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RANDOM UTILITY MODELS OF RECREATIONAL FISHING: CATCHING FISH USING A POISSON PROCESS

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Abstract *This paper presents a Poisson model of expected angler catch during a sportfishing trip and employs the expected catch in a random utility model of site choice. The approach permits greater heterogeneity in expected catch and in individual welfare estimates from policies such as creel limits.*

Keywords Sportfishing, creel limits, expected catch.

Introduction

In modelling the demand for recreation, the random utility maximization (RUM) model has some appealing features. These stem in part from its stochastic structure and the modelling of recreation as a generic good. Sites are assumed to be the same except for qualities which are measurably different across them. The different qualities or attributes become arguments in the indirect utility function, and their effects on site selection are estimated as part of the model. Policies can influence people through changing quality attributes. The convenient form of the probability functions follows from the extreme value assumption for the errors.

The effectiveness of the RUM in modelling the impact of policy on quality variables depends on the choice and construction of the quality variables. Many types of variables have been used to measure the quality of recreational resources. For all of the measures of quality, the individual's choices should be guided by *ex ante* beliefs about quality—that is, quality is not known until the individual gets to the site. The good cannot be examined and then rejected, as one might a car or an orange. For fishing and hunting, expectations of quality should vary among individuals. Because of innate skills, such as sight or touch, good anglers will on average catch more fish than less talented ones. In addition, predetermined or exogenous influences on quality differ among individuals. For example, some hunters are more experienced than others and expect higher bags. Finally, the quality attribute varies across people who purchase different inputs

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for the activity, such as an angler hiring a guide or a hunter renting a premium goose blind.

While RUM models can be used to measure the value of access to recreational sites, they have frequently been employed to measure the scarcity of resource stocks. In fisheries, this scarcity may be induced with pollution, which injures the stocks, or by excessive commercial or recreational harvest. The pathway by which policy remedies these effects typically starts with the making of regulations. These alter the behavior of polluters or harvesters which in turn changes the size and composition of the stocks of the relevant species, which then change the attractiveness of the sites. When the recreation quality improves at various sites, people choose the improved sites more frequently, revealing welfare measures through these changes in behavior. Consequently, the quality variable plays a critical role. Resource policies ultimately make their impact on recreation through this variable.

RUM models that have been estimated on marine sports fishing have contained simple treatments of catch rates and other measures of the trip's quality. Catch rates have typically been constant across anglers. That is, the catch rate varies from one site to another, but different anglers at the same site expect the same catch rate. This use of constant measures of quality may be traced to modelling constraints improved by data. Typically, only central tendencies of catch by site, not by individual, are available. Table 1 shows the measurement of the different quality variables for many studies of recreational fishing. These studies measure fishing success at a site that is represented by the central tendency of catch per trip or other unit of time.

Catch rate and success variables can be classified into three types: historic, sample-specific, and subjective. The historic variables are usually based on a creel survey such as the NMFS intercept survey.[1] This survey was designed to measure catch per trip for the "representative" trip, by mode, species and season. The NMFS survey also allows the calculation of the percent of successful anglers. Bockstael *et al.* (1989), Morey et al. and Thomson use this type of quality variable. The sample-specific catch rate is derived from catch statistics which are gathered during the same sampling process that secures the basic trip and cost information. Such surveys ask anglers about their trip, socioeconomic variables and catch. The catch data can be used individually or averaged across sites. The Milon, Kaoru, and Arndorfer and Bockstael studies use this type. The subjective type is simply an index, created by persons knowledgeable about the sites and the activities that take place there. The Wegge *et al.* and Bockstael *et al.* (1986) studies use a subjective index. In modelling the effects of a quality variable, there is a tradeoff between subjective perceptions of quality objective measures of quality. Perceptions motivate actions. Indeed, all sources of knowledge filter through perceptions. But policy actions are easier to link empirically to objective measures of quality.

Of the studies in Table 1, only Bockstael *et al.* (1989) use an objective measure of quality which varies among individual anglers. They interact a mean historic catch with an individual-specific dummy variable associated with a species. But this only assures that the correct mean catch rate applies to an angler seeking a

[1] The MRFSS intercept survey (Marine Recreational Fishing Statistical Survey) samples anglers on site which they are fishing.

