Water Quality and Recreational Angling Demand in Ireland

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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 estimated additional benefit of fishing in waters with high versus low ecological status is €122/day for game anglers but there is a decline in benefit of €93/day for coarse anglers.

Keywords: recreation, angling, travel cost, count data, water quality, Water Framework Directive

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). However, 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 waters. A more complex indicator of water quality, such as ecological status, may be more useful in recreational angling demand models.

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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, 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. Among the earliest studies to consider the benefits of improvements in water quality for recreational water users are Bockstael et al. (1987, 1989). These studies use a variety of water quality metrics but when considering recreational anglers the only quality metric available was catch rates. Catch rates may be thought of as a proxy for water quality conditions but there is no explicit linkage between catch and water quality. Subsequent studies by Kaoru (1995) and Tay et al. (1996) explicitly model angler demand (site choice and trip length) as a function of objective water quality measures (e.g fecal coliform bacteria, suspended solids, phosphorus discharge, biochemical oxygen demand). While their results vary by angling site and quality metric, they establish a clear positive relationship between higher levels of water quality and angler demand. Ahn et al. (2000) find a similar result for trout fisheries in the Appalachian mountains but use a water quality metric that is effectively an amalgamation of scientific assessments of whether streams can support wild or hatchery trout. Their water quality metric has a correspondence with the status classes within the WFD's classification scheme. Englin et al. (1997) follow a different approach, jointly estimating angler demand and catch functions. Their estimated demand model for a trout fishery exhibits a positive relationship between predicted total catch and the number of trips, whereas predicted catch increases with reduced turbidity and higher levels of dissolved oxygen. Massey et al. (2006) also use a two equation approach but within the context of a bioeconomic model. Their result is slightly different, finding that improved water quality (i.e. dissolved oxygen) increases fish abundance rather than catch rates but like Massey et al. find that anglers are more likely to visit sites with higher total catch. Revealed preference approaches have also been used to measure the impact of water pollution events on angler demand, such as an oil spill (Alvarez et al., 2014), while stated preference approaches have been used to measure the impact of water quality on angling behaviour (Eiswerth et al., 2008).

Finding whether recreational anglers are responsive to the WFD classification system is analogous to the study by Egan et al. (2009) in the United States. Water quality status may not be observable to an angler, as the WFD status is not normally posted at fishing sites. Separate from whether WFD status is observable to anglers, an important research issue is whether 'good quality' differs by use type. What swimmers and anglers might consider 'good quality' may differ due to the nature of their activity. In the same way different types of anglers might have diverse views on what is 'good quality' from the perspective of their activity. If so, 'good quality' from an angling perspective may not align with the definition of good water quality measured by WFD status. What we wish to establish is whether water quality, as defined by WFD status, is a fishery characteristic that can affect anglers' experience and choices. In Ahn et al. (2000) the water quality metric is somewhat analogous to the WFD classification, where they find that anglers' perspective of a 'good quality' Appalachian trout fishery aligns well with their water quality metric. It is an empirical question whether anglers in other fisheries will be responsive to the WFD classification.

The analysis in the paper provides greater insight into preferences for angling within Ireland but the research also has wider policy relevance. It indicates the usefulness of the WFD classification system to both anglers and fishery managers to signal better quality fisheries, *ceteris paribus*. However, given the diversity in angler preferences, especially coarse versus game fishers, not all anglers may be affected similarly by improvements in water quality.

2. Methodology

2.1. Data

Angler data were 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 with respect to 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 last 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 are 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.

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 observations were limited to anglers with 26 or less trips per year (i.e. $\leq$ 1 trip per fortnight). This restriction 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 these anglers may have preferences substantially different than the majority of anglers.

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, individual's 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.

$$y_i = f(x_i) \tag{1}$$

where y_i is individual i's demand for site trips (or days), and x_i represents variables explaining angling demand, including travel cost, income, angler socioeconomic characteristics and fishing site attributes.

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 function of regressor variables, x_i. 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, such that

$$ln\lambda_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \tag{4}$$

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

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

where z are variables measuring angler characteristics.

2.3. *Welfare*

Anglers' 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. There is a

[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).

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. For surveyed 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). We present calculations for both.

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. The second type of model estimates angling days demanded 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.

Table 1: Summary statistics 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.

[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.

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.

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. While a positive coefficient is expected on the income variable, there is no *a priori* expectation for the coefficient on $MissInc$.

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. Anglers that travel longer distances, especially from overseas, might be anticipated to take trips of longer duration. For this reason we expect positive coefficients on these variables in the model estimating trip days demanded but negative coefficients for the model estimating annual trip demand, as international anglers are likely to make fewer trips per year.

Other explanatory variables used during estimation include whether the angler was aged 65 or above, angler group size and fish stocks. On the assumption that anglers who are retired have more time available to fish we expect a positive coefficient on the age variable. Because it is often more difficult to coordinate larger group activities we anticipate that larger groups fish less frequently and therefore anticipate a negative signed coefficient. The fish stock variable is an angler assessment of fish stocks and we surmise that anglers spend more time fishing if they positively rate fish stocks.

