ESRI

Working Paper No. 521

December 2015

Water Quality and Recreational Angling Demand in Ireland

John Curtis and Brian Stanley

Abstract: Using on-site survey data from sea, coarse and game angling sites in Ireland, this paper estimates count data models of recreational angling demand. The models are used to investigate the extent to which anglers are responsive to differences in water quality, with the water quality metric defined by the EU's Water Framework Directive. The analysis shows that angling demand is greater where water quality has a higher ecological status, particularly for anglers targeting game species. However, for coarse anglers we find the reverse, angling demand is greater in waters with lower ecological status. On average, across the different target species surveyed, anglers have a willingness to pay of €371 for a day's fishing. The additional benefit of angling in waters with high versus low ecological status was the highest for game anglers at a mean of €122 per day.

**Corresponding Author(s): john.curtis@esri.ie*

Keyword(s): recreation; angling; travel cost; count data; water quality; Water Framework Directive

Acknowledgements: Funding from Inland Fisheries Ireland is gratefully acknowledged. Our thanks to Gavin Smith for assistance with the accessing the water quality data, to Inland Fisheries Ireland for providing the TDI angler survey dataset, and to Paul O'Reilly for useful comments. All errors or omissions are our own.

1 Introduction

Marine and inland waterways provide many recreational opportunities including angling, boating, walking and wildlife viewing. In developed economies as many as half of the adult population participate in water-based recreational activities (Curtis, 2003; Environment Agency, 2009; Outdoor Foundation, 2013). And it is widely recognised that the enjoyment of water-based recreational activities is enhanced by higher water quality status, including in swimming (Arnold et al., 2013; Wade et al., 2010), boating, canoeing/kayaking, fishing and rowing (Dorevitch et al., 2015, 2011), as well as tourism more generally (Aminu et al., 2014; Lee and Lee, 2015). Though not all recreational users recognise poor water quality or its associated risks (Burger et al., 1993; Westphal et al., 2008).

Establishing the link between improved water quality status and enhanced recreational experiences is not trivial. In the first instance it is important to have a meaningful water quality indicator recognisable and understood by recreational users. Both objective and subjective measures of water quality have been successfully used to explain water-based recreational activity (Poor et al., 2001). Objective measures have included levels of suspended solids (Egan et al., 2009), levels of harmful bacteria (Parsons et al., 2003) and water clarity (Vesterinen et al., 2010). Subjective measures have also included water clarity (Loomis and Santiago, 2013), as well as Likert scales (Hanley et al., 2003). Water clarity may be a useful indicator of water quality for activities such as swimming and boating but may be less useful for anglers who are more interested in fish stocks and catch rates. Fish catch rates are a commonly used quality indicator within angling recreational demand models (Chen et al., 1999). But catch rates are endogenous, depending on angler skill and fishing pressure. In addition, while water clarity may be a useful quality indicator for game species, such as trout and salmon that need high quality water habitat, coarse species can thrive in more eutrophic murky waters. A more complex indicator of water quality, such as ecological status, may more useful in recreational angling demand models.

The European Union Water Framework Directive (WFD) requires that water bodies be of good ecological status, a description that covers indicators such as biological quality (i.e. fish, benthic invertebrates, aquatic flora), hydromorphological quality, physical-chemical quality, and chemical status. Vesterinen et al. (2010) suggest that ecological status, as defined within the WFD, may not be a quality indicator easily observable or understood by the public in a manner that would effect their recreation behaviour. Nonetheless, if recreational behaviour such as angling is affected by water quality, revealed behaviour of anglers will reflect the underlying ecological status of water bodies. For example, without knowledge of WFD status, game anglers may visit water bodies with high ecological status more than water bodies with a poor or bad status. In the United States Egan et al. (2009) find that anglers are responsive to the full set of water quality measures used by biologists. And furthermore, that that changes in these quality measures translate into changes in the recreational usage patterns and well-being of anglers.

There are five status classes within the WFD's classification scheme for water quality: high, good, moderate, poor and bad. These are nominally easy to understand though the water assessment process for classification is multifaceted and complicated (Directive 2000/60/EC, 2000). The use of WFD ecological status classifications is relatively recent, being first used to assess Irish river water quality in 2010 (McGarrigle et al., 2010). At the time our angling dataset was collected the WFD classifications would not have been widely familiar to anglers or the general public. But if recreational usage patterns of Irish anglers are responsive to the WFD ecological status categories, similar to the Egan et al. (2009) study, the WFD classifications are an ideal metric for conveying water quality information to prospective anglers at specific fishing sites.

The primary research question in this paper is whether recreational anglers are responsive to water quality, as measured by the EU's WFD classification. Recreational angling demand may be a function of many things, such as catch rates or angler facilities but may also be a function of water quality either directly or indirectly. In fact, water quality status may not be observable to an angler, as the WFD status is not normally posted at fishing sites. What we wish to establish is whether water quality, as defined by WFD status, and not necessarily observable to anglers is a fishery characteristic that can affect anglers' experience and choices. The research also is relevant for wider fisheries policy questions. The estimated models will provide a greater insight into preferences for angling within Ireland enabling fishery managers enhance the quality of their angling product.

There are many studies in the grey literature about recreational angling in Ireland but there are relatively few studies that estimate demand functions (O'Neill and Davis, 1991; Curtis, 2002; Hynes et al., 2015; McGrath, 2015). And none assess angling demand as a function of water or fishery quality. The recent papers by Hynes et al. (2015) and McGrath (2015) are based on national surveys covering all types of angling, i.e. game, coarse and sea angling (Tourism Development International, 2013). This paper also utilises some of the Tourism Development International (TDI) data but additionally supplements it with WFD water quality data associated with the angling sites surveyed (McGarrigle et al., 2010).

2 Methodology

2.1 Data

Angler data was collected by on-site survey at sites around the Republic of Ireland. The survey was undertaken between March and November 2012 and included the prime angling season in respect of each angling category. In total 903 anglers were interviewed. The survey collected travel cost data for the intercepted trip, as well as information on the number of trips in the preceding 12 months. A full description of the survey design and implementation is available in Tourism Development International (2013).