Table 1
Approximate Measures of Success in Random Utility Models of Recreational Fishing

Authors	*Measure of Quality*
Arndorfer and Bockstael	Actual catch rates are reported although there is a discussion of preliminary regressions which used expectations.
Bockstael, Graefe, Strand and Caldwell (1986)	Expectations of catch at different artificial reef sites. Also expectations of the likelihood of being skunked.
Bockstael, McConnell and Strand (1989)	Catch rate from NMFS survey[a] for one of four species/mode group interacted with dummy variable which determined whether angler sought a species within the group.
Kaoru	Average number of fish actually caught by anglers interviewed at each site, from North Carolina recreational fisheries survey which generated trip data.
Milon	Mean pounds of fish (kept or released) per unit fishing effort for each site from mail survey of Dade County Florida; coefficient of variation for pounds of fish per unit effort, from mail survey of Dade County, Florida; survey also generated choice data.
Morey, Rowe and Shaw[b]	Mean catch per angler by species group, from NMFS data; Mean catch per angler catching the species, from NMFS data; Mean catch per angler targeting the species, from NMFS data.
Thomson	Percent of anglers In NMFS survey targeting species who caught at least one of the species, by mode and area; Percent of all anglers, by mode and area, who land at least one fish of any species, from NMFS survey.
Wegge, Carson, and Hanemann	An index of the quality of fishing for each species group, by site and week; A site rating for species at the site.

Notes
[a]All data in this table which are described as NMFS survey data come from the NMFS intercept survey.
[b]As defined in Rowe et al., page 4–24.

particular species group. Catch rates are the same for anglers seeking a given species at a given site.

In this paper, we model several critical aspects of the catch rate. By considering catch to be an expectation formed by a Poisson process, we allow the catch to be random. By allowing attributes of anglers to influence the mean, we allow for systematic variation of catch across anglers. When attributes of anglers are used to predict the distribution of catch among them, the differential effects of constraints on catch (*e.g.* creel limits) can be estimated for different classes of anglers. Welfare effects should be rather widely dispersed when angling ability is crucial to catching fish. And, as we show below, the specification provides an intuitively appealing pathway to analyze the effects of changes in populations of fish. We apply the model to smallgame fishing in Maryland.

Combining Site Choice with the Poisson Process

The RUM approach to modelling choice among marine recreational fishing sites assumes that anglers know the costs and qualities for each site in their choice set. They then choose which site to visit on the basis of the utility that each site generates. Assume that the angler's indirect utility is given by

$$u(y_j - c_i, q_{ij}) = v(y_j - c_i, q_{ij}) + \epsilon_{ij} \tag{1}$$

where y_j is income for the jth angler, c_i is the cost of visiting the ith site, q_{ij} is quality that the j^{th} angler expects to find at the i^{th} site, and ϵ_{ij} is a term known to the angler but random to the researcher. The workings of this model are well known. (For a description of the model, see Bockstael *et al.*, 1989). As we have argued, the q_{ij} may reasonably conceived to vary across anglers who have different information and expectations about sites, different skills for exploiting opportunities at the site, and different expenditures on inputs used to catch fish. The latter source of variation implies a household production function process, and while it is an intuitively attractive way to explain the behavior in marine sportfishing in that way, it becomes empirically intractable when the budget constraint is imposed. (See Bockstael and McConnell, 1981, 1983).

We propose a simple alternative to the household production function. The angler combines his time with the stock of fish at the site to influence the distribution of the number of fish caught per trip. The RUM is normally applied on a "per trip" basis, without regard for past and future trips. Thus, the difficulties that are outlined in Bockstael and McConnell (1981, 1983) are eliminated because the budget constraint is not invoked directly. Further, the time that goes into the production process itself is predetermined in the decision to go fishing. Thus, this process allows the intuitive appeal of describing how fish are caught without the econometric difficulties that accompany nonlinear budget constraints and endogenous prices.

