advantages. It is straightforward to run and is easily implemented. In contrast to some other models, it also works with a large number of sellouts.

Our empirical analysis models recreational sportfishing boat and trip choices as a function of the type of fish catch. Estimates of the amount that consumers would be willing to pay for proportional increases in highly valued catch landed were generally lower in the standard model: WTP estimates in a naively estimated model were different from the proposed model by $2.85 per percentage-point increase on a two-day trip [long, linear model]. This large discrepancy may be explained by the popularity of the trip—they are so popular they sell out. Analysis of the relationship between the size of the bias and the incidence of sellouts is a promising area for future research.

Bibliography

Boxall, P.C. 1995. "The Economic Value of Lottery-Rationed Recreational Hunting." *Canadian Journal of Agricultural Economics* 43(1):119-31.

Carson, R.T., W.M. Hanemann, and T.C. Wegge. 2009. "A Nested Logit Model of Recreational Fishing Demand in Alaska." *Marine Resource Economics* 24(2):101-29.

Carter, D.W., and C. Liese. 2010. "Hedonic Valuation of Sportfishing Harvest." *Marine Resource Economics* 25(4):391-407.

Conlon, C.T., and J.H. Mortimer. 2013. "Demand Estimation Under Incomplete Product Availability." *American Economic Journal: Microeconomics* 5(4):1-30.

DeShazo, J.R., T.A. Cameron, and M. Saenz. 2009. "The Effect of Consumers' Real-World Choice Sets on Inferences from Stated Preference Surveys." *Environmental and Resource Economics* 42(3):319-43.

Dimara, E., and D. Skuras. 1998. "Rationing Preferences and Spending Behavior of Visitors to a Scarce Recreational Resource with Limited Carrying Capacity." *Land Economics* 74(3):317-27.

Fox, J.T. 2007. "Semiparametric Estimation of Multinomial Discrete-Choice Models Using a Subset of Choices." *RAND Journal of Economics* 38(4):1002-19.

Greene, G., C.B. Moss, and T.H. Spreen. 1997. "Demand for Recreational Fishing in Tampa Bay, Florida: A Random Utility Approach." *Marine Resource Economics* 12(4):293-305.

Gupta, V., M. Çakanyıldırım. 2016. "A WTP-Choice Model: Empirical Validation, Competitive and Centralized Pricing." *Production and Operations Management* 25(11):1866-84.

Haab, T.C., and R.L. Hicks. 1997. "Accounting for Choice Set Endogeneity in Random Utility Models of Recreation Demand." *Journal of Environmental Economics and Management* 34:127-147

Haab, T.C., and R.L. Hicks. 1999. "Choice Set Considerations in Models of Recreation Demand: History and Current State of the Art." *Marine Resource Economics* 14(4):271-81.

Hauber, A.B., G.R. Parsons. 2000. "The Effect of Nesting Structure Specification on Welfare Estimation in a Random Utility Model of Recreation Demand: An Application to the Demand for Recreational Fishing." *American Journal of Agricultural Economics* 82(3):501-14.

Hicks, R.L., and I.E. Strand. 2000. "The Extent of Information: Its Relevance for Random Utility Models." *Land Economics* 76(3):374-85.

Hilger, J. 2014. "2013 California Marine Recreational Fishing Trip Effort and Economic Impact Estimates." National Marine Fisheries Service, Southwest Fisheries Science Center, La Jolla, CA.

Hilger, J., and J.R. Sweeney. 2013. CA CPFV Skipper Logbook Trip-Type Classification:1995-2012.

Hynes, S., N. Hanley, and E. Garvey. 2007. "Up the Proverbial Creek Without a Paddle: Accounting for Variable Participant Skill Levels in Recreational Demand Modelling." *Environmental and Resource Economics* 36(4):413-26.

Jakus, P.M., D. Dadakas, and M.J. Fly. 1998. "Fish Consumption Advisories: Incorporating Angler-Specific Knowledge, Habits, and Catch Rates in a Site Choice Model." *American Journal of Agricultural Economics* 80(5):1019-24.