Water quality data for the period 2007–2009 from water quality monitoring stations proximate to the angling survey sites were downloaded from `http://gis.epa.ie/`. Water quality monitoring and data is summarised in McGarrigle et al. (2010). We used the WFD ecological status as an indicator of quality and created a dummy quality variable distinguishing between 'High/Good/Moderate' or 'Poor/Bad' ecological status.

2.2 Model

The travel cost method (TCM) is commonly used to estimate recreational demand models (Martínez-Espiñeira and Amoako-Tuffour, 2008; Egan et al., 2009; Ovaskainen et al., 2012; Hynes and Greene, 2013). The TCM relies on the assumption that although access to recreational sites may have no explicit price, individuals' travel costs, including transportation, accommodation, and sometimes the value of lost wages and time can be used to approximate an implicit price associated with their recreational activity. Anglers respond to changes in travel costs in the same way they would respond to changes in an entry fee, so the number of trips to a fishing site and or their duration should decrease as travel costs increase.

$$y_i = f\left(TC_i, I_i, E_i, S_i\right) \tag{1}$$

where y_i is individual i's demand for site trips (or days), TC_i is travel cost and I_i is income. Angler socioeconomic characteristics, E_i, or fishing site attributes, S_i, may also be included in the demand function as shift parameters (Larson and Shaikh, 2001).

Count models have become the standard in estimating recreational demand models (Martínez-Espiñeira and Amoako-Tuffour, 2008; Ovaskainen et al., 2012; Hynes and Greene, 2013) following a theoretical underpinning provided by Hellerstein and Mendelsohn (1993). The count variable, e.g. number of trips or days, comprises non-negative integers, often all positive, while count data distributions are usually left-skewed and characterised with probability mass concentrated on a few values. Usually within the literature a series of count models including those based on the Poisson and negative binomial distributions are estimated. Within the analysis presented here we focus on models based on the negative binomial because it is less restrictive than the Poisson.[1] The Poisson distribution, which is a special case of the negative binomial, assumes that the mean and variance are equal but this is rarely found in empirical studies (Carson, 1991).

There are two features of recreation demand data collected on-site that must be accommodated within model estimation: truncation and endogenous stratification. When the data is collected on-site the distribution of Y is truncated at zero. The issue of endogenous stratification arises because the likelihood of being sampled is positively related to the number of trips taken to the site.[2] The issue of truncation in count models was addressed by Carson (1991), whereas endogenous stratification was first addressed by Shaw (1988). Englin and Shonkwiler (1995) developed an application of a truncated, endogenously stratified negative binomial model, which we follow here. Assuming a population density function to be a negative binomial with mean λ_i, the likelihood function for the on-site sample is

$$L = \prod_{i=1} \frac{y_i \Gamma\left(y_i + \alpha_i^{-1}\right) \alpha_i^{y_i} \lambda_i^{y_i - 1} \left[1 + \alpha_i \lambda_i\right]^{-\left(y_i + \alpha^{-1}\right)}}{\Gamma\left(\alpha_i^{-1}\right) \Gamma\left(y_i + 1\right)} \tag{2}$$

with

$$\begin{aligned} E\left(y_i | x_i\right) &= \lambda_i + 1 + \alpha_i \lambda_i \\ Var\left(y_i | x_i\right) &= \lambda_i \left(1 + \alpha_i + \alpha_i \lambda_i + \alpha_i^2 \lambda_i\right) \end{aligned} \tag{3}$$

where $\Gamma(\cdot)$ is the gamma function, and α_i is the over-dispersion parameter. The model is extended into a regression framework by defining λ_i as a func-

[1] Martínez-Espiñeira and Amoako-Tuffour (2008) and Cameron and Trivedi (2001) provide an exposition of differences between the Poisson and negative binomial models.

[2] Haab and McConnell (2002) discuss in further detail (p.175).

tion of regressor variables, x_i, as described in equation 1. The conventional approach is to model expected latent demand, λ_i, as a semi-logarithmic function of price, i.e. travel cost, and other independent variables x_j, such that

$$ln\lambda_i = \beta_0 + \beta_p TC_i + \beta_1 X_{1i} + \cdots + \beta_j X_{ji} \tag{4}$$

The estimation of the over-dispersion parameter, α_i, has been problematic (Cameron and Trivedi, 1986). A common approach has been to restrict it to a common value for all observations, such that $\alpha_i = \alpha$. Less restrictive approaches are also used, for example Englin and Shonkwiler (1995) specify $\alpha_i = \alpha_0/\lambda_i$, whereas Martínez-Espiñeira and Amoako-Tuffour (2008) apply a more flexible approach specifying α_i as a function of visitor characteristics. We estimate both the restrictive and flexible approaches using STATA™modules NBSTRAT and GNBSTRAT (Hilbe and Martínez-Espiñeira, 2005; Hilbe, 2005; Martínez-Espiñeira and Hilbe, 2008). For ease of estimation the parameter $ln(\alpha_i)$ rather than α_i is estimated and defined as

$$ln\,(\alpha_i) = \gamma_0 + \gamma_1 z_{1i} + \gamma_2 z_{2i} + \ldots \tag{5}$$

where z are variables measuring angler characteristics.

2.3 Welfare

An angler's consumer surplus is derived by integrating the demand function (4) over the relevant price range and is given by (6) (Hellerstein and Mendelsohn, 1993).

$$CS = \int \lambda_i dTC = \frac{-\lambda_i}{\beta_p} \tag{6}$$

where β_p is the coefficient on the travel cost variable. Frequently angler CS is reported per trip (or per day), as it has more policy relevance in that format. This is usually calculated as $CS = -1/\beta_p$ implying that the mean trip denominator relates to all anglers, including those with zero trips demanded during the survey period. However, if the policy issue relates to sampled anglers the appropriate denominator is mean trip demand given in equation 3 and mean consumer surplus per trip (or day) for sampled anglers becomes $CS = -\lambda_i/\beta_p(\lambda_i + 1 + \alpha_i\lambda_i)$, similar to Martínez-Espiñeira and Amoako-Tuffour (2008).