In this process, the number of fish caught is a random variable whose distribution depends on policy variables and individual attributes. An explicit random form allows direct calculation of expected utility and it permits a more precise modelling of policies which influence the distribution of catch. For example, bag limits work by truncating the distribution from above. This truncation affects all the moments of the distribution, so that the use of a distribution would allow the modelling of risk averters as well as risk neutral agents. In the standard approach using mean catch rate, it is difficult to model the effect of a bag limit. To model the effect of the bag limit on the mean, one needs the distribution of catch. The major disadvantage is the imposition of an explicit functional form which may not reflect reality.

An angler's catch of fish per trip is influenced by many factors. The abundance of fish, the mode of fishing (*e.g.* boat, shore or pier), type of gear and baits, the tidal situation, the weather, water clarity and temperature, the age and experience of an angler, and the hours fished all influence catch. Our survey was not designed to model this production process, and hence we have measured only a few of these factors. We control for mode by using only shore fishing. For the skill of an angler, we use the experience of the angler. Hours fished is a proxy for effort, and historic catch rates measure stock abundance.

The empirical application combines two surveys: a household survey of recreational fishing activity and the MRFSS intercept survey. Combining the surveys enables us to model the fish catching activities of anglers on individual trips. We concentrate on anglers who have targeted small game and who are fishing in Maryland. (A complete description of the study and the surveys can be found in Strand *et al.*).

We model the total number of fish caught per trip, Q, but assume that utility depends on the catch rate, q, the number of fish caught per hour, Q/h. This specification gets the essential ingredients, fish and time, into the utility function. Yet the assumption that time on site is exogenous eliminates a conceptual difficult joint optimization problem—site selection by maximizing utility and choosing the optimal quantity of time.

We assume that the distribution of fish caught is Poisson:

$$P(n) = Q^n e^{-Q}/n! \quad \text{for } n = 0, 1, \ldots, \infty \tag{2}$$

where P(n) is the probability of catching n fish and Q, the mean total catch depends on household and site characteristics. The specific form is

$$Q_{ij} = \exp(\alpha_0 + \alpha_1 cr_i + \alpha_2 \ln(h_j) + \alpha_3 s_j) \tag{3}$$

where

Q_{ij} = number of fish caught at site i by angler j;
cr_i = mean catch rate at site i from NMFS historic intercept data;
h_j = hours spent at the site by angler j;
s_j = skill or experience in saltwater fishing by angler j.

When $\alpha_2 = \alpha_3 = 0$, individual differences do not influence catch. However, the finding that additional time spent fishing is not rewarded, on average, with more catch is especially unlikely.

This specification works best if $\partial h_j/\partial cr_i = 0$. That is, hours fished should be exogenous. If time on site responds to the catch rate, parameter estimates are subject to simultaneous equation bias. Time constraints on individuals and the fixity of tidal cycles and daylight make it more difficult for anglers to adjust their hours fished as their catch changes. Further, casual experience from Kathryn Chandler Associates failed to find a systematic relationship between time spent fishing and the catch rate.[2] Moreover, the effect of simultaneous equation bias is slightly offset because the hours fished remain the same across sites and some of

[2] During the late 1970's, researchers from KCA under contract with NMFS tried to determine whether anglers interviewed in the middle of a trip would stay longer if they were catching fish more frequently. Results were inconclusive.

the effect would be diminished. Endogenous on-site time is a potential problem and some work on it has begun (McConnell, 1992).

The Poisson is a discrete distribution for count data. The Poisson process describes the frequency of an event per period of time. In the production process we model fish caught per trip, which is an integer. Catch rate is not an integer and cannot be modeled via a count process. The arrival of fish per trip is conditioned on the number of hours per trip, the historic catch rate at the site and the experience of the angler. The distribution of catch per trip naturally varies with the number of hours per trip. When an angler spends more time fishing, the arrival rate ought to be higher. If the coefficient α_2 is not significantly different from 1, then we can assert that the arrival rate is proportional to the hours spent on site. The assumption that $\alpha_2 = 1$ implies that

$$Q_{ij} = h_j \exp(\alpha_0 + \alpha_2 cr_i + \alpha_3 s_j), \tag{4}$$

or

$$Q_{ij}/h_j \equiv q_{ij} = \exp(\alpha_0 + \alpha_2 cr_i + \alpha_3 s_j).$$

That is, the catch rate ($Q_{ij}/h_j = q_{ij}$ = catch per hour at site i for angler j) is independent of the number of hours spent fishing and is determined by historic catch rate at the site and the individual's experience. In general, $Q_{ij} = h_j^{\alpha_1} \exp(\alpha_0 + \alpha_2 cr_i + \alpha_3 s_j)$. The catch per hour increases with hours if $\alpha_1 > 1$. We consider this most likely due to the fixed set up time of starting to fish. The specification in (4) allows the influence of policy variables such as stock enhancement through the historic catch rate cr_i.

