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Working Paper Series

Working Paper 15-WP-SEMRU-04

A comparison of an on-site versus a household survey approach to modelling the demand for recreational angling.

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A comparison of an on-site versus a household survey approach to modelling the demand for recreational angling.

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Abstract

This paper compares recreational fishing Travel Cost demand modelling results from an on-site angler intercept survey to results from a household survey where the respondents represent the same underlying population of interest. We employed a Poisson and negative binomial count data model with and without the econometric corrections for the on-site sampling issues of endogenous stratification and truncation as the on-site modelling approach and use Poisson and negative binomial count data hurdle specifications to control for excess zeros in the household modelling approach. We find that welfare estimates differ substantially across the two samples and argue that the underlying samples may represent two different types of anglers.

Keywords: On-site and household sampling, recreation demand, hurdle count data models, truncation, endogenous stratification, angling.

JEL Classification: Q22, Q26.

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This work was funded through the Beaufort Marine Research Award, which is carried out under the Sea Change Strategy and the Strategy for Science Technology and Innovation (2006-2013), with the support of the Marine Institute, funded under the Marine Research Sub-Programme of the National Development Plan 2007–2013.

1. Introduction

Recreational pursuits represent an important category of cultural ecosystem service benefits obtained from human interaction with a wide variety of ecosystems. The travel cost method (TCM) has been an important tool in estimating the value of this particular cultural ecosystem service benefit. In this paper we develop travel cost models of recreation demand related to angling, using both an on-site and a household survey. Unusually, the on-site angler intercept survey and the household survey was carried out at the same time and asked the same trip frequency questions of respondents. Using the responses to these surveys we then compare a hurdle household recreation demand model to an on-site model that corrects for the three statistical issues of overdispersion, truncation and endogenous stratification. While previous research has been carried out that compares zero-inflation household models to on-site models, this is the first direct comparison of a hurdle household recreation demand model to an on-site model in the recreation demand literature.

When modelling the demand for such an activity as angling count data travel cost modelling approaches have often previously been employed due to the discrete non-negative nature of the dependent variable; the number of fishing trips taken over a certain time period. In setting out to estimate a model of recreation demand the researcher must also decide whether the information to be used will be gathered from an on-site survey of users or from a general household survey. In the former case, care must be taken to account for the on-site sampling issues of endogenous stratification and truncation and in the latter the researcher needs to adjust for the likely specification issues surrounding the presence of excess zero responses for angling trips taken. Simply treating all zeros in the household sample as anglers, who took no trips in the period under investigation, will introduce an downward bias in the demand and welfare measures.

On the other hand, in the case of the *on-site* sample, demand is truncated at one since the anglers being interviewed are on-site so must have made, at least, that single trip in the period. In this case, welfare estimates will tend to have higher standard errors. The sampling issue of endogenous stratification (the probability of sampling individuals with higher trip frequencies) will also lead to an upward bias in demand estimation and welfare measures. Englin and Shonkwiler (1995) and Shaw (1998) have shown how the on-site issues of truncation and endogenous stratification can be adjusted for in recreation demand models. It is also possible to resolve the issue of excess zeros in household survey data by separating the recreation ‘participation’ decision from the trip ‘consumption’ decision using a two stage modelling approach such as a double hurdle or zero inflated count model (Anderson, 2009). In this paper we use both an on-site survey of Irish anglers and a household based survey to estimate our recreational fisheries demand functions. In doing so we examine if, after correcting for the sampling issues in each case both modelling approaches produce similar welfare estimates for the value of recreation angling amongst the Irish population.

Very few travel cost studies have attempted to directly compare recreational benefits derived from household and on-site surveys. Martínez-Espiñeira et al. (2008), Meisner and Wang (2006), Loomis (2003) and Shaw (2003) being the exceptions. Only Meisner and Wang (2006) and Martínez-Espiñeira et al. (2008) compare a household recreation demand model to an on-site model that corrects for the three statistical issues of overdispersion, truncation and endogenous stratification. In the case of Meisner and Wang (2006) they compare it to a zero-inflation model while Martínez-Espiñeira et al. (2008) compare to a standard negative binomial model. In this paper we use the same on-site modelling approach as Martínez-Espiñeira et al. (2008) but compare it to a hurdle household model. To the best of our knowledge this is the first such comparison in the recreation demand literature.

As Meisner and Wang (2006) point out, if it can be shown that welfare estimates derived from cost-effective on-site surveying techniques are similar to household survey results, then this may justify using on-site surveys in lieu of large and costly population-based surveys. In this paper we also raise the question as to whether it may be the case than even if one is as careful as possible with the econometric models applied using both sampling approaches it still may be the case that the type of recreationist one gets from an on-site survey will be fundamentally different from the type one finds in a household survey.

In what follows we briefly review the approaches that have been taken in the literature previously to estimate the demand for recreational angling. In section 3 we then present the on-site and house survey methodologies and review the count data modelling specifications applied to both data sets. Section 4 then presents the model results and welfare estimates, while section 5 presents a discussion of results and offers some conclusions.

2. Estimating the value of recreational angling

The recreation value of angling has been extensively investigated in the literature (see for example Curtis, 2002; Shrestha et al., 2002; Bilgic and Florkowski, 2007). Indeed, Johnston *et al.* (2006) identified over 450 non-market valuation studies that deal with recreational fishing benefits and values. In an earlier study, Loomis et al. (1999) carried out a meta-analysis involving 109 CS estimates of recreational fishing demand in the United States. The most common form of modelling approach employed in these studies has been the revealed preference travel cost model (Loomis and Walsh, 1997; Curtis, 2002, Murdock, 2006).

Within this modelling framework the Poisson and the Negative Binomial count data model specifications have remained particularly popular due to the non-negative integer nature of the demand for pursuits such as recreational fishing (as measured by the frequency of trips) (Zhang et al., 2015). As shown in the next section whether this trip data is collected on-site or at the household level will have a bearing on the ultimate specification used. With on-site surveys, data issues such as truncation and endogenous stratification need to be controlled for as in Curtis (2002) model of salmon angling demand while at the household level the fact that you are likely to see a high proportion of zero trips amongst any given sample need to be addressed. The latter issue has been dealt with previously in the recreational fishing demand modelling literature using zero inflation models (Loomis, 2002) or hurdle models (Bilgic and Florkowski, 2007)[1]. More recently, Czajkowski et al. (2015) applied a Zero-Inflated Negative Binomial model to estimate the annual number of recreational trips to the Baltic Sea coast that allows the modelling of both the probability of non-participation and over-dispersion in distribution of the number of trips.

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[1] For a more general discussion of hurdle count-data models in recreation demand analysis the interested reader should review Shonkwiler and Shaw (1996).

Travel cost random utility models have also been applied in a number of studies of recreational fishing (see for example Train, 1998; Morey et al., 2002; Johnstone & Markandya, 2006; Murdock, 2006; Mkwara and Marsh, 2011). In these cases, the demand for angling pursuits at alternative sites is modelled as a function of the attributes associated with each site such as potential catch rates, species on offer and distance to each site. Contingent Behaviour travel cost models are another approach to valuing recreational fishing demand where the standard count data models have been expanded to include additional information about how users might change their behaviour if certain contingent conditions existed (Hynes and Greene, 2013).