2.4 Model specification and variables

Three types of models are estimated in this paper. The first uses solely data on the current or intercepted angling trip and estimates a demand function for angling days within the trip. The dependent variable is $TripDays$, defined as the number of days spent angling on the current trip. Total CS, as defined by equation 6, represents mean trip consumer surplus. The second type of model estimates angling demand (in days) per annum. This model employs the same data as the previous model, as well as data on the number of trips taken in previous 12 months, $TripsYear$. The dependent variable is $DaysYear$, which is number of days spent angling in the past 12 months and calculated as follows: $DaysYear_i = TripDays_i \times TripsYear_i$.[3] In estimating this model we make the implicit assumption that all angling trips are the same. The third type of model estimates trip demand per annum, which also assumes that all trips are the same in terms of costs and duration.[4] Descriptive statistics for these and other variables are presented in Table 1.

All the estimated models include an interaction term between an angler's target species and water quality. We use the relative magnitude between the coefficient estimates on these interaction variables to show the effect of water quality on angling demand. For example, the relative difference in magnitude of the coefficients on ($Game \times LowWaterQ$) and ($Game \times HiWaterQ$) will show whether differences in water quality status affect game anglers' demand. The reference category in the estimated models are anglers targeting Sea Bass and other sea fish. All survey sites where Sea Bass were targeted had waters of a High/Good/Moderate ecological status, as defined by WFD.

There are 63 angling sites in our data and these were categorised into 9 groups based on broad spatial proximity (e.g. west, midlands, south-west, etc.). These spatial variables jointly have explanatory power within the models estimated but are not reported due to space constraints. These variables are potentially capturing regional characteristics that affect angling demand but may not be specifically related to angling. For instance, some regions are more scenic than others and have more tourist amenities to offer, which are factors that could influence angler demand at a particular site.

[3] Bowker et al. (1996) and Bhat (2003) have previously employed a similar approach in generating the dependent variable.

[4] McGrath (2015) take a different approach with the same dataset using anglers' own estimates of annual angling trip costs whereas the approach in this paper was to assume that an angler's estimate of trip costs on the intercepted trip was representative of all trips taken during the year.

Table 1: Summary descriptives of variables used in models

Variable	Mean	SD	Min	Max	Description
$TripDays$[a]	2.60	2.73	1.00	14.00	Days angling on current trip
$TripsYear$[b]	5.24	5.55	1.00	26.00	No. trips in previous 12 months
$DaysYear$[c]	10.69	12.99	1.00	182.00	Fishing days in previous 12 months
$DailyCost$[d]	0.19	0.39	0.00	7.00	Per angling day costs, €'000
$DailyCostadj$[e]	0.11	0.26	0.00	4.20	Per angling day costs excl. permits & fees
$TripCost$[b]	0.29	0.45	0.00	4.20	Travel,angling,food & accommodation
$AnnualFees$[b,c]	0.05	0.17	0.00	1.54	Annual angling fees, e.g. licences
$Age65+$	0.13	0.34	0.00	1.00	=1 if aged 65+
$Adults3+$	1.59	0.91	1.00	3.00	=1 if 3+ adults in angling group
$Income$	36.75	24.25	5.00	300.00	Annual gross income, €'000
$MissInc$	0.49	0.50	0.00	1.00	=1 if Income not reported
$Game$	0.36	0.48	0.00	1.00	Angler targets game species
$Coarse$	0.24	0.43	0.00	1.00	Targets coarse species
$SeaBass$	0.21	0.41	0.00	1.00	Targets sea fish incl. sea bass
$Combo$	0.20	0.40	0.00	1.00	Targets multiple fish types
$HiWaterQ$	0.89	0.31	0.00	1.00	=1 if quality High/Good/Moderate
$LowWaterQ$	0.11	0.31	0.00	1.00	=1 if quality Poor/Bad
$Ireland$	0.64	0.48	0.00	1.00	=1 if angler from Republic of Ireland
$NIreland$	0.10	0.31	0.00	1.00	=1 if angler from Northern Ireland
$Elsewhere$	0.26	0.44	0.00	1.00	=1 if angler from elsewhere
$FishStock$	0.85	0.35	0.00	1.00	=1 if rates fish stocks positively
$Club$	0.58	0.49	0.00	1.00	=1 if affiliated to angling club
$OwnTime$	0.07	0.26	0.00	1.00	=1 if angler retired or self-employed

[a] *TripDays* is dependent variable for within trip days demand model. Trip costs averaged across angling days, *DailyCost*, include expenses such as travel, bait, food, licences, permits and competition fees.

[b] *TripsYear* is dependent variable for annual trip demand model. Travel costs are distinguished between costs that occur on annual basis (*AnnualFees*) and other trip costs excluding annual fees (*TripCost*).

[c] *DaysYear* is dependent variable for annual angling days demand model. Costs are distinguished between daily costs (*DailyCostadj*) and annual fees (*AnnualFees*).

[d] DailyCost is calculated as sum of trip angling and travel expenses divided by number of angling days.

[e] *DailyCostadj* is calculated similar to *DailyCost* but excludes expenses for licences, permits (i.e. *AnnualFees*), which may relate to the entire angling season. *DailyCostadj* also excludes competition fees.

Not all anglers provided information about their income. As a means of preserving observations for model estimation we assigned the median sample income level to observations with missing values but included a dummy variable $MissInc$ in model estimation to identify those observations.

Almost two-thirds of anglers in the sample are resident in the Republic of Ireland and are the reference category in our estimated models. About 10% live in Northern Ireland and the majority of the balance live in Europe with some anglers from North America.

For the models that estimate $ln(\alpha_i)$ we model it as a function a number of variables. The first is whether the angler is affiliated to an angling club ($Club$), as membership will affect angling access opportunities independent of travel cost. A second variable is whether an angler is either retired or self-employed ($OwnTime$), as anglers of these types may have greater flexibility in allocating their time to angling. The third variable that we use to allow angler-specific variables affect demand within the estimated model is income, specifically $ln(Income)$. As well as a direct income effect, income may proxy other visitor characteristics that affect the variance of trip demand.

While the original angler dataset had 903 observations, for reasons outlined below observations were omitted in model estimation, including 139 observations where the interviewed angler paid the expenses of multiple anglers. A further 21 observations were omitted where trip length exceeded 14 days on the assumption that the primary purpose of these trips may not have been solely angling. For example, the longest trip length specified was 120 days. Ten observations were excluded as they reported no travel cost data. In the estimation of trip demand models ($TripsYear$) observations were split between anglers with 26 or less trips per year (i.e. ≤ 1 trip per fortnight) and those with more. This split was made because the estimated likelihood function using all observations was not concave. There are 100 observations in our dataset where anglers take more than 26 trips per year (some fish almost every day) and the estimated model suggests that these anglers have preferences substantially different than the majority of anglers.