In this specification of the Poisson, one of the conditioning factors is the hours spent on site. This deserves additional explanation. In this framework, having decided to fish, the angler allocates a fixed amount of time to spend at the site fishing. This is part of the decision to go fishing, and the site choice is made conditional on this decision. Call this time h_j, the time on site for the j^{th} angler. Conditional on this h_j, the angler decides which site to visit, a decision in which the implicit or explicit cost of travel time is relevant. It is explicit if the angler could have worked, implicit if the cost of time is simply the opportunity cost of the discretionary time. When anglers spend more time on site, they presumably get higher utility, other things equal. The utility function for those anglers who can trade time for money at the wage rate (*i.e.*, who have flexible working hours) can be described by

$$v_{ij} = v_{ij}(y_j - c_i - t_{ij}w_j, q_{ij}, h_j) \tag{5}$$

where t_{ij} is the travel time for angler j going to site i, w_j is the opportunity cost (wage rate) for angler j, and h_j is the hours spent on site for angler j. For anglers without flexible hours, where travel time has an implicit cost, the conditional indirect utility function becomes

$$v_{ij} = v_{ij}(y_j - c_i, q_{ij}, D_j - t_{ij} - h_j). \tag{6}$$

where D_j is the angler's discretionary time. In this formulation of the utility function, travel time is costly (and perhaps brings utility, if the utility it brings is the same to all sites) while on-site time brings only utility. This is due to the conditional nature of the indirect utility function. It is conditional on the decision to go fishing already having been made, and with the hours devoted to the activity (but not to travel) having been fixed prior to the choice of site. Site selection is determined on the basis of the difference between the indirect utility at the different sites.

Some specifications of (5) and (6) imply that time on site will not influence the choice of site. Suppose that the utility function for angler j is

$$u(y_j - c_i - t_{ij}w_j, q_{ij}, h_j) = \beta(y_j - c_i - t_{ij}w_j) + \gamma q_{ij} + \lambda h_j + \epsilon_{ij} \tag{7}$$

for anglers who can choose their work hours and

$$u(y_j - c_i, q_{ij}, t_j) = \beta(y_j - c_i) + \gamma q_{ij} + \delta(D_j - t_{ij} - h_j) + \epsilon_{ij} \tag{8}$$

for anglers who cannot choose their hours of work. Maximum likelihood estimates of the parameters under the assumption that the ϵ_{ij} are distributed as extreme value depend on differences of indirect utility among sites. For individual j who cannot choose hours of work, the probability of choosing site k is

$$\text{Prob (choose k)} = \frac{1}{1 + \sum_i \exp[\beta(c_i - c_k) + \gamma(q_{ij} - q_{kj}) + \delta(t_{ij} - t_{kj})}.$$

This shows that the discretionary time and time on site variable fall out. Consequently, time on-site influences site choice only through the catch rate variable q_{ij}. Of course, one can specify more complicated models from nonlinear utility functions in which the time spent fishing does not drop out of the utility difference.

Integrating the Poisson production process and the random utility model illuminates how the model combines technology and tastes. Write the deterministic part of the utility function (dropping subscripts) as

$$v(y - c, q) = \beta(y - c) + \gamma q$$

and q, the mean catch rate, is determined by

$$q = \exp(\alpha_0 + \alpha_1 cr + \alpha_2 \ln(h) + \alpha_3 s)/h.$$

When this is substituted into the utility function, we have

$$\begin{aligned} v(y - c, q) &= \beta(y - c) + \gamma[\exp(\alpha_0 + \alpha_1 cr + \alpha_2 \ln(h) + \alpha_3 s)/h] \\ &= \beta(y - c) + \theta\exp(\alpha_1 cr) \end{aligned} \tag{9}$$