In a typical recreation contingent behaviour model the respondents are first asked about the frequency of past trips. They are then presented with a hypothetical scenario with different site conditions and asked if they would change their intended number of visits. The revealed and stated trip responses are then analysed using panel count data modelling techniques. In a fisheries related application, Prayaga et al. (2010) used a panel data truncated negative binomial contingent behaviour model to estimate the change in the value of recreational fishing as conditions along the Capricorn Coast in Central Queensland, Australia were varied.

Although there have been a number of studies on recreational fishing in Ireland that have analysed angler numbers and expenditure patterns using surveys (e.g. Whelan and Marsh, 1988; Marine Institute, 1997; Inland fisheries Ireland, 2013), only two Irish studies have involved the estimation of demand functions for recreational fishing. One other involved estimating the non-market value of preserving the current quality of recreational angling. This is despite the fact that fishing is one of the most popular recreational activities in Ireland. In a comprehensive study by Inland fisheries Ireland (2013) the contingent valuation method was employed to estimate the value to the general public and to anglers, respectively, of preserving Ireland’s natural fish stocks and the current quality of recreational angling in Ireland. Based on their model results the aggregate non-market value of the angling resource to the Irish public (where there are 3,608,000 individuals above the age of 15) was estimated to be €57.6 million per annum. The equivalent figure for the 406,000 estimated active anglers using Irish waters on a yearly basis was €27 million per annum.

In an earlier Irish study, O'Neill and Davis (1991) estimated an angling demand function for coarse and game angling in Northern Ireland but only relied on an OLS modelling approach. The only other estimated recreational fisheries demand function in Ireland was by Curtis (2002). In that study Curtis estimated the demand and economic value of salmon angling in Co. Donegal, Ireland. Using a truncated negative binomial travel cost model that allowed for endogenous stratification and truncation he estimated consumer surplus per angler per day of IR£138. Angling quality, age and nationality of participants were the main factors found to affect angling demand.

We add to the above literature by developing two recreational angling demand models for the Irish population where the total demand for angling trips in Ireland is estimated. We compare the results from an on-site angler intercept survey, with econometric corrections for on-site sampling issues, to results from a household survey where the issue of excess zeros is addressed using a hurdle modelling approach; a comparison that has not been made previously in the literature. Both samples were collected concurrently and asked the same trip frequency and angler related questions so we are in a unique position to test if the models used yield similar benefit estimates.

3. Research design and model estimation methods

In order to obtain information relating to the participation levels of the Irish public generally and dedicated anglers in particular in the recreational pursuit of freshwater and marine angling both a general household survey and an on-site survey of anglers was conducted in Ireland in 2012. The on-site *survey of recreational anglers* was carried out over a 9 month timeframe from March to November 2012. In total, 903 recreational anglers were interviewed. All interviews were carried out by the company Tourism Development International. The sample for the *on-site survey* comprised of individuals age 15 plus from the Republic of Ireland, Northern Ireland and overseas markets whose main purpose of visit was recreational angling. The timing of the *on-site survey* was scheduled to coincide with the full angling season in respect of each angling category. A master list of fisheries throughout Ireland was drawn up and from this 50 fisheries/sampling locations were chosen at random. This approach was used to maximise the overall representativeness of the survey and to ensure that all regions and all angling categories were fully covered.

- **Figure 1 here**

All interviews took place at these 50 sampling locations/fisheries (see figure 1). Interviewers were issued with strict guidelines on the interviewing approach to be adopted. Some anglers were happy to be interviewed at the fishery (i.e. lake, river, sea shore, etc.) while others expressed a preference to be interviewed at the end of the days angling (i.e. at their accommodation or at the local public house). Some anglers opted to complete the survey by telephone or on-line. Fieldwork administrators monitored interview activity throughout to ensure that the sample of recreational anglers was fully representative of the population of anglers provided as outlined by Inland Fisheries Ireland, the semi-state body with responsibility for recreational angling in Ireland. Since the purpose of the analysis presented in this paper is to compare the welfare estimates from both an on-site and household TC modelling approach only the domestic (Irish) observations from the sample are used[2]; a sample of 451 individuals.

The *household survey* comprised a sample of 2,011 Irish adults. The sample was representative of the Irish population (also aged 15 plus). The household survey was conducted in two waves in 2012 by Millward Brown Lansdowne (in May and October). The collection of the survey followed a quota controlled sampling strategy. The quotas used were based on known population distribution figures for age, sex and region of residence taken from the Irish National Census of Population, 2006. Pilot testing of both the on-site and household survey instruments were conducted prior to the main surveys. Along with expert judgment and observations from earlier focus group discussions, results from the pilots were used to refine the questions asked in the main surveys.

[2] This was done since we wanted to compare the estimates to the household where we are obviously only dealing with domestic residents.

Respondents to the on-site survey were first asked about the type of angling they pursued (game, coarse, bass, etc.) and the frequency and costs of angling trips taken in Ireland. Specifically, respondents were asked how many angling trips they had taken in the previous 12 months. Additional information was collected about the expenditure incurred under a number of different category headings related to fishing tackle, the hire of equipment, licences and permits, transport, etc. Respondents were also asked a number of Likert scale attitudinal questions related to the quality of the angling resource in Ireland.

- **Figure 2 here**

In the household survey respondents were first asked whether they had fished or not in the last 12 months. Only those who answered that question in the affirmative were then presented with the same angler related questions as were present in the on-site survey. Of the 2011 completed surveys only 122 indicated that they had participated in angling in the previous 12 months. Also contained in both surveys were socio-demographic questions regarding each respondent's age, gender, education level attained, number in household, occupational status and income[3]. Table 1 presents summary statistics for the population of anglers in both the on-site and household samples while figure 2 shows the distribution of fishing trips amongst the angling population over the previous 12 month period.

- **Table 1 here**

In order to model the demand for angling recreation amongst the Irish population from both surveys it is necessary to account for the unique sampling issues connected with an on-site surveying methodology and the excess zeros related to trip frequencies one is likely to encounter in a household survey of recreational demand. Given that the angling trip counts are limited to non-negative integers and the distribution of trips tends to be positively skewed towards zero (see figure 2), the use of a standard ordinary linear regression model is not recommended and a count data modelling approach is generally preferred (Cameron and Trivedi 2005).

[3] Information on education level attained and number in household was only attained in the household sample.