3 Model Estimates

Model estimates are reported in Table 2, where three sets of results are presented. Columns 1 & 2 are demand estimates for angling days on the trip the anglers were surveyed. The model is estimated conditional on anglers paying their own costs and for trip lengths not exceeding two weeks. Columns 3 & 4 are demand estimates for angling days per year and assumes that anglers' trips are of the same duration as the surveyed trip. These models are estimated for anglers with not more than 26 trips per year, which excludes 100 anglers compared to models estimated in columns 1 & 2. Columns 5 & 6 report estimates of annual trip demand among the same anglers. Columns 7 & 8 report demand estimates for high frequency anglers, i.e. more than 26 trips per annum. These latter two models are miss-specified, as they assume truncation at zero whereas trip demand is truncated at 26. The estimates are reported to consider whether high trip frequency anglers have substantially difference demand than other anglers. This is discussed in further detail in section 3.1.1.

3.1 Model selection

The models are estimated with two specifications for the over dispersion parameter, either $\alpha_i = \alpha_0$ or as specified in equation 5. Likelihood ratio tests indicate that in all cases presented the more flexible model specification provides a better fit for the data. The most significant angler-specific characteristics that affect the the variance of angling demand through α_i are membership of a fishing club and flexibility with one's time (via the $OwnTime$ variable).

Model estimates of mean fishing days demanded are 1.5 days for the intercept trip and 9.4 days for the previous 12 months with both instances evaluated at the mean of the data. This compares to actual means of 2.6 days for the intercept trip and 10.7 days annually so the estimated models slightly underestimate angling demand.

The models estimating annual angling trip demand (models 5&6) are not very satisfactory. In the first instance, the coefficient on the travel cost variable, $TripCost$, is not statistically significant. It is not obvious why this is so, especially as both McGrath (2015) and Hynes et al. (2015) with the same TDI dataset but using anglers' estimates of annual travel cost expenditure (as opposed to current trip expenditure used here) estimate an annual trip demand model with a statistically significant coefficient on their travel cost variable that is also stable across a number of model specifications. However, it is also the case that the estimated annual trip demand model is not consistent with one of the basic assumptions of travel cost models, that the decision unit should be trips of roughly equal length (Haab and McConnell, 2002, p.148). In our data, trip length varies up to 14 days so the good in

Table 2: Estimation Results

Dependent variable	(1) TripDays	(2) TripDays	(3) DaysYear	(4) DaysYear	(5) TripsYear	(6) TripsYear	(7) TripsYear	(8) TripsYear
DailyCost	-1.524***	-1.569***						
	(-5.69)	(-6.16)						
DailyCostadj			-0.742***	-0.710***				
			(-4.15)	(-4.07)				
TripCost					-0.0815	-0.0607	0.867	0.705
					(-0.58)	(-0.45)	(1.35)	(1.27)
AnnualFees			0.876**	0.885***	0.275	0.339	-0.206	-0.868
			(3.19)	(3.37)	(0.85)	(1.11)	(-0.09)	(-0.47)
Age 65+	0.378**	0.269*	0.191	0.190	0.0930	0.0379	-0.232*	-0.167
	(3.17)	(2.45)	(1.60)	(1.62)	(0.71)	(0.30)	(-2.02)	(-1.60)
Adults 3+	0.113	0.108	-0.202*	-0.193*	-0.383***	-0.385***	0.0901	-0.0309
	(1.25)	(1.32)	(-2.24)	(-2.20)	(-3.81)	(-4.00)	(0.67)	(-0.25)
Income	0.00551**	0.00383*	0.00546**	0.00526*	0.00387*	0.00304	0.00248	0.00244
	(3.13)	(2.03)	(3.20)	(1.99)	(2.06)	(1.09)	(1.04)	(1.12)
MissInc	-0.128	-0.0744	-0.155	-0.129	-0.0461	-0.0158	-0.125	-0.145
	(-1.38)	(-0.89)	(-1.87)	(-1.54)	(-0.51)	(-0.17)	(-1.46)	(-1.83)
Combo × LowWaterQ	-14.18	-13.01	-0.800	-0.786	-0.374	-0.421	-1.654***	-1.320*
	(-0.02)	(-0.04)	(-1.75)	(-1.73)	(-0.80)	(-0.92)	(-3.30)	(-2.19)
Game × LowWaterQ	-1.205**	-1.478**	0.0833	0.120	0.292	0.326	-1.328**	-1.097
	(-2.83)	(-3.25)	(0.26)	(0.38)	(0.87)	(1.00)	(-3.01)	(-1.90)
Coarse × LowWaterQ	0.668*	0.895**	0.761**	1.058***	0.350	0.721*	-1.163**	-1.002
	(2.07)	(2.94)	(2.69)	(3.67)	(1.15)	(2.41)	(-2.88)	(-1.85)
Combo × HiWaterQ	-0.766**	-0.609*	0.0149	0.0909	0.339	0.391	-0.677***	-0.434
	(-3.05)	(-2.57)	(0.07)	(0.43)	(1.44)	(1.70)	(-3.34)	(-1.67)
Game × HiWaterQ	-0.297	-0.206	0.0906	0.189	0.298	0.367	-0.758***	-0.458
	(-1.22)	(-0.91)	(0.42)	(0.88)	(1.26)	(1.60)	(-4.01)	(-1.76)
Coarse × HiWaterQ	0.166	0.239	0.331	0.424	0.323	0.358	-0.898***	-0.602*
	(0.55)	(0.86)	(1.26)	(1.63)	(1.14)	(1.30)	(-3.78)	(-2.10)
FishStock	0.426**	0.396**	0.101	0.131	-0.0933	-0.0373	0.219	0.217
	(2.90)	(2.86)	(0.89)	(1.19)	(-0.77)	(-0.31)	(1.74)	(1.88)
NIreland	1.531***	1.576***	0.620***	0.661***	0.143	0.197	-0.294	-0.376
	(9.17)	(9.61)	(4.48)	(4.83)	(1.01)	(1.44)	(-1.54)	(-1.86)
Elsewhere	2.815***	2.878***	0.605***	0.733***	-1.224***	-1.030***		
	(22.90)	(23.62)	(5.92)	(7.00)	(-8.31)	(-7.20)		
Constant	-1.998***	-1.820***	0.354	0.449*	0.361	0.634**	3.969***	3.734***
	(-8.48)	(-8.28)	(1.45)	(2.06)	(1.38)	(2.92)	(23.60)	(21.41)
ln (α)								
Club		1.051		0.494***		0.839***		-1.818***
		(1.55)		(3.58)		(4.92)		(-3.96)
OwnTime		2.327**		-0.0419		-0.0592		-0.312
		(3.01)		(-0.17)		(-0.21)		(-0.32)
ln(Income)		1.099		-0.0335		-0.0408		0.641
		(1.80)		(-0.20)		(-0.22)		(1.41)
γ_0	-1.367***	-6.760*	1.055***	0.687	1.037***	0.265	-2.001***	-2.830
	(-3.45)	(-2.44)	(4.01)	(1.17)	(3.64)	(0.40)	(-11.07)	(-1.78)
N	707	707	607	607	607	607	100	100
Log likelihood	-827.0	-818.7	-1920.1	-1913.4	-1442.6	-1428.8	-428.1	-418.0