We specified $ln(\alpha_i)$ 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.

3. Model Estimates

Model estimates are presented in Table 2. We report estimates for the models using the more flexible specification for the overdispersion parameter from equation 5.[5] Column 1 contains the 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. Column 2 contains the demand model for angling days per year and assumes that anglers' trips are of the same duration as the surveyed trip. This model is estimated for anglers with not more than

[5]Likelihood ratio tests indicate that the more flexible model specification provides a better fit for the data. Estimates of the models with the overdispersion parameter specified as $\alpha_i = \alpha$ are available on request from the authors.

26 trips per year, which excludes 100 anglers compared to model (1). Column 3 reports estimates for the annual trip demand model.

Table 2: Angling Demand Model Estimates

	(1)	(2)	(3)
Dependent variable	TripDays	DaysYear	TripsYear
DailyCost	-1.569***		
	(-6.16)		
DailyCostadj		-0.710***	
		(-4.07)	
TripCost			-0.0607
			(-0.45)
AnnualFees		0.885***	0.339
		(3.37)	(1.11)
Age 65+	0.269*	0.190	0.0379
	(2.45)	(1.62)	(0.30)
Adult 3+	0.108	-0.193*	-0.385***
	(1.32)	(-2.20)	(-4.00)
Income	0.00383*	0.00526*	0.00304
	(2.03)	(1.99)	(1.09)
MissInc	-0.0744	-0.129	-0.0158
	(-0.89)	(-1.54)	(-0.17)
Combo × LowWaterQ	-13.11	-0.786	-0.421
	(-0.04)	(-1.73)	(-0.92)
Game × LowWaterQ	-1.478**	0.120	0.326
	(-3.25)	(0.38)	(1.00)
Coarse × LowWaterQ	0.895**	1.058***	0.721*
	(2.94)	(3.67)	(2.41)
Combo × HiWaterQ	-0.609*	0.0909	0.391
	(-2.57)	(0.43)	(1.70)
Game × HiWaterQ	-0.206	0.189	0.367
	(-0.91)	(0.88)	(1.60)
Coarse × HiWaterQ	0.239	0.424	0.358
	(0.86)	(1.63)	(1.30)
FishStock	0.396**	0.131	-0.0373
	(2.86)	(1.19)	(-0.31)
NIreland	1.576***	0.661***	0.197
	(9.61)	(4.83)	(1.44)
Elsewhere	2.878***	0.733***	-1.030***
	(23.62)	(7.00)	(-7.20)
Constant	-1.820***	0.449*	0.634**
	(-8.28)	(2.06)	(2.92)
ln (α)			
Club	1.051	0.494***	0.839***
	(1.55)	(3.58)	(4.92)
OwnTime	2.327**	-0.0419	-0.0592
	(3.01)	(-0.17)	(-0.21)
ln(Income)	1.099	-0.0335	-0.0408
	(1.80)	(-0.20)	(-0.22)
Constant	-6.760*	0.687	0.265
	(-2.44)	(1.17)	(0.40)
N	707	607	607
ll	-818.7	-1913.4	-1428.8

t statistics in parentheses

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

3.1. Overview

We begin by looking at angler-specific characteristics that that affect the the variance of angling demand through α_i. The most significant factors are membership of a fishing club and flexibility with one's time (via the $OwnTime$ variable). Fishing club membership may afford priority access to fishing sites, as well as lower access fees, though not necessarily zero travel costs, whereas anglers that are not club members may have less access to fishing sites. The $OwnTime$ variable was significant in model 1 only, so may be important in determining length of trip but not number of trips.

The non-negative coefficient on the travel cost variable, $TripCost$, for annual trip demand (model 3), albeit insignificant, goes against demand theory. 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, which 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 question, i.e. what $TripCost$ is purchasing, varies substantially across anglers. The good in question in model 1 and 2 is broadly similar for all anglers, i.e. one day's angling. 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. For the remainder of the paper we focus the results from models 1 and 2.

Model estimates of mean fishing days demanded are 1.5 days for the intercept trip and 9.4 days for the last 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.

3.2. Travel costs

There is a negative coefficient on both the $DailyCost$ or $DailyCostadj$ variables in models 1 and 2. As daily costs increase, fewer angling days are demanded. The price elasticity of within trip demand among surveyed fishers 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.[6] 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.[7]

3.3. Income

The estimated coefficients on the income variable are relatively small though statistically significant. In many recreational demand model estimates the income effect is zero (Martínez-Espiñeira and Amoako-Tuffour, 2008; Ovaskainen et al., 2012). In the case of days demanded annually, a 3% increase in income would lead to roughly 1 additional day 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 instance, is there a significant difference in angling demand in water bodies with lower versus higher water quality status? The *a priori* expectation was that angling demand would be greater in waters with high WFD ecological 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. We test the null hypothesis that the coefficient with high water quality is greater or equal than the coefficient with low water quality for each species targeted against a null that angling demand is greater in lower quality waters. For game anglers the null and alternative hypotheses are $H_0 : \beta_{Game \times HiWaterQ} \geq \beta_{Game \times LowWaterQ}$ and $H_1 : \beta_{Game \times HiWaterQ} < \beta_{Game \times LowWaterQ}$. One-tailed z-tests are reported in Table 3. We fail to reject the null hypothesis for game and 'combo' anglers but not coarse anglers. On average within the surveyed trip, game anglers fished in waters with higher ecological status for roughly 0.3 days

[6]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.