To illustrate the family of count model alternatives available to use when modelling recreational fishing demand (number of angling trips in some time period) we start with the Poisson model. In applying the Poisson regression in angling demand analysis, let T be the number of fishing trips made during period j. The Poisson model is then defined with a probability density function (PDF) given by:

$$\Pr(T = t) = F_p(t) = e^{-\lambda}\frac{\lambda^t}{t!}, \quad t = 0,1,... \qquad [1]$$

where λ, the Poisson parameter and expected number of trips, is modelled as a function of the explanatory variables thought to influence T, which often include travel cost, time, site attributes, as well as other demographic and location variables. That is:

$$\lambda = exp(\beta X) \qquad [2]$$

where β is a vector of unknown regression coefficients that can be estimated by standard maximum likelihood methods (Greene 1997), and X is the vector of variable thought to influence trip demand. The Poisson model implies *equidispersion* whereby the conditional mean and variance are equal for the Poisson distribution such that $E(T \mid X) = Var(T \mid X) = \lambda$ (Martínez-Espiñeira and Amoako-Tuffour, 2007).

For data exhibiting overdispersion (i.e. where the conditional mean and variance equality restriction does not hold), the negative binomial model is a frequently used alternative. The distribution includes an ancillary parameter α which is an estimate of the degree of overdispersion. When α is equal to zero, the negative binomial distribution is the same as [1]. The larger is α, the greater the amount of overdispersion in the data. The negative binomial density is:

$$\Pr(T = t) = F_{NB}(t) = \left[\frac{\Gamma(t+\alpha^{-1})}{\Gamma(t+1)\Gamma(\alpha^{-1})}\right]\left[\frac{\alpha^{-1}}{\alpha^{-1}+\lambda}\right]^{1/\alpha}\left[\frac{\lambda}{\alpha^{-1}+\lambda}\right]^{t}, \; t = 0,1,... \qquad [1]$$

where Γ denotes the gamma function, and α and λ are the parameters of the distribution. For count data models the negative binomial distribution can be thought of as a Poisson distribution with unobserved heterogeneity or as a mixture of Poisson and gamma distributions. The conditional mean is λ and the variance equals $\lambda(1+\alpha\lambda)$. Where T exhibits overdispersion, the negative binomial model is a consistent estimator and preferred to the Poisson model.

When dealing with an on-site sample, two additional important issues need to be addressed in estimation. First, those anglers who make no trip in the time period under consideration are not observed and thus the sample will be truncated at zero. In other words such samples do not observe non-participants as all survey respondents must by definition have taken at least one trip. The second issue for estimation arises due to the fact that n anglers' likelihood of being sampled is positively related to the number of trips they have made to the site. Endogenous stratification implies "over-sampling of those who visit more frequently" (Hilbe, 2007) and both the traditional and truncated Poisson and negative binomial models have been extended to account for endogenous stratification. Indeed a number of previous studies have considered applications (Englin and Shonkwiler 1995; Curtis, 2002; Englin et al. 2003; Martínez-Espiñeira and Amoako-Tuffour, 2007).

The PDF for the zero-truncated, endogenously stratified negative binomial model, which unlike the truncated and stratified Poisson also accounts for overdispersion is given by:

$$\Pr(T=t \mid T>0) = F_{TSNB}(t) = t \cdot \left[\frac{\Gamma(t+\alpha^{-1})}{\Gamma(t+1)\Gamma(\alpha^{-1})} \right] \alpha^{t} \lambda^{t-1} (1+\alpha\lambda)^{-(t+1/\alpha)} \quad t = 1,2,... \qquad [6]$$

The conditional mean and variance are equal to $E(T \mid X, T>0) = \lambda + 1 + \alpha\lambda$ and $Var(T \mid X) = \lambda(1+\alpha+\alpha\lambda+\alpha^2\lambda)$ respectively. Estimating a travel cost model for anglers in Ireland, and correcting for zero-truncation and endogenous stratification, allows us to recover the underlying latent demand function for angling trips for the entire population of anglers in the country, assuming the sample is representative of this population[4].

When employing a general population household survey to access the demand for a particular recreation pursuit the researcher will typically be confronted with censored data due to the fact that there will be a large number of zeros (Shaw, 1988; Grogger and Carson, 1991; Hellerstein, 1991). This is especially true in the case of

[4] A simple adjustment used to correct for endogenous stratification in the univariate Poisson model, is to transform the dependent variable (number of trips taken by individual i (Yi) to equal Yi – 1 (this adjustment is possible only when assuming a univariate Poisson distribution for the dependent variable and Shaw's (1988) derived on-site sampling distribution).

recreational angling where only a small fraction of the population are likely to be active participants. Simply treating all zeros in the sample as anglers will therefore introduce a bias in the demand and welfare measures. The Poisson or negative binomial models outlined previously assume that all individuals surveyed are potential users of the good in question, and that the same variables influence all potential users similarly. In the presence of a large number of zeros, as in the case of our general household survey, this assumption may not be valid.

With this in mind and following Bilgic and Florkowski (2007) a count data hurdle model was used to estimate the demand for angling trips amongst the general population represented in the household survey sample. A hurdle model involves two stages. In the first stage, a binomial probability model directs the binary outcome of whether a count variable has a value of zero or a positive value (the participation decision). In the second stage, a count model is estimated based on the assumption that when the individual participates the number of trips will be positive (the consumption decision). The participation decision and consumption decision need not necessarily be constrained to be the same in the model. In the context of this research, a logit hurdle mechanism was used to explain the choice of whether or not to participate in angling. Both the hurdle and the count models are estimated simultaneously[5]. Some individuals in the household sample may actually be anglers, but optimally choose not to go on an angling trip in the last 12 months. These anglers do not therefore get over the hurdle. The structural equations in this case are:

$P(T > 0) = F(x_1)$ (estimated with a binary choice model)

$T = f(x_1, \varepsilon_2)$ for $n_i > 0$ (estimated with a count model such as the Poisson and Negative Binomial)

where $\boldsymbol{x}_1$ represents a vector of variables pertaining to the participation decision and $\boldsymbol{x}_2$ contains variables that explain angling trip frequency. For the purposes of this paper, the hurdle model employs a logit specification to examine the participation decision and Poisson and Negative Binomial models to explain angling trip frequency.

[5] LIMDEP 10 and its associated commands for count hurdle model were used in the estimation of the Poisson and negative binomial hurdle models.

We also compare the on-site models and the household hurdle models in terms of the welfare measures that they imply. We estimate the total value of a site is *via* a per-trip per-person value estimate, which, following Englin and Shonkwiler (1995), is easily estimated from a travel cost model as:

$$CS_{perTrip} = \frac{1}{-\hat{\beta}_{TC}} \qquad [7]$$

The aggregate access value of the site follows by multiplying this estimate by the total number of trips in the relevant time period, such that:

$$CS_{Total} = CS_{perTrip}.T \qquad [8]$$

where T is the total number of trips over the relevant season.