Johnson, R.J., M.H. Ranson, E.Y. Besedin, and E.C. Helm. 2006. "What Determines Willingness to Pay Per Fish? A Meta-Analysis of Recreational Fishing Values." *Marine Resource Economics* 21(1):1-32.

Kaoru, Y., V.K. Smith, J. Long Liu. 1995. "Using Random Utility Models to Estimate the Recreational Value of Estuarine Resources." *American Journal of Agricultural Economics* 77(1):141-51.

Kuriyama, K., J. Hilger, and M. Hanemann. 2013. "A Random Parameter Model with Onsite Sampling for Recreation Site Choice: An Application to Southern California Shoreline Sportfishing." *Environmental and Resource Economics* 56(4):481-97.

Lanz, B., and A. Provins. 2013. "Valuing Local Environmental Amenity with Discrete Choice Experiments: Spatial Scope Sensitivity and Heterogeneous Marginal Utility of Income." *Environmental and Resource Economics* 56(1):105-30.

Larson, D.M., and D.K. Lew. 2013. "How do Harvest Rates Affect Angler Trip Patterns?" *Marine Resource Economics* 28(2):155-73.

Lew, D.K., and D.M. Larson. 2011. "A Repeated Mixed Logit Approach to Valuing a Local Sport Fishery: The Case of Southeast Alaska Salmon." *Land Economics* 87(4):712-29.

Little, J.M., K.M. Grimsrud, P.A. Champ, and R.P. Berrens. 2006. "Investigation of Stated and Revealed Preferences for an Elk Hunting Raffle." *Land Economics* 82(4):623-40.

McConnell, K.E. 1977. "Congestion and Willingness to Pay: A Study of Beach Use." *Land Economics* 53(2):185-95.

McFadden, D. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics*, ed. P. Zarembka, 105-42. Academic Press: New York.

Musalem, A.M., M. Olivares, E.T. Bradlow, C. Terwiesch, and D. Corsten. 2010. "Structural Estimation of the Effect of Out-of-Stocks." *Management Science* 56(7):1180-97.

National Marine Fisheries Service. 2014. "Fisheries Economics of the United States 2012," NOAA

Technical Memorandum NMFS-F/SPO-137.

National Park Service. 2015. "Campgrounds – Grand Canyon National Park." Available via the Internet Archive Wayback Machine. https://web.archive.org/web/20150205165808/http://www.nps.gov/grca/planyourvisit/campgrounds.htm.

National Park Service. 2017. "Campground Reservations – Yosemite National Park." Available via the Internet Archive Wayback Machine. https://web.archive.org/web/20170629013501/https://www.nps.gov/yose/planyourvisit/camping.htm.

Parsons, G.R., and A.B. Hauber. 1998. "Spatial Boundaries and Choice Set Definition in a Random Utility Model of Recreation Demand." *Land Economics* 74(1):32-48.

Parsons, G.R., A.J. Plantinga, and K.J. Boyle. 2000. "Narrow Choice Sets in a Random Utility Model of Recreation Demand." *Land Economics* 76(1):86-99.

Parsons, G.R., and M.J. Kealy. 1992. "Randomly Drawn Opportunity Sets in a Random Utility Model of Lake Recreation." *Land Economics* 68(1):93-106.

Putler, D.S., S. Lele. 2003. "An Easily Implemented Framework for Forecasting Ticket Sales to Performing Arts Events." *Marketing Letters* 14(4):307-20.

Reeling, C., V. Verdier, and F. Lupi. 2016. "Valuing Natural Resources Allocated by Dynamic Lottery." Paper presented at the 2016 Agricultural and Applied Economics Association, Boston, 31 July-2 Aug 2016.

Rodrigues, L.C., J.C.J.M. van den Bergh, M.L. Loureiro, P.A.L.D. Nunes, and S. Rossi. 2016. "The Cost of Mediterranean Sea Warming and Acidification: A Choice Experiment Among Scuba Divers at Medes Islands, Spain." *Environmental and Resource Economics* 63(2):289-311.

Schuhmann, P.W. 1998. "Deriving Species-Specific Benefits Measures for Expected Catch Improvements in a Random Utility Framework." *Marine Resource Economics* 13(1):1-21.