where $\theta = \beta\exp(\alpha_0 + \alpha_2\ln(h) + \alpha_3 s)]$ is a parameter which varies across individuals. The parameter θ may be interpreted as a parameter of the utility function or part of the production process. The model in (9) has two equivalent interpretations. In its initial form, it is a model of constant tastes defined on the quality variable, q, determined for each individual. In the form as written in (9), it is a model of variable tastes, defined on the historic catch rate, cr, where variations in tastes are systematically explained. When we express the model as in equation (9), it is clear that there is a very thin line between tastes and technology. One can approximate the model with explicit production by allowing the parameter θ to vary systematically across individuals.

Data and Data Sources

Two distinct models are estimated: the RUM model of site choice and the Poisson model which explains the number of fish caught per trip. These models are estimated from different datasets, though there is some overlap. The data are described in greater detail in Strand *et al.*

The trip destination data for the RUM model are based on a large survey of Atlantic Coast anglers conducted for the University of Maryland in 1987 and 1988. This survey was a phone survey, executed by Kathryn Chandler Associates in conjunction with the National Marine Fisheries Service (NMFS), and the Marine Recreational Fishing Statistical Survey (MRFSS). The survey covered the Atlantic Coast from New York through the east coast of Florida, excluding the Keys. Anglers who were intercepted as the part of the 1988 MRFSS were recruited for the Maryland survey. They were asked if they would answer an additional telephone survey concerning their household demographics and marine fishing activities for the entire two month period. (In MRFSS parlance, a two month period is a wave.) If they agreed to participate, they were then called about their fishing activity during the preceding wave. As part of the MRFSS intercepts, anglers' catch are identified by species, counted, weighed and measured. This creel data set provides the dependent variable of the Poisson model.

The sample of observations used in this paper is a subsample of the larger University of Maryland East Coast survey. It includes only Maryland residents who went shore fishing and who targeted small gamefish. Anglers who target species groups are presumably more knowledgeable than anglers who do not target, and hence have more predictable behavior. Also shore anglers have greater latitude for choice of sites than anglers with boats, especially anglers with boats in marinas. Hence this subsample is more mobile and probably better informed than a randomly selected subset of anglers from our survey.

The sites for the RUM model are Maryland counties or combinations of counties. The available sites included the counties of Anne Arundel, Calvert, Worcester, and the combination counties of Baltimore/Harford, Caroline/Kent/Queen Anne/Talbot, Charles/St. Mary's, and Dorchester/Somerset/Wicomico. The percent of trips to these sites is 5.1%, 1.2%, 2.0%, 7.0%, 22.1%, 35.0%, and 27.6%, respectively.

The Poisson model for the catch per trip also required use of a different dataset. Recall the Poisson mean is postulated as

$$Q_{ij} = \exp(\alpha_0 + \alpha_1 cr_i + \alpha_2 \ln(h_j) + \alpha_3 s_j). \tag{10}$$

For estimation, this model requires information on catch per trip at site i by angler j, historic catch rate at site i, and skill levels for angler j. The time on site (h_j) and experience (i_j) come from the University of Maryland survey, which also provided the dependent variable. The historic catch rates by site are computed from MRFSS historical datasets for the period 1980–1988, based on specific sites. The NMFS sites were aggregated to the county level sites and the mean catch per day of small game for the period 1980–1988 was calculated. The primary species sought north of Cape Hatteras are bluefish (*Pomatomus saltatrix*), striped bass (*Morone saxitilis*), and weakfish (*Cynoscion regalis*). Although these species, especially bluefish, are also highly sought south of Cape Hatteras, fisherman in the southern area more often tend to seek mackerel, mostly Spanish (*Scomberomorus maculatus*) and King (*Scomberomorus regalis*), spotted seatrout (*Cynoscion nebulosus*), and red drum (*Sciaenops ocellata*). Because the main focus of the study is on Maryland's anglers, only data on individuals intercepted north of Cape Hatteras were used to estimate the Poisson.