4. Results

4.1 Results from the On-Site Travel Cost Models

Count data models were first used to estimate Irish anglers demand for fishing trips over a 12 month period. In our chosen model, *the number of trips taken = f (travel cost per fishing trip (travel, bait, boat hire, ghillies*[6]*), annual investment (in tackle, licence, clothing), Age, Retired, Social class, sea trout targeted, sea bass targeted, pike/ and other coarse fish targeted, affiliated with angling club, gross income, number of days taken per trip and fishing group size)*[7]. Following Parson's (2003) recommendation that when defining trip cost for recreational demand models all expenses required to make a trip possible should be included, the travel cost variable includes the self reported average cost of transport, bait, boat hire and ghillies per trip. Expenditure on other items such as tackle, licence and clothing was considered to be an investment in the sport that would last beyond the period and is

[6] A Ghillie refers to an individual who acts as a guide or attendant to an angler at a particular water body. He or she may show the visiting angler the best spots for fishing on that particular stretch of water and make recommendations on suitable flies or bait to use.

[7] While it is common and good practice to include the travel cost to substitute sites in a single site demand function, we avoid the need in this case as our demand function is for all trips in a season to all possible sites in Ireland; the choice set being the same for both the on-site and household samples.

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included as a separate variable in the model. The same explanatory variables were used in all specifications. These explanatory variables were chosen based on a review of the literature and *a priori* expectations of the characteristics that we believed should influence the total number of trips an angler might take in a season.

- **Table 2 here**

The parameter estimates for the on-site angling travel cost model are presented in Table 2. Several alternative specifications of the demand equation were estimated. We first present the standard Poisson models and negative binomial models. As expected a test of overdispersion indicates a preference for the negative binomial specification over the Poisson. In order to test the hypothesis that $\alpha = 0$ (and therefore indicating that the Poisson model would be more appropriate) a likelihood ratio-test was performed. The χ^2 value of 4207 implies that the probability that one would observe these data conditional on $\alpha = 0$ is virtually zero. These alternative models gave results similar in magnitude and with the same signs. They were both however rejected in favor of the negative binomial model that adjusts for the on-site sampling issues of endogenous stratification and truncation (hence forth referred to as the on-site negative binomial model). As expected, this model was also found to best fit the data in terms of the log likelihood value and information criteria statistics.

As with the standard negative binomial model, in the preferred on-site negative binomial model, α, the overdispersion parameter is positive and significant, indicating that the data is overdispersed. The estimated coefficients for travel costs across all models are of the expected sign and significant at the 95 percent level of confidence. They are also very similar in magnitude across the three models. Also as expected the higher the level of investment in tackle, license or gear over the season the higher the trip frequency is likely to be. Only in the basic Poisson specification is age, being retired and social class found to be significant. The insignificance of the parameter estimate on gross income suggests that there is no income effect on the number of fishing trips demanded over the season. As noted by Meisner and Wang (2006) this relative insensitivity to income changes is a common finding among recreational demand studies and is a similar result to that found previously in onsite travel cost models for Irish anglers by Curtis (2002) and for anglers in Armenia by Meisner and Wang (2006) and for anglers in the Great Barrier Reef, Australia by Prayaga et al. (2010). Indeed, Prayaga et al. (2010) conclude that recreational fishing is price inelastic, income inelastic and catch inelastic indicating and that other factors like enjoyment, being outdoors, being with family etc. are more important. This insensitivity to income changes is also evident in on-site travel cost demand models for other recreational pursuits (e.g. Hynes and Hanley, 2006).

As one might expect, being affiliated with a angling club – an indication of a high level of involvement in the sport – indicates that the number of fishing trips demanded is likely to be higher. The dummy variables denoting the type of angling being pursued were also found to be highly significant in explaining trip demand. Those anglers who are mainly targeting sea bass or who are involved in coarse angling are likely to make a higher number of trips in the season compared to salmon, brown trout or other sea species anglers while those mainly targeting sea trout are likely to making a lower number of fishing trips over the season. The longer the number of days on average in any trip the fewer the number of trips likely to be taken over the season. Given the time commitments involved in longer trips this is not a surprising result. Finally the size of the group that the respondent goes fishing with was found to negatively influence the number of fishing trips demanded over the season although this parameter was only significant at the 10% level in the preferred on-site negative binomial model. The on-site negative binomial model's estimate of the mean number of angling trips demanded amongst Irish anglers was estimated to be 6.81. This is a much lower figure than the actual mean of 28 trips observed in the sample or the figure of 28.61 as predicted by the standard negative binomial model that does not control for the on-site sampling issues[8].

[8] Englin and Shonkwiler (1995) suggest that the Negative Binomial model works best where the respondents are taking fewer trips, as those taking a higher frequency of trips may have significant unobservable differences from those taking a lower frequency of trips. We tested this by limiting our sample to those who take a maximum of 30 trips. We find that the on-site NB models produce similar parameter estimates and the important (from a welfare estimation perspective) travel cost parameters are statistically equivalent in magnitude. Similar to the full sample model the restricted sample model also generates an expected trip frequency that is over three times less than the actual number of trips observed (3.17 trips predicted versus 11.46 in the actual sample).

4.2 Results from the Household Hurdle Model

The household sample was modelled using a Poisson and negative binomial Hurdle specification. As in the case of the on-site sample, the negative binomial model was found to be the preferred estimation approach based on the test for overdispersion. The results of both models are shown in table 3. The decision to undertake a fishing trip (the participation choice) was estimated using the logit binary specification. Following Bilgic and Florkowski (2007) it was assumed that this decision was influenced mainly by socio-economic and demographic characteristics rather than by indicators of successful fishing.

- **Table 3 here**

In our chosen logit model, the decision to participate in fishing is assumed to be a function of being *male, a person's age, social class, having a third level education, being unemployed, having a part-time job and being a rural dweller.* From the results of the preferred negative binomial hurdle model it can be seen that being male is a significant indicator of participation in recreational fishing activity. Given the predominance of men in the sport this is not a surprising result. Having more time on ones hands as a retired person would also seem to increase the probability of undertaking a fishing trip but in contrast to that the age parameter would suggest that being older would significantly reduce the probability of participation. Somewhat unexpectedly residing in a rural area decreases the probability of participation in angling. *Apiori* one might expect those living closer to the rivers and lakes (which in Ireland's case are mainly in the countryside) would be more likely to participate in recreational fishing but this does not appear to be the case. It would also appear that having a third level education decreases the probability of a member of the Irish population undertaking a fishing trip (but only with a 10% level of significance). Belonging to social class DE (semi and unskilled manual workers, state pensioners, casual or lowest grade workers) also reduces the probability of participation. Having a part-time job or being unemployed were found to be insignificant in explaining the participation decision.

The second part of the hurdle specification, that models the trip frequency decision, was estimated with many of the same parameters as specified in the on-site models.

In the chosen model *the number of trips taken = f (travel cost per fishing trip (travel, bait, boat hire, ghillies), annual investment (in tackle, licence and clothing), age, retired, Social class, third level education, part-time job, number in household, living in Munster, living in Connaught/Ulster, game species targeted, pike/other coarse fish targeted, sea bass targeted, affiliated with angling club).* Unlike the on-site survey, information on gross income, number of days taken per trip and fishing group size was not collected in the household survey so could not be included in the model[9].