[7]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 $DailyCostadj$.

more than anglers fishing in lower status waters. 'Combo' anglers (i.e. targeting multiple species) fished 4 days more per annum in high compared to low ecological status waters. Although not known, it is likely that the 'combo' category of anglers are targeting games species: salmon, sea trout and brown trout. In the case of coarse fishing we reject the null hypothesis, angling demand is greater in 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. Coarse anglers fishing in lower ecological status waters spend roughly 0.7 days more per trip than those fishing in high status waters, and across the year fish approximately 9 days more. What these results indicate is that good water quality is associated with higher levels of angling demand, particularly for game species. However, it also highlights the fact that high water quality within the context of the WFD and improvements thereof appear not to align with coarse anglers' perspective on water bodies associated with good coarse fishing.

Table 3: Hypothesis tests: H_0: angling demand in high quality waters is no less than angling demand in low status waters

Model/ Species	(1)	(2)	(3)
Combo	0.00	2.11	1.97
Game	3.13	0.26	0.17
Coarse	3.20***	2.68***	1.43*

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

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 (model 1). When angling group size is 3 or more adults, both the number of days per annum and trips per annum are lower (models 2 & 3). 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 rate fish stocks as poor; in total spending an average of one day more angling per year.

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

Table 4: Estimated consumer surplus welfare estimates, €

Model	1	2
CS/day (surveyed anglers)	181	375
	(0.2–661)	(246–657)
CS/day (all anglers)	637	1,408
	(500–869)	(1,001–2,362)

95% confidence intervals in parentheses

The results in Table 2 are used to calculate consumer surplus anglers enjoy from their recreational activity, which are reported in Table 4. The estimated mean CS for surveyed anglers is €181/day compared to €637/day for all anglers. Mean angling days by surveyed fishers is higher hence their mean CS/day is lower. These estimates are consistent with Hynes et al. (2015) and McGrath (2015) who have used the same TDI data but estimating trip demand models compared to angling day demand models here. With an estimated mean angling demand for all anglers of just over 0.4 days the mean CS for the intercepted trip is €264, which is sandwiched by estimates of €232 and €278 of Hynes et al. (2015)[8] and McGrath (2015). The only other 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 game anglers' total willingness to pay for a day's fishing in high status waters is €407.

The estimates in column 2 of Table 4 relate to annual angling days demand. Interviewed anglers have an estimated CS of €375 per day's angling. For all anglers the estimate is €1,408/day. These estimates are more than double the CS/day estimates from model 1. Intuitively we would have expected them to be broadly similar. Greater weight should be placed on the estimates from model 1, as the data are the most appropriate for that model. The estimate of annual angling days demanded (model 2) 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 on 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/day for an angler at a $LowWaterQ$ site versus a $HighWaterQ$ site represents an estimate of anglers' mean value of high versus low water quality status. For game anglers the estimated mean CS/day at sites with low status waters is €71/day (35–139).[9] At sites with low status waters mean CS is €193/day (141–275), a difference of €122. For coarse anglers CS declines with a change from low to high status waters from €343/day (249–493) to €250/day (180–369), a difference of €93.

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. Conclusions

This paper estimates a travel cost model of recreational angling demand in Ireland and is the first study in an Irish setting that quantifies how angling demand is affected by water quality. Anglers, particularly game 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.[10] Game 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.

The primary research focus was to investigate the extent to which angling demand adjusts to differences in water quality, as measured by the EU's WFD classification. We find clear evidence that anglers are responsive to the WFD's

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

[9]Figures in parenthesis are 95% confidence intervals.

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

water quality measures but that the response is not uniform. In the case of game angling the results are as one might anticipate. Demand for angling in waters with a relatively good ecological status is no less that angling demand in waters with poor or bad status. As improvements in WFD water quality status are associated with more sustainable conditions for game species (Kelly et al., 2007), it is reasonable to say that improvements in water quality have the potential to increase angling demand and associated benefits for game species, especially if improvements in fish stocks and catch rates are associated with water quality improvements.

For coarse angling the policy implications are more subtle. The paper finds evidence is that fishing demand among coarse anglers is greater in waters with low ecological status. Does this mean that mean that improvements in water quality will lead to a reduction 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. However, the research does suggest that improvements in WFD water quality status appear not to align with anglers' perspective on good quality coarse fisheries. Due to the diversity in angler preferences not all are affected similarly by efforts that seek to improve water quality and such improvements should be viewed with nuance.

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