For the Poisson regression, there are 109 observations. The geographic distribution of anglers by state had New York with 38 percent, Maryland and New Jersey each with 19 percent and Virginia, North Carolina, and Delaware with the remainder. Maryland had the second highest percentage of observations in the sample so that the use of the data for estimating a model for Maryland anglers does not stretch credulity. The distribution of species is relatively homogeneous for smallgame fishing in the New Jersey, Delaware, Maryland, and Virginia region, which accounts for nearly 60% of the sample.

The skill or experience of the angler is measured by the number of years of fishing. This variable varies from as few as one year to as many as 65. The individuals ranged in age from 18 to 80, with an average age of 37.9. On average, anglers have been fishing for half of their lives.

Results of Estimation

There were two models estimated: the Poisson model of the catch process and the RUM model of site choice (Table 2):

Poisson Regression

The model, as specified in equation (10), was estimated using the 109 anglers who sought small game from north of Cape Hatteras and who were intercepted in the NMFS intercept survey. The estimated coefficients in this model are all statistically different from zero at the 1% level. All variables have the expected positive effect on catch rate. These coefficients were used to calculate expected catch rate for each individual at each site. Note that coefficient on log(h) is significantly greater than one, which supports the modelling of catch per trip, rather than catch rate.

The RUM Model

All coefficients of the RUM model are also consistent with expectations and significantly different from zero. The marginal rate of substitution of travel time for travel costs, inferred from the ratio δ/β, indicates people with fixed working

Table 2
Estimated Coefficients for Poisson and RUM Choice Models

Poisson Regression for Expected Catch			RUM Model for Site Choice		
Variable	Parameter	Estimated Coefficient (T-statistic)	Variable	Parameter	Estimated Coefficient (T-statistic)
Constant	α_0	−3.044 (8.2)	Travel cost (c)	β	−0.011 (2.5)
Historical catch rate (cr)	α_1	1.775 (6.5)	Travel time (t)	δ	−.008 (5.5)
Log hours fished (ln h)	α_2	1.526 (8.7)	Catch/hour (q)	γ	13.5 (7.9)
Years fishing (s)	α_3	.011 (8.2)			
Chi-squared		538.4		122.18	
		109 observations			258 choice occasions; 7 sites

schedule would trade about \$1.50 to avoid one hour of travel time. This figure is substantially less than the average wage in the sample.

Modelling Welfare Effects

To demonstrate the effects of using the Poisson to predict the catch rate, we calculate two types of benefit measures: one based on individual characteristics and one based on average characteristics of the sample. The latter in effect ignores differences in individual anglers. The policy variable for the simulation is the historic site catch rate. This serves as a surrogate for the stock, the variable most likely to be influenced by commercial or recreational fisheries policy or by changes in pollution levels. We assume a five percent change in the historic catch rates at each site. This means that the angler's increased expected catch becomes:

$$Q^*_{ij} = \exp(\alpha_0 + \alpha_1 cr_i(1 + k) + \alpha_2 \ln(h_j) + \alpha_3 s_j) \qquad (11)$$

where the estimates of α_i are found in Table 2 and $k = .05$. The increased catch rate is the Q^*_{ij}/h_j. The base case is predicted from equation (11) with $k = 0$. Using the standard definition of welfare changes in the discrete choice model (see Hanemann), we calculate the welfare change for each individual. The mean increase in benefits is \$9.42. This is the mean amount per trip occasion that angler would pay to have the index of abundance, historic catch rates at the site, increase by five percent.

This estimate may be judged as being toward the high end of estimates of values from increases in catch rates from other studies. Freeman has summarized many such studies. For a 20–25% increase in catch rates, the estimate are \$13.40, \$11.05 and \$7.10 for various species. Even a 100% increase in salmon and striped bass catch rates was valued only at \$33.

To see the impact on welfare estimates of permitting individual variation of the catch rate vis-a-vis a change for the representative angler, we use the same parameters as before, but instead of calculating the catch per trip for each individual according to equation (11), we predict the increased expected catch as

$$Q_i^* = \exp(\alpha_0 + \alpha_1 cr_i(1 + k) + \alpha_2 mh + \alpha_3 ms) \tag{12}$$

where mh is the mean log hours fished and ms is the mean skill level and $k = .05$. The catch rate per individual is then Q_i divided by mean hours per trip. The pre-change catch is calculated with $k = 0$. Using the same approach to calculating benefits as before, we find a mean increase in willingness to pay per trip of $8.15.