The estimated coefficients for travel cost is of the expected sign and significant at the 95 percent level. As with the on-site models the level of investment in tackle, license or gear over the season is a significant and positive driver of fishing trip demand. While third level education, being retired and social class were found to significantly influence the fishing participation decision they do not appear to have a significant influence on the trip frequency decision as judged by the negative binomial specification. Having a part-time job is also insignificant. Unexpectedly, being affiliated with an angling club was found to be insignificant. The dummy variables denoting the type of angling being pursued are also not as influential in explaining trip demand as they were in the on-site specification.

Only those anglers who are mainly targeting game species are likely to make a higher number of trips in the season compared to any other types of anglers. Finally, the number of persons in the respondent's household was found to positively influence the number of fishing trips demanded over the season although this parameter was only significant at the 10% level in the preferred negative binomial specification. The household hurdle negative binomial model's estimate of the mean number of angling trips demanded amongst Irish anglers was 0.743. This is a lower figure than the actual mean of 7.69 trips observed for the anglers identified in the household sample.

[9] Following the very poor response to the income question in the pilot, the income question was dropped from the main survey. As discussed in relation to the on-site models, the absence of income from the model may not be problematic as it is often found to have an insignificant impact on trip demand.

4.3 Welfare estimates

The welfare estimates derived from both the on-site and household modelling approaches are presented in table 4. Consumers' surplus was estimated following Englin and Shonkwiler (1995) as outlined in section 3. In the preferred on-site negative binomial model, this implies that consumers' surplus per trip is €232. The estimate of per-trip consumer surplus is estimated with 95% confidence to be between €193 and €294.

- **Table 4 here**

In the case of the household negative binomial model the consumers' surplus per trip is estimated to be a much lower €49.97 with an associated 95% confidence interval between €32.5 and €107.2. By combining the average consumer surplus per angler with the average travel cost for the anglers in each respective sample we get a measure of the average willingness to pay for an angling trip. As shown in table 4, multiplying this by the predicted number of trips per year implies that the annual recreational value of angling to Irish residents or willingness-to-pay by the estimated 252,000 domestic anglers in the state is €574 million according to our on-site negative binomial model corrected for truncation and endogenous stratification and €15.3 million according to our household negative binomial hurdle model.

As is evident from the above figures there is a significant difference between welfare estimates derived from the on-site and household travel cost models. This of course is a reflection of the sensitivity of trip demand to price, as reflected in the travel cost coefficient in the respective models. It is interesting to note that even if we constrain our on-site sample to those observations with a trip frequency no higher than that observed in the household sample and run our preferred models based on that sample, the difference in consumer surplus estimates remain. Why this difference in sensitivity exists is discussed in the following section.

5. Discussion and Conclusions

In this paper we have been concerned with the comparison of the travel cost modelling results from an on-site angler intercept survey to results from a household survey. We employed a Poisson and negative binomial count data model with and without the econometric corrections for the on-site sampling issues of endogenous stratification and truncation as the on-site modelling approach and Poisson and negative binomial count data hurdle models as the household approach in the valuation exercise. In the case of the on-site sample, estimated coefficients across the negative binomial models, whether adjusted for on-site sampling issues or not, were not significantly different. This result meant that accounting for endogenous stratification and truncation did not yield any significant differences in welfare estimates but did result in a major difference in estimates of trip demand. This similarity of coefficient estimates across on-site count data models has also been found elsewhere in the literature (Ovaskainen et al., 2001; Englin et al., 2003; Meisner and Wang, 2006, Hynes and Hanley, 2006). It is also worth noting that the significant variables in both the on-site and household hurdle models indicate the same direction of influence on trip frequency.

We were also particularly interested in examining if the consumer surplus per trip estimates from the on-site modelling approach were statistically different from the household population based modelling approaches. In our study we found that the on-site based approach (On-site NB model) provided a welfare estimate (WTP) that was 4 times higher than the preferred household modelling approach (Negative Binomial Hurdle Model). An examination of the confidence intervals indicates that the difference between the methodologies is significant at the 95% level. In contrast, Loomis (2003), Martínez-Espiñeira et al. (2008) and Meisner and Wang (2006), the only other studies to compare an onsite based travel cost model to a household based one found that correcting for endogenous stratification in the on-site sample produced consumer surplus per-day estimates nearly identical to the household survey. It should be noted though that in the case of Loomis (2003) the samples were constrained such that only on-site trips with maximum travel cost no larger than the household sample maximum were retained. Loomis (2003) also does not adjust for truncation in his on-site model or deal with the prevalence of zeros in his comparative household sample or consider their relative influence on expected trip demand or welfare. Martínez-Espiñeira et al. (2008) use the same dataset as Loomis (2003) but extend the on-site model to account for truncation as well as endogenous stratification. Like Loomis however, they still just apply a standard negative binomial model to the household sample.

The fact that our welfare estimates differ so substantially across the two samples in comparison to the previous comparative studies mentioned above raises questions in relation to the type of angler represented in our two samples. An examination of the summary statistics for the anglers from each sample (shown in table 1) would suggest that they come from different underlying distributions. The on-site sample of fishers appear to be serious anglers who take a high frequency of trips (29 per season) at a relatively high cost per trip, invest substantially in their equipment and are more likely than not to be members of an angling club. In contrast the anglers identified in the household sample make on average just under 8 trips per year, have only a third of the travel costs of the on-site surveyed angler and invests only 12% of what the on-site surveyed angler invests in his/her equipment. While the negative relationship between frequency of trips and travel cost holds within each survey it is clear that the on-site surveyed anglers are willing to take on a higher frequency of trips at a higher average cost that the household surveyed anglers.

It could be argued that by surveying at some of the most popular angling locations the on-site survey is mainly only picking up on what Failte Ireland (2009) refer to as the *Expert Angler* which they define as “Individuals or small groups of friends who research fishing opportunities, are highly knowledgeable about destinations, and visit or re-visit places they know offer excellent fishing opportunities. They are highly expert in their approach; and fishing is the only reason for the trip.” We would argue that the household survey is less likely to pick up on these individuals and more likely instead to be picking up anglers who only make a couple of short fishing trips in a year or the more opportunistic angler, the type of person who might go out of a summers evening to catch a few mackerel from the shore if there is a big shoal in or catch a few fish in the local canal that they know has been recently restocked. From a policy perspective then fishery managers might be better of employing a household survey based model if they wish to determine for example the value of urban waterway stocking program aimed at getting urban youths into angling while the on-site modelling approach may be more appropriate if the managing authority is more interested in the experience and welfare value associated with the activity of expert anglers.