Schuhmann, P.W., K.A. Schwabe. 2004. "An Analysis of Congestion Measures and Heterogeneous

Angler Preferences in a Random Utility Model of Recreational Fishing." *Environmental and Resource Economics* 27(4):429-50.

Scrogin, D., K. Boyle, G. Parsons, and A.J. Plantinga. 2004. "Effects of Regulators on Expected Catch, Expected Harvest, and Site Choice of Recreational Anglers." *American Journal of Agricultural Economics* 86(4):963-74.

Shaw, W.D., and M.T. Ozog. 1999. "Modeling Overnight Recreation Trip Choice: Application of a Repeated Nested Multinomial Logit Model." *Environmental and Resource Economics* 13(4):397-414.

Yeh, C.Y., T.C. Haab, and B.L. Sohngen. 2006. "Modeling Multiple-Objective Recreation Trips with Choices over Trip Duration and Alternative Sites." *Environmental and Resource Economics* 34(2):189-209.

Yoder, J.K., A.M. Ohler, and H.H. Chouinard. 2014. "What Floats Your Boat? Preference Revelation from Lotteries over Complex Goods." *Journal of Environmental Economics and Management* 67(3):412-30.

Tables

Table 1.

Trip Types—Fish Caught

	AM ½-Day	PM ½-Day	¾ Day	Evening	Full Day*	Overnight*	1½ Day	2 Day	Multiday	
Bass	42%	48%	24%	40%	30%	5%	3%	1%	1%	Bass
Rockfish	27%	23%	33%	11%	18%	9%	9%	7%	4%	Rockfish
Other	30%	28%	36%	31%	28%	8%	7%	4%	6%	Other
Five Species	1%	1%	6%	18%	24%	76%	80%	86%	89%	Five Species
Other Tuna	0%	0%	0%	0%	1%	3%	1%	2%	0%	Other Tuna

* “1 day” in equations refers to “overnight,” which are trips around 24 hours. “Full day” refers to trips that are typically one fisherman’s workday.

Table 2.
Parameter estimates from the standard model.

	SHORT MODEL	CORR. WTP	LONG MODEL	CORR. WTP
BEAM X LENGTH	0.000648***		0.000648***	
	(32.34)		(32.30)	
VESSEL AGE	0.0116**		0.0138***	
	(3.24)		(3.60)	
SQUARE VESSEL AGE	-0.000111**		-0.000136**	
	(-2.68)		(-3.08)	
PRICE	-0.00174***		-0.00188***	
	(-23.02)		(-23.21)	
PR X OVERNIGHT	0.0647	37.13	0.153**	81.27**
	(1.48)	(1.47)	(3.25)	(3.23)
PR X 1½ DAY	0.143***	82.23***	-0.0354	-18.83
	(4.66)	(4.73)	(-0.48)	(-0.48)
PR X TWO DAY	0.404***	231.8***	-0.0190	-10.09
	(11.16)	(12.73)	(-0.19)	(-0.19)
Ξ UNAVAILABLE†	0.0981***		0.0915***	
	(5.83)		(5.40)	
1½-DAY BINARY			0.229**	121.9**
			(3.25)	(3.28)
2-DAY BINARY			0.474***	252.1***
			(4.87)	(5.11)
N	707277		707277	
PSEUDO R^2	0.0203		0.0206	
AIC	129141.3		129114.9	
LOG LIK.	-64562.7		-64547.4	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table demonstrates the coefficients recovered and the corresponding willingness to pay parameters for the standard random utility model. Based on the random utility model in the long specification, an overnight trip for which half of the catch is the five species of interest is valued \$81.27(10%) = \$8.13 more than an overnight trip for which 40% are the five species of interest—and \$81.27(20%) = \$16.25 more than an overnight trip for which 30% are the five species of interest.

† Ξ unavailable parameter is described in the text. If a Ξ was not found, we used the average for Ξ and a binary variable. The coefficient for the binary variable is shown. *t*-statistics in parenthesis.

Table 3.