t statistics in parentheses

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

question, i.e. what *TripCost* is purchasing, varies substantially across anglers. At least in both within trip demand (in days, models 1&2) and annual demand (in days, models 3&4) the good in question is broadly similar for all anglers, i.e. one day's angling. Even though the trip demand models presented here are not very satisfactory, the results presented do suggest that preferences among high frequency anglers may be substantially different than the wider angler population.

3.1.1 High trip frequency anglers

As mentioned at the start of this section, models 7 and 8 in Table 2 are miss-specified. Angling trip data for these models was truncated at 26 trips, whereas the specified models assume truncation at zero. Reprogramming the software code to enable estimation of the model was beyond the scope of this paper. However, the parameter estimates do suggest that anglers with high trip frequency have substantially different preferences than other anglers. We also estimated demand functions controlling for the appropriate truncation using STATA's TNBREG command, which generated coefficient estimates broadly similar to those reported in model 7. Irrespective of the model estimated there are substantial differences in many of the estimated demand coefficients for high-frequency anglers (models 7 and 8) versus those estimated in models 5 and 6. For example, the estimated coefficient on *TripCost* is an order of magnitude higher and the opposite sign and the coefficients on the target species-water quality interaction variables are substantially different. In models 5 and 6 the angling group size ($Adults3+$) is a significant determinant of trip demand (larger groups demand fewer trips), whereas group size does not impact on trip demand among high frequency anglers. The policy implication is that the needs and preferences of high-frequency anglers are likely to be substantially different from the majority of anglers but further research is required to substantiate this.

3.2 Travel costs

The first three rows of Table 2 comprise coefficients on travel cost variables. There is a negative coefficient on either the *DailyCost* or *DailyCostadj* variables in models 1 to 4. As daily costs increase, fewer angling days are demanded. The price elasticity of within trip demand among surveyed anglers for angling days is -0.14, implying that for a 7% increase in *DailyCost* the number of days demanded within the trip falls by 1 day.[5] The elasticity value for angling days demanded per annum among surveyed anglers is -1.13. For a 1% increase in *DailyCostadj* the number of days demanded over the year declines by 1 day.[6]

3.3 Income

Across the models estimated there is mixed evidence of an income effect on angling demand, which is a common feature of recreation demand model estimates. Where there is a statistically significant income effect it is relatively small within a single trip, however, a 1% increase in income would lead to between 1–2 days additional angling per annum.

3.4 Water quality

The impact of water quality on fish stocks can vary by species. Coarse species are more tolerant of poor water quality than games species. To allow for this the estimated models include interaction terms between the angler's target species and the level of water quality. The inclusion of water quality as an explanatory variable in angler demand leads to the estimated models being a better fit, based on log-likelihood ratio tests.

What is of primary interest is the relative difference between the coefficient estimates for each target species. For example, is there a significant difference in angling demand among anglers targeting game species in water bodies with lower versus higher water quality status? If the coefficient with $HiWaterQ$ is greater in magnitude than the coefficient with $LowWaterQ$, angling demand is higher for the given target species in waters with higher water quality status. Table 3 reports Wald test statistics for equality of water quality coefficients. The *a priori* expectation was that demand for game angling would be greater in waters with high WFD ecological status for which we find empirical support in models 1 and 2. On average within the surveyed trip game anglers fished in waters with higher ecological status for roughly 0.3 days more than anglers fishing in lower status waters. In the case of coarse fishing the effect is the opposite, fishing days demanded is higher in

[5] The price elasticity for surveyed anglers is calculated as $\frac{\partial(\lambda_i + 1 + \alpha_i\lambda_i)}{\partial DailyCost} DailyCost$ and evaluated at mean values.

[6] The equivalent elasticity estimates for all anglers are -0.12 and -0.34 and calculated as $\frac{\partial\lambda}{\partial K}K$, where K is either $DailyCost$ or $DailyCostadj$.

water bodies with poor or bad water quality status. As mentioned earlier, coarse species can thrive in more eutrophic waters and may support better coarse fishing. On average coarse anglers fishing in lower ecological status waters fish roughly 0.7 days more per trip than those fishing in high status waters, and across the year fish approximately 9 days more. Anglers that target a combination of species have a higher level of demand in waters with higher water quality status. Unfortunately, the dataset does not quantify the exact combination of target species but it is likely that this category of anglers are targeting games species: salmon, sea trout and brown trout. On average anglers targeting multiple species in high ecological status waters fish 4 days more per annum than those fishing in waters with low ecological status.

These results are the first that show the impact of water quality on angling demand at Irish sites and provides a further justification of the merits improving water quality to good status under the WFD.

Table 3: Wald test statistics for equality of water quality coefficients

Model/ Species	(1)	(2)	(3)	(4)
Combo	0.00	0.00	3.83*	4.47**
Game	6.37**	9.81***	0.00	0.07
Coarse	5.07**	10.22***	3.34*	7.18***

t statistics in parentheses

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

3.5 Other characteristics

There is some evidence that angler's age and angling group size affect demand. Anglers aged 65 and above demand more days within angling trips (models 1 & 2). When angling group size is 3 or more adults, both the number of days per annum or trips per annum are lower (models 3–6). This is not surprising as more coordination and trip planning is required once group size increases. An implication for fishery managers is whether there is additional latent demand among large angler groups that could be served by better accommodating their specific needs.