While the underlying samples may represent different types of anglers, the share of consumer surplus in average willingness to pay per trip was very similar across the samples; 61% and 69% based on the results of the on-site NB model and the NB Hurdle models, respectively. This implies that a significant proportion of the value of a recreational fishing trip in Ireland, undertaken by domestic anglers, is retained by them in the form of consumer surplus. This finding would suggest that there is scope for those in charge of managing recreational fisheries resources in Ireland to manipulate the access fees currently in place in a manner that might raise additional funding to cover the costs of operating the fish hatcheries that restock rivers and lakes around the country, costs that are currently mainly paid for through central government funding. There is also considerable debate at present relating to the conflicts between large scale aquaculture developments and angling pursuits (Flynn, 2013). As pointed out previously by Curtis (2002), the capture of anglers' consumer surplus for use as compensation to commercial sea fisheries or aquaculture fish farm production units could be pursued as a management strategy to alleviate this conflict situation. Of course the property rights in this case may make that management option difficult as it is not always clear who owns the resource. The State issues licences to allow fish farms to produce but angling rights and permits are not always owned and issued by the State. In Britain and Ireland for instance the right to fish on certain waters may belong to a private estate. Even if the State controls the water bodies and the issue of angling permits, establishing the de facto property rights may be difficult given one is usually dealing with migratory fish species.

This study is limited in the sense that the number of anglers observed in the household sample was quite small. Also, since we were focussed on a comparison of an on-site to a household angling demand model we had to limited ourselves to just investigating the domestic anglers in our on-site sample. Further investigation of the data where the overseas anglers are also included in the model will give a better indication of the total welfare value of angling recreation in Ireland. Estimating the preferences of anglers for alternative water bodies as a function of site characteristics and angler characteristics is an obvious extension of this work. It would also be interesting to investigate the impacts on welfare and trips of alternative rationing mechanisms such as the imposition of car-parking fees and measures to increase access time.

Cost or time considerations usually have an important influence on the choice between an on-site versus a household survey when about to carry out a recreation demand study. It has been shown elsewhere that once the sampling issues are controlled either approach can produce equivalent welfare estimates. However, based on the findings in this paper we would caution that care needs to be taken to insure that both sampling approaches pick up the entire spectrum of participants in the recreational pursuit in question. Different sites used for on-site sampling may attract different types of participants. This was shown to be the case for different types of climbers (Scarpa and Thiene, 2005) and for kayakers of different skill levels (Hynes et al. 2007). If the researcher is interested in the recreation demand associated with a single large site then which survey technique to use may not be an issue. However, when the objective of the research is to model total demand for a recreational activity across numerous sites in a season then care is needed to ensure that whichever survey technique is chosen, participants of all skill levels, and with differing incentive structures (some recreationalist may be training at different sites for competitions in their recreational pursuit, some may be just trying out the recreation at the nearest possible location for the first time, etc), are picked up on.

References

Bilgic, A., Florkowski, W., 2007. Application of a hurdle negative binomial count data model to demand for bass fishing in the southeastern United States. Journal of Environmental Management. 83 (4), 478–490.

Czajkowski, M., Ahtiainen, H., Artell, J., Budziński, W., Hasler, B., Hasselström, L., Meyerhoff, J., Nõmmann, T., Semeniene, D., Söderqvist, T., Tuhkanen, H., Lankia, T., Vanags, A., Zandersen, M., Żylicz, T., and Hanley, N., 2015. Valuing the commons: An international study on the recreational benefits of the Baltic Sea. Journal of Environmental Management, 156, 209-217.

Englin, J., Shonkwiler, J., 1995. Estimating Social Welfare using Count Data Models: An Application to Long-run Recreation Demand under Conditions of

Endogenous Stratification and Truncation. The Review of Economics and Statistics. 77, 104-112.

Englin, J., Holmes, T., Sills, E., 2003. Estimating forest recreation demand using count data models. In: Sills, E., ed, Forests in a Market Economy, Kluwer Academic Publishers, Dordrecht, pp 341–359.

Fáilte Ireland, 2009. A New Strategy on Irish Angling Tourism. Fáilte Ireland, Dublin.

Flynn, G., 2013. Allegations of misleading and false information surround salmon farm debate. Inshore Ireland. 9 (5), 1-14.

Greene, W. H., 2007. NLOGIT 4 Econometric Modeling Guide, Volume 2, Econometric Software, Inc. New York

Grogger, J., and Carson, R. (1991), Models for truncated counts', J.Applied Econometrics, 6 (3), pp 225–238.

Hellerstein, D.M. 1991. Using count data models in travel cost analysis with aggregate data. American Journal of Agricultural Economics 73(3), 860-866.

Hynes, S., Greene, W., 2013. A Panel Travel Cost Model accounting for endogenous stratification and truncation: A latent class approach. Land Economics. 89 (1), 177-192.

Hynes, S., Hanley, N., 2006. Preservation versus Development on Irish Rivers: Whitewater Kayaking and Hydro Power in Ireland. Land Use Policy. 23, 170 - 180.

Hynes, S., Hanley, N.,Garvey, E., 2007. Up the Proverbial Creek without a paddle: Accounting for variable participant skill levels in Recreational Demand Modelling. Environmental and Natural Resource Economics 36: 413 – 426.

Inland Fisheries Ireland, 2013. Socio-Economic Study of Recreational Angling in Ireland. Inland Fisheries Ireland, Dublin.

Johnstone, C., Markandya, A., 2006. Valuing river characteristics using combined site choice and participation travel cost models. Journal of Environmental Management. 80, 237-247.

Loomis, J., 2003. Travel cost demand model based river recreation benefit estimates with on-site and household surveys: Comparative results and a correction procedure. Water Resources Research. 39(4), 1105

Loomis, J., Rosenberger, R., Shrestha, R., 1999. Updated Estimates of Recreation Values for the RPA Program by Assessment Region and Use of Meta-Analysis for Recreation Benefit Transfer. Final Report for the USDA Forest Service, Colorado State University, Fort Collins.

Loomis, J., Walsh, R., 1997. Recreation Economic Decisions: Comparing Benefits and Costs, 2nd ed. Venture Publishing, Inc, Pennsylvania.

Marine Institute, 1997. A National Survey of Water-based Leisure Activities. Marine Institute, Dublin.

Martínez-Espiñeira, R., Loomis, J., Amoako-Tuffour, J., Hilbe, J., 2008. Comparing recreation benefits from on-site versus household surveys in count data travel cost demand models with overdispersion. Tourism Economics. 14 (3), 567-576.

Martınez-Espineira, R., Amoako-Tuffour, J., 2007. Recreation Demand Analysis Under Truncation, Overdispersion, and Endogenous Stratification: An Application to Gros Morne National Park. Journal of Environmental Management. 88 (4), 1320-1332.

Meisner, C., Wang, H., 2006. Welfare measurement bias in household and on-site surveying of water-based recreation: An application to Lake Sevan, Armenia. World Bank Policy Research Working Paper Series No. 3932.

Mkwara, L., Marsh, D., 2011. Valuing trout angling benefits of water quality improvements while accounting for unobserved lake characteristics: An application to the Rotorua Lakes. New Zealand Agricultural & Resource Economics Society Conference, Nelson, New Zealand, August 25-26, 2011.

Morey, E., Breffle, W., Rowe, R., Waldman, D., 2002. Estimating recreational trout fishing damages in Montana's Clark Fork River basin: Summary of a natural resource damage assessment. Journal of Environmental Management. 66, 159-170.

