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Sea bass angling in Ireland: A structural equation model of catch and effort

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Abstract: The relationship between angling effort and catch is well-recognised, in particular that effort influences catch rates. But increased catch, which can be considered an attribute of fishery quality, may influence effort in terms of number of fishing trips. This suggests bi-directional feedback between catch and effort. In many travel cost applications little attention has been given to this endogeneity problem. In this paper we expand the application of structural equation models to address this issue by jointly estimating demand (effort) and catch functions. Using a cross-section dataset of sea bass anglers we propose two separate joint models. First, we include expected catch as an explanatory variable in the demand equation. In the second, we reverse the causality and use the expected number of fishing days as a covariate in the catch function. The two approaches produce similar model estimates, and perform better at predicting anglers' catch and effort than standard models. The findings confirm that 'catch & release' does not curtail fishing activity and that sea bass angling is highly valued. Furthermore higher catches result more days fished, on average in a 2:1 ratio. Whereas on average, an additional fishing day results in 3-4 additional bass caught.

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1. Introduction

Sea angling is a popular and economically important recreational activity. For example, during 2010 there were 353,000 sea anglers in Canada (FOC, 2012), 884,000 in England who spent Stg£1.23 billion on the sport (Armstrong et al., 2013) and in excess of 100,000 anglers in Ireland spending €174 million, including on travel and accommodation (IFI, 2015). In addition to the economic contribution, sea anglers appreciate and value a variety of cultural ecosystem services associated with the marine environment (Armstrong et al., 2013; Jobstvogt et al., 2014). Continued sustainable management of the sea angling target species is important to maintain angler satisfaction as well as protect the associated economic benefits, which often accrue in coastal communities.

Sea bass (*Dicentrarchus labrax*) is a popular species among Irish and UK sea anglers, with 30% of sea anglers in Ireland specifically targeting this quarry (IFI, 2015). Due to its biological characteristics sea bass is a particularly vulnerable species and can be easily overfished. Sea bass grow slowly and in Irish coastal waters only reach sexual maturity at 5–8 years old (Pickett and Pawson, 1994). In addition, sea bass exhibit strong site fidelity, returning to the same coastal site each year after spawning. Juvenile bass are also vulnerable, as they tend to occupy nursery areas close to exposed estuaries (Pickett et al., 2004). The life-cycle and traits of sea bass make them easily susceptible to over fishing. In European Union (EU) waters total biomass of sea bass has declined in recent years due to an extended period of poor recruitment and increasing fishing mortality (Graham et al., 2014). There are both national and EU controls on commercial and recreational fisheries for sea bass, which range from a moratorium on commercial fishing for sea bass around Ireland, minimum landing sizes, weekly or monthly boat limits in some commercial fisheries, closures of nursery areas in England and Wales, and some closed seasons for French fleets (Graham et al., 2014). Commercial fishing is just one source of pressure on sea bass stocks, as roughly 25% of bass harvested in European waters are caught by recreational anglers (Graham et al., 2014). Bag limits for recreational fisheries exist in several countries, including in Ireland where the bag limit is one fish per day from July through December with a catch and release policy otherwise. Concern about potential overfishing by recreational anglers is not unique to sea bass. In general recreational angling is responsible for about 12% of the worldwide fish catches (Cooke and Cowx, 2006), while Lewin et al. (2006) report that worldwide recreational landings of some popular species, such as largemouth bass (*Micropterus salmoides*), rainbow trout (*Oncorhynchus mykiss*), sockeye salmon (*Oncorhynchus nerka*) and yellow perch (*Perca flavescens*) are larger than commercial catches.

McPhee et al. (2002) argue that recreational angling without constant monitoring is not sustainable in the long-term. Zarauz et al. (2015) is a particularly relevant example with respect to sea bass in the Basque Country, where the first estimate of recreational sea bass landings represented between 48-68% of the total catch. Quantifying the recreational harvest, as well as understanding the factors that influence catches are critical for effective stock management. Recreational harvests are broadly determined by two factors: anglers' demand for recreational fishing, and success in catching fish. Fishery managers may increase the effectiveness of bass conservation by policies controlling either angling demand or catch efficiency (i.e. catch per unit effort, CPUE). But these two variables may be endogenous to each other. For example, catch rates may be a predictor of recreational demand, because catch may be perceived as a measure of site quality (Parsons and Needelman, 1992; Englin and Lambert, 1995). Furthermore, using self-reported catch as a demand predictor also leads to measurement error due to recall bias (Tarrant et al., 1993; Morey and Waldman, 1998). Structural equation models have been used to circumvent this issue. A catch function is estimated in a first equation, the predicted value of which is then used as an explanatory variable in a second equation, the demand model (Englin et al., 1997; Huszar et al., 1999). A similar approach has also been recently used in examining how hunting success affects hunting demand (Pang, 2017). But the relationship between catch and recreational demand is bidirectional. Catch is a function of anglers' fishing effort, while effort is increasing in the number of fishing occasions. It is reasonable to assume that people who spend more days angling will also catch more fish, all else held equal. For this reason, recreational demand may enter the catch model as a predictor, measuring effort in the fishing activity; and catch may enter the demand model, measuring fishery quality. Ideally a panel dataset is necessary to estimate such a reciprocal model in which catch and angling occasions are observed over time (Kline, 2006). But most recreational activity datasets have a cross-sectional format only, from which it is generally not considered appropriate to estimate reciprocal relations (Cook and Campbell, 1979; Organ and Bateman, 1991), though a mathematical solution for feedback loops is potentially available (Wong and Law, 1999).