The variable *FishStock* is a dummy variable indicating whether the angler considered fish stocks to be better than poor. Anglers with a strong rating for fish stocks undertook angling trips of longer duration on average than anglers that rates fish stocks as poor; in total spending one day more angling per year on average.

The number of angling days demanded varies by angler country of residence. From the survey data Republic of Ireland anglers fished for 1.3 days on the current trip, Northern Ireland anglers 2.2 days, and anglers from overseas 6.1 days. Model estimates of mean angling days demanded in the current trip were slightly lower in the case of Republic of Ireland (-8%) and Northern Ireland (-13%) anglers but the underestimate for overseas anglers was substantially greater at -30%.

3.6 Welfare

The results in Table 2 are used to calculate welfare measures in terms of consumer surplus anglers enjoy from their recreational activity. For policy purposes CS is often reported on a per day basis, CS divided by mean trip demand, but there is a question whether estimated parameters from truncated demand models can be extrapolated to non-visitors. Hellerstein (1991) indicate that this is only reasonable if non-visitors have the same demand function as visitors but we have no way of testing. It may be reasonable to conclude that surveyed anglers have similar preferences to those not interviewed, however, further research is necessary to determine whether the preferences of occasional anglers are similar to the angling enthusiast. We proceed making calculations for both in Table 4.

Table 4: Estimated welfare measures, €

Model	1	2	3	4
CS	249	264	2,935	3,510
CS/day (all anglers)	656	637	1348	1408
CS/day (surveyed anglers)	169	181	311	375

The first line of Table 4 provides an estimate of CS for the current trip in the case of models 1 and 2, whereas for models 3 and 4 it represents CS for the year. Model 2, which was the preferred model for within trip demand, provides a mean CS estimate of €264 for the intercepted trip. This estimate is sandwiched by estimates of €232 and €278 (Hynes et al., 2015; McGrath, 2015) using the same TDI data but estimating trip demand models compared to angling day demand models here.[7] Mean latent angling demand is just over 0.4 days for all anglers, which gives a mean CS/day of €637. There is some uncertainty on the reliability of this estimate on the basis of the representativeness of the survey data for all anglers, i.e. occasional versus enthusiast anglers. For surveyed anglers estimated mean CS is €181/day, with mean estimated angling days demanded of 1.5 days. The only broadly comparable CS estimate in the literature for Irish angling is from Curtis (2002), which estimated IRL£138/day for salmon angling within Co. Donegal in 1992. Denominated in Euro that is a nominal value of €175/day and equivalent to approximately €283/day when inflated with the consumer price index. It appears that angler consumer surplus has declined over the 20 year interval but the two studies are not like-for-like comparable. Specifically for game angling, the estimate of total willingness to pay (incl. trip expenditure) from the two studies are within 5% of each other. Our estimate of surveyed anglers' total willingness to pay for a day's fishing by in high status waters is €371. For surveyed game and coarse anglers their mean willingness to pay are similar and slightly higher at approximately €410/day.

The CS estimates in columns 3 and 4 of Table 4 relate to annual angling demand and again the more flexible specification (4) was the preferred model. Mean annual CS is €3,510 or €1,408/day based on a latent angling demand of 2.5 days, whereas interviewed anglers have an estimated CS of €375 per day's angling. This estimate is more than double the CS/day estimate from model 2. Intuitively we would have expected them to be broadly similar. Greater weight should be placed on the lower estimate, as the data on which it is based is the most appropriate to the model estimated. The estimate of annual angling days demanded (models 3&4) assumed that all angling trips are of equal length and that costs are the same as those incurred during the intercepted trip, which may be untrue. The large divergence between the two CS estimates throws doubt the merits of assuming all trips are similar. It may be a reasonable assumption that day trips have similar costs but in this dataset 35% of trips were of longer duration up to 14 angling days. Consequently, assuming an angler's intercepted trip is representative of all trips during a year may be unreasonable and introduce bias into welfare estimates.

Among the surveyed anglers we can estimate the benefit to them of higher water quality, since consumer surplus is a function of water quality, i.e. $CS(\lambda(\text{water quality}))$. The difference in CS for an angler at a $LowWaterQ$

[7]The estimate by Hynes et al. (2015) is for Republic of Ireland resident anglers only.

site versus a $HighWaterQ$ represents an estimate of anglers' mean value of high versus low water quality status. For game anglers the change in CS associated with higher status water quality is €122/day, and for 'combo' anglers €52/day.[8] CS declines for coarse anglers when water quality status improves with an estimates ranging between €16–93/day depending on model selected.

CS estimates for the current trip by angler country of residence differed substantially. Anglers resident in the Republic of Ireland have a CS of €90/day, for Northern Ireland anglers it is €249/day, and for other anglers it is €401/day. The wide variation in the CS estimates by country of residence is in contrast to the estimates in Curtis (2002), where the variation is much smaller.

3.7 Discussion and conclusion

This paper estimates a travel cost model of recreational angling demand in Ireland. The primary research focus was to investigate the extent to which angling demand is responsive to water quality, as measured by the EU's WFD classification. But the research also is relevant for wider fisheries policy questions, providing greater insight into preferences for angling within Ireland.

This is the first study in an Irish setting that quantifies how angling demand is affected by water quality. We find clear evidence that demand for game angling in waters with poor or bad ecological status is less than demand in high status waters, whereas for coarse fish species, including pike, there is evidence of the opposite. Anglers are not directly concerned about water quality, instead their focus is likely to be the level of fish stocks or catch rates at fishing sites. Though our dataset set has no information on stocks or catches it is likely that there would be multi-collinearity between these variables and water quality. It is therefore reasonable to draw some policy conclusions. For game fisheries we can say that improvements in water quality have the potential to increase angling demand and associated benefits, especially if improvements in fish stocks and catch rates are associated with water quality improvements. For coarse fisheries the policy implications are more subtle. The evidence is that coarse anglers currently spend on average 0.7 days less per trip fishing in high versus low ecological status waters. Does this mean that mean that improvements in water quality will lead to a reduc-

[8]Estimates are reported only where significant Wald tests were reported in Table 3

tion in coarse angling demand? The answer is not clear because site specific issues such as ease of access or the likelihood of specimen fish are potentially important issues affecting demand and there may be a (coincidental) correlation between water quality and these site specific characteristics. So while the current model indicates that coarse anglers have a preference towards angling sites with lower status water quality, further research is necessary to better understand how coarse angling demand would evolve with improved water quality. Supplementing the dataset with data on site characteristics is one potential avenue of research.