Murdock, J., 2006. Handling unobserved site characteristics in random utility models of recreation demand. Journal of Environmental Economics and Management. 51, 1-25.

O'Neill, C., Davis, J., 1991. Alternative Definitions of Demand for Recreational Angling in Northern Ireland, Journal of Agricultural Economics. 42 (2), 174-179.

Ovaskainen, K., Mikkola, J., Pouta, E., 2001. Estimating recreation demand with onsite data: an application of truncated and endogenously stratified count data models. Journal of Forest Economics. 7 (2), 125-144.

Parsons, G.R., 2003. The Travel Cost Model. In: Champ, P.A., Boyle, K.J., Brown, T.C. (Ed.), A Primer on Nonmarket Valuation. Kluwer Academic Publisher, Dordrecht.

Prayaga, P, Rolfe, J., Stoeckl, N., 2010. The value of recreational fishing in the Great Barrier Reef, Australia: a pooled revealed preference and contingent behaviour model, Marine Policy: the International Journal of Ocean Affairs. 34 (2), 244-251.

Scarpa, R., Thiene, M., 2005. Destination choice models for rock-climbing in the North-Eastern Alps: a latent-class approach based on intensity of participation. Land Economics 81, 426-444.

Shaw, D., 1988. On-Site Sample's Regression: Problems of Non-Negative Integers, Truncation, and Endogenous Selection. Journal of Econometrics. 37, 211-223.

Shaw, D., Fadali, E., Lupi, F., 2003. Comparing consumer's surplus estimates calculated from intercept and general survey data. Proceedings of the W-133 (U.S.D.A.) Regional Economics Group, compiled by J. S. Shonkwiler. Las Vegas, Nevada, February, 2003.

Shrestha, K., Seidl, A., Moraes, A., 2002. Value of recreational fishing in the Brazilian Pantanal: a travel cost analysis using count data models, Ecological Economics, 42 (1–2), 289–299.

Shonkwiler, J., Shaw, D., 1996. Hurdle Count-Data Models in Recreation Demand Analysis. Journal of Agricultural and Resource Economics. 21, 210-219.

Train, K.E., 1998. Recreation demand models with taste differences over people. Land Economics. 74 (2), 230-239.

Whelan, B., March, G., 1988. An Economic Evaluation of Irish Angling. A report prepared for the Central Fisheries Board by the Economic and Social Research Institute (ESRI), Dublin.

Zhang, F., Hu Wang, X, Nunes, P. and Ma, C., 2015. The recreational value of gold coast beaches, Australia: An application of the travel cost method, Ecosystem Services, 11, 106–114.

Tables

Table 1. Summary Statistics

Variable	**Onsite Sample (Domestic Anglers Only) (n = 451)** Mean (Std. Dev.)	**Household Sample (Anglers Only) (n = 122)** Mean (Std. Dev.)
Number of trips in previous 12 months	28.91 (25.39)	7.69 (8.59)
Travel cost per fishing trip (travel, bait, boat hire, ghillies)	102.63 (128.26)	31.66 (39.59)
Investment (tackle, licences, clothing)	631.99 (765.86)	75.98 (157.53)
Age	47.9 (13.09)	41.27 (14.29)
Proportion of sample retired	0.03 (0.17)	0.1 (0.3)
Proportion affiliated with angling club	0.69 (0.46)	0.14 (0.35)
Proportion targeting game fish	0.1 (0.31)	0.23 (0.42)
Proportion targeting Pike and coarse fish	0.16 (0.37)	0.13 (0.34)
Proportion targeting sea bass	0.06 (0.24)	0.04 (0.2)
Proportion of males	0.98 (0.13)	0.83 (0.38)
Proportion of sample unemployed	0.02 (0.14)	0.19 (0.39)
Proportion of sample in Social Class C1	0.52 (0.5)	0.25 (0.43)
Proportion of sample in Social Class C2	0.33 (0.47)	0.33 (0.47)
Proportion of sample in Social Class DE	0.04 (0.21)	0.23 (0.42)
Number in household	N/A	3.12 (1.38)
Proportion with third level education	N/A	0.45 (0.5)
Proportion of rural dwellers	N/A	0.38 (0.49)
Gross Income /1000	37.05 (21.79)	N/A
Number of days for Fishing Trip	1.36 (1.09)	N/A
Fishing Group Size	2.5 (2.36)	N/A

Table 2. Alternative Specifications for On-site Travel Cost Models

Variable	Poisson	Negative Binomial	On-Site Negative Binomial
Travel cost per fishing trip (travel, bait, boat hire, ghillies)	-0.0036 (0.001)***	-0.0038 (0.001)***	-0.0043 (0.001)***
Annual investment in tackle, licence, clothing	0.0002 (0.0001)***	0.0003 (0.0001)***	0.0003 (0.0001)***
Age	0.002 (0.001)***	0.002 (0.003)	0.002 (0.003)
Retired	0.227 (0.049)***	0.278 (0.228)	0.295 (0.251)
Social class C2	-0.032 (0.02)*	-0.001 (0.081)	-0.001 (0.089)
Sea trout targeted	-1.136 (0.19)***	-1.319 (0.426)***	-1.533 (0.467)***
Sea bass targeted	0.668 (0.03)***	0.773 (0.151)***	0.820 (0.167)***
Pike/ Coarse fish targeted	0.315 (0.022)***	0.345 (0.099)***	0.362 (0.109)***
Affiliated with angling club	0.440 (0.022)***	0.549 (0.079)***	0.591 (0.087)***
Gross income /1000	-0.001 (0.001)	-0.001 (0.002)	-0.001 (0.002)
Number of days for trip	-0.095 (0.013)***	-0.106 (0.039)***	-0.115 (0.043)***
Fishing group size	-0.02 (0.004)***	-0.031 (0.0159)*	-0.031 (0.017)*
Constant	3.335 (0.046)***	3.208 (0.179)***	2.177 (0.235)***
Over dispersion parameter	-	0.518 (0.037)***	1.738 (0.197)***
LR chi2(12)^	2668	187	225
Log likelihood	-3955	-1852	-1848

Absolute value of z statistics in parenthesis. * indicates significance at 10%, ** indicates significance at 5%, *** indicates significance at 1%. ^This is a Wald chi2(12) statistic in the case of the On-site Model. The variable *Social class C2* refers to skilled manual workers.