	Linear Probability Model	Logit Model
Number of Anglers in the Market	0.000248	0.00136
	(1.88)	(1.96)
Price × Overnight	-0.00163	-0.0131*
	(-1.62)	(-1.97)
Price × 1½ Day	0.000101	0.00423
	(0.06)	(0.39)
Price × 2 Day	-0.0022	-0.0146
	(-1.66)	(-1.76)
July Binary	-0.238**	-1.285**
	(-3.06)	(-3.10)
August Binary	-0.0553	-0.303
	(-1.12)	(-1.19)
1½-Day Binary	-0.418	-4.207
	(-0.94)	(-1.36)
2-Day Binary	0.809	4.996
	(1.39)	(1.36)
N	557	520
R^2 / Pseudo R^2	0.277	0.205
AIC	681.9	628.3
Log Likelihood	-303.9	-282.1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

t-statistics in parenthesis. For linear model, these are robust standard errors; for logit, they are standard. Vessel fixed effects included (with base constant).

This is the result of the first-stage of the sell-out model. We also ran a linear model with squared number of anglers in the market; however, the AIC was lower than the linear probability model reported.

The standard deviation of the forecast for the linear second stage does not use robust standard errors; however, both standard errors are very close, and the standard deviation of the forecast is larger than the robust alternative standard deviation of prediction.

Table 4.
One draw of each sell-out model

	LINEAR 1ST STG SHORT MODEL	CORR. WTP	LINEAR 1ST STG LONG MODEL	CORR. WTP	LOGIT 1ST STG SHORT MODEL	CORR. WTP	LOGIT 1ST STG LONG MODEL	CORR. WTP
BEAM X LEN	0.00113***		0.00113***		0.00120***		0.00120***	
	(55.45)		(55.48)		(58.00)		(58.02)	
AGE	0.0284***		0.0328***		0.0467***		0.0511***	
	(7.83)		(8.54)		(12.86)		(13.36)	
AGE²	-0.000313***		-0.000360***		-0.000550***		-0.000598***	
	(-7.51)		(-8.24)		(-13.21)		(-13.73)	
PRICE	-0.00189***		-0.00200***		-0.00178***		-0.00188***	
	(-25.32)		(-25.22)		(-24.11)		(-24.05)	
PROP X	0.299***	157.9***	0.389***	195.0***	0.338***	189.8***	0.434***	230.6***
OVERNIGHT	(6.68)	(6.29)	(8.13)	(7.73)	(7.41)	(6.85)	(8.84)	(8.26)
PROP X 1½	0.397***	209.8***	0.0939	47.00	0.371***	208.1***	0.0580	30.86
DAY	(12.85)	(12.26)	(1.26)	(1.26)	(11.93)	(11.32)	(0.79)	(0.79)
PROP X 2	0.821***	434.2***	0.559***	279.6***	0.940***	527.7***	0.699***	371.5***
DAY	(22.68)	(22.72)	(5.41)	(5.17)	(25.89)	(23.40)	(6.81)	(6.36)
PROP N/A,	0.231***		0.221***		0.272***		0.264***	
USED AVG.	(13.16)		(12.55)		(15.35)		(14.74)	
1½ DAY BIN			0.341***	170.6***			0.352***	187.1***
			(4.83)	(4.86)			(5.05)	(5.07)
2 DAY BIN			0.322**	161.4***			0.305**	162.0**
			(3.24)	(3.34)			(3.07)	(3.16)
N	485806		485806		486107		486107	
PSEUDO R²	0.0547		0.0550		0.0568		0.0570	
AIC	111908.7		111882.6		111765.5		111738.4	
LL	-55946.4		-55931.3		-55874.7		-55859.2	

t-statistics in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

This table presents one draw of each sell-out model: One draw using the linear first stage and one draw using the logit first stage. The sell-out model is run (separately for linear and logit) 1000 times, and medians are provided in in Table 5. All draws are shown graphically in the online appendix.

Table 5.
Medians of sell-out model vs. standard model

	Short Standard	Short Linear	Short Logit	Long Standard	Long Linear	Long Logit
WTP 1½ day				$122	$165	$191
WTP 2 day				$252	$165	$159
Pr × Overnight	$37	$161	$191	$81	$198	$232
Pr × 1½ day	$82	$209	$209	-$19	$52	$27
Pr × 2 day	$232	$434	$527	-$10	$275	$375