The difference between the sample mean calculated with individual heterogeneity (11) and at sample means (12), is about 13% of $9.42. The relative closeness of the two estimates of sample mean benefits does not tell the whole story. The variation comes from the sample, not the estimation. There is more dispersion in the welfare effects calculated from the individual catch rates. Table 3 shows some simple statistics for the welfare measures. The main consequence of allowing individual variation in the catch rate (while holding the parameters constant) is to increase the variation in the individual welfare estimates. This change in the model increases the realism of the application, but does not substantially change this sample's estimate of the aggregate welfare effects. An analysis of a bag limit reveals quite a different story.

Modelling the Effects of a Bag Limit

One of the most widely used tools in managing recreational fisheries is the creel or bag limit. This policy instrument works by constraining the number of fish kept per angler to be less than or equal to a given target per outing. Note that the bag limits typically restricts the number of fish kept, not the number caught. Bag limit restrictions are written in terms of the number of fish possessed by the angler. The bag limit does not influence the distribution of the catch of fish. The logic of the regulation holds if anglers get utility from keeping their catch. Without bag limits, the distribution of catch and of fish kept would be the same for desirable species such as small game. Since *ex ante* the angler does not know exactly what the catch will be, one way to model the effect of the bag limit is to allow it to truncate the distribution of fish kept, thus changing the distribution and the mean catch.

For the Poisson catch, the original distribution is given by $P(n) = Q^n e^{-Q}/n!$ for

Table 3
Welfare Effects of a Five Percent Increase in Catch Rates (1988 dollars)

Model Assumption	Sample Mean Welfare Effect	Standard	Minimum	Maximum
Individual fishing characteristics (equation 11)	$9.42	9.05	4.40	39.10
Mean fishing characteristics (equation 12)	$8.15	7.70	.86	25.40

$n = 0, 1, \ldots, \infty$. When the bag limit is imposed, at k fish, the distribution of fish kept becomes

$$P^*(n) = Q^n e^{-Q}/n! \quad \text{for } n = 0, \ldots, k - 1$$

$$P^*(k) = \text{Prob}(n \geqslant k) = \sum_{n=k}^{\infty} Q^n e^{-Q}/n! \tag{13}$$

Then the expected number of fish kept is lowered, and as long as anglers are risk neutral with respect to fish, only the expected number matters. The expected number of fish kept is calculated using the standard definition of expected value with the distribution in (13). It will be less the individual's expected mean catch for the unconstrained Poisson mean as long as the limit is effective in a stochastic sense, that is $\text{Prob}(n > k) > 0$. As with $P^*(n)$, the expected number kept will vary across anglers. The bag limit will have a greater impact on better anglers, where $\text{Prob}(n \geqslant k)$ is high. For many anglers, $\text{Prob}(n \geqslant k)$ will be zero, so that the bag limit will have no impact.

For the Poisson catch model given by the parameters in Table 2, we have imposed the bag limit that the number kept be four or less small gamefish, most of which are bluefish for our sample. We can find the welfare effects of this policy by calculating the individual's implied mean kept and mean per hour. We hold the historic catch rate constant, recognizing the reason for creel limits is to improve catch. (Naturally one would hope for an increase in stock abundance from this policy, but we do not know how this truncation would affect catch rates in the long-run). We then calculate the compensating variation of this catch rate compared with the base catch rate. The compensating variation is the amount of money that the angler would pay to have the bag limit removed because of its effect on the mean catch. When $\text{Prob}(n \geqslant k)$ is quite small, as it is for some anglers, the bag limit will have no effect. Then $P^*(n) \approx P(n)$.

The estimated welfare effects from the establishment of a creel limit, shown in Table 4, however, are quite dramatic, especially when compared with the almost negligible effect of the "heterogeneous" model on the estimated value of catch rate. The effect of a bag limit is felt most strongly by anglers who would expect to catch quite a lot of fish. For some the effect is negligible, hence the minimum of zero. For others, the effect is substantial. The range from 0 to $287.49 represent the influence of heterogeneity. In this case, it would those anglers who had fished long hours, substantial experience, or who lived near sites which had high historic catch rates.