Table 3. Alternative Specifications for Household Travel Cost Models

	Poisson Hurdle Model	**Negative Binomial Hurdle**
	Poisson model	Negative Binomial model
Travel cost per fishing trip (travel, bait, boat hire, ghillies, other)	-0.018 (0.001) ***	-0.0201 (0.005)***
Annual investment in tackle, licence, clothing	0 .004 (0.001) ***	-0.005 (0.001)***
Age	0.018 (0.001) ***	0.033 (0.013)**
Retired	0.304 (0.088) ***	-0.238 (0.926)
Part-time employed	-0.044 (0 .093)	-0.791 (0.869)
Third level education	-0.154 (0.0371) ***	-0.76 (0.562)
Affiliated with angling club	-0.250 (0.056) ***	-0.568 (0.451)
Resident in Munster	0 .509 (0.034) ***	0.209 (0.299)*
Resident in Connaught/Ulster	-0.305 (0.041) ***	-0.774 (0.653)
Number in household	0 .228 (0.009) ***	0.27 (0.151)*
Social class C1	0.103 (0.039***	-0.319 (0.602)
Game species targeted	0.940 (0.032) ***	0.776 (0.298)**
Pike/ Coarse fish targeted	0.242 (0.036) ***	0.363 (0.648)
Sea bass targeted	-0.101 (0.127)	-0.133 (1.081)
	Zero hurdle equation	*Zero hurdle equation*
Retired	1.465 (0.371) ***	1.503 (0.338) ***
Male	0 .622 (0.231) ***	0.704 (0.219) ***
Age	-0.068 (0.006)***	-0.064 (0.006) ***
Social Class DE	-0.629 (0.267) **	-0.688 (0.248) ***
Third level education	-0.302 (0.204)	-0.36 (0.195)*
Unemployed	0.164 (0.295)	0.086 (0.277)
Part-time	-0.480) (0.325)	-0.501 (0.32)
Rural Dweller	-0.471 (0.214) **	-0.551 (0.198) ***
Over dispersion parameter		1.455(0.453) **
Log likelihood	-987	-797
AIC	2022	1642
Chi squared Statistic [1 d.f.]	1836	2218

Absolute value of z statistics in parenthesis. * indicates significance at 10%, ** indicates significance at 5%, *** indicates significance at 1%.

Table 4. Expected Trips and Benefit Estimates

	Poisson	Negative Binomial	On-Site Negative Binomial	Poisson Hurdle	Negative Binomial Hurdle
Predicted Trips	22.06	22.45	6.81	0.657	0.743
Consumer surplus per trip (€)[a]	277 (258, 298)	263 (218, 330)	232 (193, 294)	55.12 (49.8, 32.6)	49.97 (32.5, 107.2)
Willingness to Pay per trip (€)[b]	379.78	365.16	334.56	87.13	81.97
Aggregate WTP (€'000)	2,162,910	2,065,844	574,142	14,425	15,349

a. Confidence intervals in parenthesis. b. willingness to pay per trip is the addition of average travel cost and consumer surplus per trip. Aggregate willingness to pay is based on: predicted trips* population of domestic anglers of 252,000*(CS per trip +average travel cost as specified in table 3).

Figure 1. On-site Sampling Points

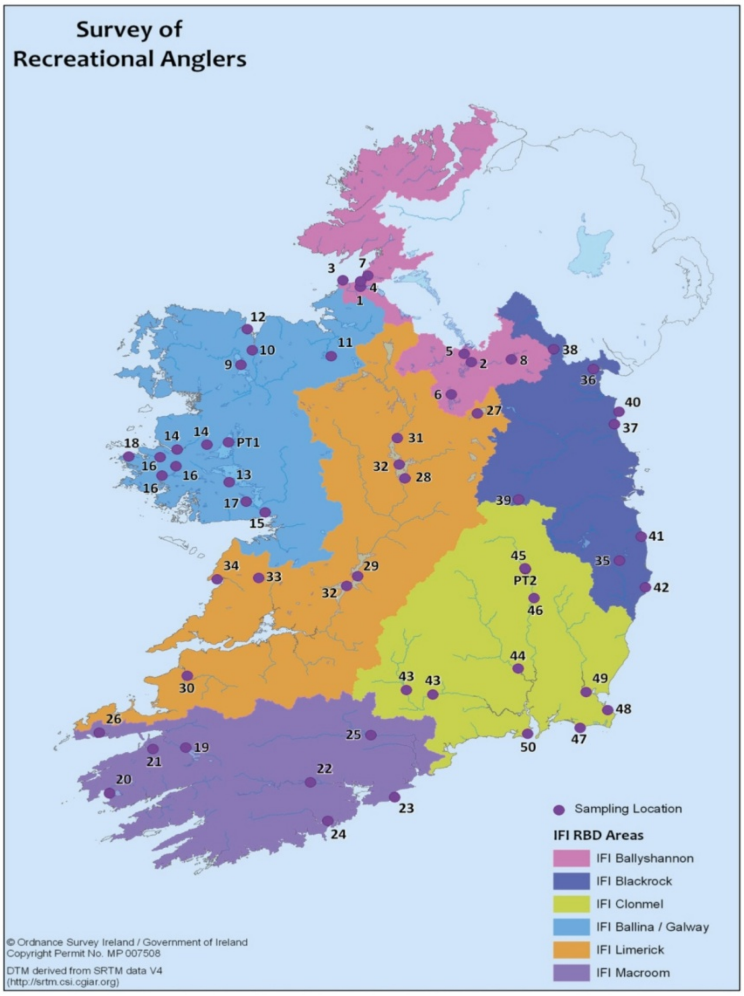
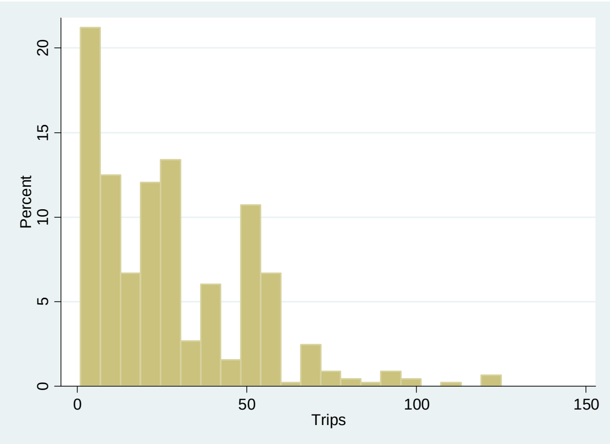
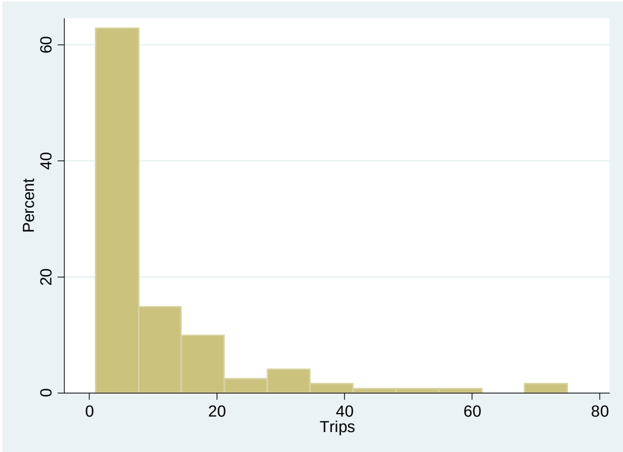


Figure 2. Distribution of Fishing Trips amongst the angling population over Previous 12 Month Period

On-Site Sample



Household Sample



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