Anglers, particularly game and 'combo' anglers, benefit from higher status water quality. The value of that benefit is highest for game anglers at €122 per day. With surveyed anglers fishing on average 10 days per annum the total loss to recreational anglers associated with poor water quality is potentially very large.[9] Anglers' high valuation of waters with high ecological status echoes the more general finding by Stithou et al. (2013) that the Irish public are willing to pay significant amounts for improvements in the ecological status of a specific river catchment.

Historically within Ireland the greatest political and policy interest within recreational angling was on game species, possibly because game angling was more highly prized and considered to have the greatest socio-economic benefit. What is clear from the analysis in this paper is that coarse or sea anglers value their day's angling just as much as game anglers. Travel costs, including travel, accommodation and fishing expenses, are generally lower for coarse and sea anglers allowing anglers to enjoy a greater consumer surplus. Consequently, it would appear that there are opportunities for fishery managers, hoteliers, and others increase their rents. However, further research is needed to better understand what characteristics of sea or coarse fisheries are most highly valued by anglers, which in turn would inform fishery managers' decisions about their fisheries.

Although not conclusive, there is some evidence to suggest that the preferences of high-trip frequency anglers many be substantially different than the average angler. For instance, the angling enthusiast may have different preferences compared to the occasional angler. Where this becomes especially important is where fishery managers attempt to accommodate the needs of these two types of anglers within one angling site.

[9] The mean number of angling days is likely to be substantially higher for surveyed anglers than all anglers due to truncation and endogenous stratification.

From a modelling perspective the analysis highlights that it may be unreasonable to assume, at least in the case of multi-day trips, that a surveyed trip is representative of all trips during an extended period such as a year. To do so may introduce bias into model and welfare estimates.

References

Aminu, M., Matori, A.-N., Yusof, K. W., Malakahmad, A., and Zainol, R. B. (2014). A GIS-based water quality model for sustainable tourism planning of Bertam River in Cameron Highlands, Malaysia. *Environmental Earth Sciences*, 73(10):6525–6537.

Arnold, B. F., Schiff, K. C., Griffith, J. F., Gruber, J. S., Yau, V., Wright, C. C., Wade, T. J., Burns, S., Hayes, J. M., McGee, C., et al. (2013). Swimmer illness associated with marine water exposure and water quality indicators: impact of widely used assumptions. *Epidemiology*, 24(6):845–853.

Bhat, M. G. (2003). Application of non-market valuation to the Florida Keys marine reserve management. *Journal of Environmental Management*, 67(4):315–325.

Bowker, J. M., English, D. B., and Donovan, J. A. (1996). Toward a value for guided rafting on southern rivers. *Journal of Agricultural and Applied Economics*, 28(02):423–432.

Burger, J., Staine, K., and Gochfeld, M. (1993). Fishing in contaminated waters: knowledge and risk perception of hazards by fishermen in New York City. *Journal of Toxicology and Environmental Health, Part A Current Issues*, 39(1):95–105.

Cameron, A. C. and Trivedi, P. K. (1986). Econometric models based on count data. comparisons and applications of some estimators and tests. *Journal of Applied Econometrics*, 1(1):29–53.

Cameron, A. C. and Trivedi, P. K. (2001). Essentials of count data regression. In Baltagi, B. H., editor, *A Companion to Theoretical Econometrics*, pages 331–348. Blackwell, Oxford, UK.

Carson, R. (1991). Models for truncated counts. *Journal of Applied Econometrics*, 6(3):225–238.

Chen, H., Lupi, F., and Hoehn, J. (1999). An empirical assessment of multinomial probit and logit models for recreation demand. In Herriges, J. and Kling, C., editors, *Valuing Recreation and the Environment: Revealed Preference Methods in Theory and Practice*. Edward Elgar.

Curtis, J. A. (2002). Estimating the demand for salmon angling in Ireland. *Economic and Social Review*, 33(3):319–332.

Curtis, J. A. (2003). Demand for water-based leisure activity. *Journal of Environmental Planning and Management*, 46(1):65–77.

Directive 2000/60/EC (2000). Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy. *Official Journal of the European Communities*, L327/1.

Dorevitch, S., DeFlorio-Barker, S., Jones, R. M., and Liu, L. (2015). Water quality as a predictor of gastrointestinal illness following incidental contact water recreation. *Water Research*, 83:94–103.

Dorevitch, S., Panthi, S., Huang, Y., Li, H., Michalek, A. M., Pratap, P., Wroblewski, M., Liu, L., Scheff, P. A., and Li, A. (2011). Water ingestion during water recreation. *Water Research*, 45(5):2020–2028.

Egan, K. J., Herriges, J. A., Kling, C. L., and Downing, J. A. (2009). Valuing water quality as a function of water quality measures. *American Journal of Agricultural Economics*, 91(1):106–123.

Englin, J. and Shonkwiler, J. S. (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*, pages 104–112.

Environment Agency (2009). *Enjoying Water: Strategic priorities for water related recreation in the East of England 2009–2014*. Environment Agency. Available online: `http://www.gov.uk/government/publications/enjoying-water`.

Haab, T. C. and McConnell, K. E. (2002). *Valuing environmental and natural resources: the econometrics of non-market valuation*. Edward Elgar Publishing.

Hanley, N., Bell, D., and Alvarez-Farizo, B. (2003). Valuing the benefits of coastal water quality improvements using contingent and real behaviour. *Environmental and Resource Economics*, 24(3):273–285.

Hellerstein, D. and Mendelsohn, R. (1993). A theoretical foundation for count data models. *American Journal of Agricultural Economics*, 75(3):604–611.

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

Hilbe, J. and Martínez-Espiñeira, R. (2005). *NBSTRAT: Stata module to estimate negative binomial with endogenous stratification*. Boston College Department of Economics. Available online: `http://econpapers.repec.org/software/bocbocode/s456414.htmi`.