Table 4
Welfare Effects of a Bag Limit of Four (1988 dollars)

Variable	Mean	Standard Deviation	Minimum	Maximum
Compensating Variation	$16.78	$18.58	$0.00	$237.49

An example using two hypothetical but plausible anglers illustrates the effect of a bag limit of four fish per day. Assume that there are two anglers, one (called A) is a far more ardent and experienced angler and the other (called B) is a novice. Assume that angler B has only fished for two years, goes fishing for two hours and chooses a site with a catch rate of one fish per hour. On the other hand, angler A has fished for 20 years, goes fishing for four hours and chooses a site which has an average catch rate of 1.5 fish per hour. Using the parameters in Table 2, we can calculate the mean number kept for A as 7.05 and for B as .83. Now consider a bag limit of four. Virtually all of B's probability lies to the left of four, so the truncation has an indiscernible effect on the mean number kept. However, Prob ($n \geq 4$) is .92 for A, so the distribution of expected catch is changed dramatically, as does the mean, from 7.05 to 3.9. The mean for B remains virtually unchanged. These results are shown in Table 5.

Modelling the effect of bag limits with the Poisson handles two elements of catch: randomness and heterogeneity. There are critical aspects of recreational catch. If there is no randomness, then the bag limit can be modelled simply by a proportionate reduction in individual catch. But the heterogeneity of individual anglers gives the randomness extra power. Differences in the distribution of catch are greater than differences in the mean catch. Imposing a limit on a fishery in which the catch is both random and heterogeneous gives the dramatic results. We caution that our model assumes risk neutrality. If anglers are risk-averse or if there is demanding marginal utility of fish kept, then the difference in welfare effects should be less.

Conclusion

This paper has demonstrated, in the context of the RUM model, the use of a production process resembling the household production function for catching fish. This process is modelled as a Poisson process. This model of angling has several implications. First, a random process like the Poisson models the effect of regulations on individual behavior much more realistically. Policy actions can be modelled as influencing the distribution of catch, not the actual catch. This eliminates the awkward modelling assumption that polices such as bag limits determine endogenous variables such as catch rates. Secondly, we've found that welfare measures when using heterogeneous catch rates appear very responsive to certain policy instruments. Creel limits, in particular, appear to impose large

Table 5
Comparing the Impact of the Bag Limits on Two Very Different Anglers

	Angler	
	A	B
Experience(s)	20	2
Hours fished (h)	4	2
Historic catch rate (cr)	1.5	1
Mean catch	7.05	.83
Truncated mean with bag limit of four	3.88	.83
Prob ($n \geq 4$)	.92	.01

average welfare losses. This bias occurs because there are a few "expert" fishermen who land substantially more than the average fisherman. These people may have relatively few alternative hobbies and are greatly affected by the limit. It is these outliers who account for a great deal of the welfare gains and losses generated by policies towards recreational fishing. Severely restricting them therefore substantially affects total welfare.

The working of the creel limit within this more realistic framework illuminates its basic economic flaw as a policy. By imposing the same constraints on all anglers, the policy is analogous to the "uniform standards" policy observed in pollution control. The goal of achieving reduced harvests by least cost can only be achieved by equating the "marginal" cost of the policy across anglers. Creel limits by their nature are not likely to be a cost-effective means of achieving reduced harvests. A tax on harvest or perhaps even higher license fees would more efficiently achieve the goal of harvest reduction.

An important aspect of catch that we have ignored is the role of expectations. As we argued at the beginning of this paper, the quality of a recreation site is unknown until the visitor arrives. In our application, we have estimated the angler's expectation by using experience and the historic number caught at the site, not the subjective expectation of the angler. A missing link in this area of research is connecting objective measures like ours with more realistic subjective assessments of quality.

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[3] In this paper we deal with small game, so the number of fish refers to the number of fish caught which are defined as small game. The small game group includes fish such as bluefish, striped bass, weakfish, and similar species. For the dataset we use, the principal species is bluefish.

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