Hilbe, J. M. (2005). *GNBSTRAT: stata module to estimate generalized negative binomial with endogenous stratification*. Boston College Department of Economics. Available online: `http://econpapers.repec.org/software/bocbocode/s456413.htm`.

Hynes, S. and 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., O'Reilly, P., and Corless, R. (2015). An on-site versus a household survey approach to modelling the demand for recreational angling amongst the Irish population: Do welfare estimates differ? 21st Annual Conference, 24-27 June, Helsinki, Finland. European Association of Environmental and Resource Economists.

Larson, D. M. and Shaikh, S. L. (2001). Empirical specification requirements for two-constraint models of recreation choice. *American Journal of Agricultural Economics*, 83(2):428–440.

Lee, L.-H. and Lee, Y.-D. (2015). The impact of water quality on the visual and olfactory satisfaction of tourists. *Ocean & Coastal Management*, 105:92–99.

Loomis, J. and Santiago, L. (2013). Economic valuation of beach quality improvements: Comparing incremental attribute values estimated from two stated preference valuation methods. *Coastal Management*, 41(1):75–86.

Martínez-Espiñeira, R. and Amoako-Tuffour, J. (2008). Recreation demand analysis under truncation, overdispersion, and endogenous stratification: An application to Gros Morne National Park. *Journal of Environmental Management*, 88(4):1320–1332.

Martínez-Espiñeira, R. and Hilbe, J. M. (2008). Effect on recreation benefit estimates from correcting for on-site sampling biases and heterogeneous trip overdispersion in count data recreation demand models (STATA). *Journal of Modern Applied Statistical Methods*, 7(1):29.

McGarrigle, M., Lucey, J., and Ó Cinnéide, M., editors (2010). *Water Quality in Ireland 2007–2009*. Environmental Protection Agency. Available online: `http://www.epa.ie/pubs/reports/water/rivers/waterqualityofriversandcanals2007-2009.html`.

McGrath, L. (2015). Economic evaluation of recreational angling in Ireland. Master's thesis, J.E. Cairnes School of Business & Economics, National University of Ireland, Galway.

O'Neill, C. and Davis, J. (1991). Alternative definitions of demand for recreational angling in Northern Ireland. *Journal of Agricultural Economics*, 42(2):174–179.

Outdoor Foundation (2013). *Outdoor Participation Report 2013*. Outdoor Foundation. Available online: `http://www.outdoorfoundation.org/pdf/ResearchParticipation2013.pdf`.

Ovaskainen, V., Neuvonen, M., and Pouta, E. (2012). Modelling recreation demand with respondent-reported driving cost and stated cost of travel time: a Finnish case. *Journal of Forest Economics*, 18(4):303–317.

Parsons, G. R., Helm, E. C., and Bondelid, T. (2003). Measuring the economic benefits of water quality improvements to recreational users in six northeastern states: an application of the random utility maximization model. *University of Delaware Manuscript*. Available online: `http://works.bepress.com/george_parsons/25`.

Poor, P. J., Boyle, K. J., Taylor, L. O., and Bouchard, R. (2001). Objective versus subjective measures of water clarity in hedonic property value models. *Land Economics*, 77(4):482–493.

Shaw, D. (1988). On-site sample regression: Problems of non-negative integers, truncation, and endogenous stratification. *Journal of Econometrics*, 37(2):211–223.

Stithou, M., Hynes, S., Hanley, N., and Campbell, D. (2013). Estimating the value of achieving "Good Ecological Status" in the Boyne river catchment in Ireland using choice experiments. *The Economic and Social Review*, 43(3):397–422.

Tourism Development International (2013). *Socio-Economic Study of Recreational Angling in Ireland.* Inland Fisheries Ireland. Available online: `http://www.fisheriesireland.ie/media/tdistudyonrecreationalangling.pdf`.

Vesterinen, J., Pouta, E., Huhtala, A., and Neuvonen, M. (2010). Impacts of changes in water quality on recreation behavior and benefits in Finland. *Journal of Environmental Management*, 91(4):984–994.

Wade, T. J., Sams, E., Brenner, K. P., Haugland, R., Chern, E., Beach, M., Wymer, L., Rankin, C. C., Love, D., Li, Q., et al. (2010). Rapidly measured indicators of recreational water quality and swimming-associated illness at marine beaches: a prospective cohort study. *Environmental Health*, 9(66):1–14.

Westphal, L. M., Longoni, M., LeBlanc, C. L., Wali, A., et al. (2008). Anglers' appraisals of the risks of eating sport-caught fish from industrial areas: lessons from Chicago's Calumet region. *Human Ecology Review*, 15(1):46.

Year	Number	Title/Author(s) ESRI Authors/Co-authors *Italicised*
2015	520	Predicting International Higher Education Students' Satisfaction with their Study in Ireland Mairead Finn and *Merike Darmody*
	519	What Factors Drive Inequalities in Carbon Tax Incidence? Decomposing Socioeconomic Inequalities in Carbon Tax Incidence in Ireland *Niall Farrell*
	518	A Menu Approach to Revealing Generator Reliability Using a Stochastic Bilevel Mathematical Program *Mel T. Devine and Muireann Á. Lynch*
	517	How Do External Costs Affect Pay-As-Bid Renewable Energy Connection Auctions? *Niall Farrell* and *Mel T. Devine*
	516	Income-Related Subsidies for Universal Health Insurance Premia: Exploring Alternatives using the SWITCH Model *Tim Callan, Brian Colgan* and *John R Walsh*
	514	Review of the Droichead Pilot Programme *Joanne Banks,* Paul Conway*, Merike Darmody*, Aisling Leavy, *Emer Smyth* and *Dorothy Watson*
	513	Firm-Level Estimates of Fuel Substitution: An Application to Carbon Pricing *Marie Hyland* and Stefanie Haller
	512	Academic Achievement among Immigrant Children in Irish Primary School *Frances McGinnity, Merike Darmody* and *Aisling Murray*
	511	Forward Price, Renewables, and the Electricity Price: The Case of Italy *Valeria di Cosmo*
	510	Carbon Dioxide (CO2) Emissions from Electricity: The Influence of the North Atlantic Oscillation *John Curtis, Muireann Á. Lynch* and Laura Zubiate