The objective of this paper is twofold. First, we develop a bass angling model in which demand and catch are structurally related. From a sea bass management perspective this approach enables fishery managers to better understand which management changes potentially have the greatest ability to influence bass angling and conservation. The approach could also assist decision makers to identify whether management options can influence the number of angling trips, anglers' catch efficiency or both. Second, within the context of a cross-sectional dataset we consider a methodological issue with respect to the feedback relationship between catch and demand. Previous papers assume a feedback loop in one direction; initially estimating a catch function and using the predicted catch value as an explanatory variable in the demand equation (Englin et al., 1997; Huszar et al., 1999; Pang, 2017). We investigate the feedback loop between catch and demand in both directions, estimating two models separately. In one model predicted catch enters demand as a measure of individual skill, similar to prior approaches. In the second model predicted angling days (i.e. angler demand) enters the catch model as a measure of effort. We show how the two approaches affect model parameter estimates and welfare analysis.

2. Methods

2.1. Data

Inland Fisheries Ireland (IFI) undertook a survey of bass anglers between April and June 2016 to elicit angler feedback on the current and proposed regulations pertaining to the Irish recreational bass fishery. The survey targeted domestic and visiting anglers who fished for bass in Ireland during 2015. The survey was conducted online and was advertised via a number of channels including the Inland Fisheries Ireland website, Facebook page, and Twitter account. Notice of the survey was also emailed to subscribers of IFI's Angling newsletter. Specialist tackle shops who cater for bass anglers were requested to alert their customers to the survey. On-line surveys are susceptible to sampling bias (Fleming and Bowden, 2009), for example older people could be under represented, but no method of survey administration has been proven superior to any other (Champ, 2003). We however acknowledge that some self selection in the sample may occur. On-line surveys do have several advantages over traditional survey methods, not least the low costs incurred and also the speed and accuracy of data collection. Data can be collected continuously regardless of date or time and also without geographical limitation (Madge, 2006). The on-line survey questionnaire can be tailored to suit the individual respondents' answers therefore guiding the respondent to the next relevant question for their specific needs. While acknowledging that a cautious view should be taken of the representativeness of our sample to the population of bass anglers fishing in Ireland we believe the survey approach undertaken was the most feasible given the difficulty of carrying out a full on-site survey of bass anglers or of locating them in randomised household surveys.

The survey generated 266 responses, of which 230 were used in the models estimated. Observations from two anglers with in excess of 200 angling days per annum were excluded as outliers, though this did not have a substantial impact on mean welfare values but reduced the estimates of the standard error.[1] The balance of omitted observations were due to item non-response of critical questions or declared annual angling expenditures that exceeded their annual income. The survey itself comprised 35 questions and took approximately 15 minutes to complete. The majority of respondents were from the Republic of Ireland (69%), 5% from Northern Ireland, 10% from Great Britain with the remainder of the sample from other European Countries. Almost all respondents were male with only 5 responses from women. Table 1 provides an overview of the variables used in the analysis. The variables *Fishing_Days* and *Total_Catch* are the number of fishing days undertaken in 2015 and the number of fish caught and are the dependent variables in the demand and catch functions estimated. On average, respondents fished for 32.5 days during 2015 with a median of 25. Mean annual catch is 32 bass (st.dev. = 50) up to a maximum of 300. In 2015 there was a 2 fish bag limit per 24 hours and a minimum size limit of 40cm for retained fish. Catches here reflect all sea bass caught, irrespective of size or whether they were retained. The variable *Trip_Cost* is an important variable in the demand model and measures average angling trip expenses and items such as travel, food, bait and angling guides. The average expenditure per angling day was roughly €48, with a high variability across respondents (standard deviation is €96). Average annual expenditure on angling equipment (*Tackle_Inv*) includes expenditure on angling equipment that can be used on recurring angling trips, e.g. rods. People that spend more on equipment are likely to fish more than the average. *Session_length*, with a mean of just above 4 hours, represents the number of hours spent fishing in a typical session. Anglers and angling activity were classified into a number of categories, including anglers that specifically target bass (*Angler_bass*), those that target multiple sea fish species including bass (*Angler_all*), anglers that fish from a boat (*Boatfishing*) and those that engage in catch and release (*Catch&Release*). The geographical range where sea bass are more common is the southern half of the country and we included dummy variables for four counties on the south coast to allow for higher stock abundance in these areas. These four counties, *Wexford*, *Waterford*, *Kerry* and *Cork*, are also the most popular locations for targeting sea bass with 78% of the sample indicating that they fished in these southern counties. The variables labelled *Ireland*, *Employed*, *Age*55+ and *University* are all dummies controlling for individual characteristics; in particular whether a respondent is from the Republic of Ireland, employed full-time, is aged 55 or above or has a university degree. The median age of anglers in the sample was 35–44 years, while average annual income is €45.5 thousand.

2.2. The Travel Cost Method

We employ the travel cost model (TCM) methodology to estimate angling demand. The TCM is a revealed preference technique for estimating use values of non-market goods (Champ et al., 2003). It is commonly applied to estimate user benefits at recreational sites, including forest sites (Bertram and Larondelle, 2017), national parks (Kawsar et al., 2015), fishing sites (Egan et al., 2009) and birdwatching (Czajkowski et al., 2014). The TCM enables the estimation of a demand curve for recreation, by establishing a relationship between the number of trips or days spent for recreation and the unit cost of a trip or day (Hanley and

[1]The words ‘trips’ and ‘days’ are used interchangeably in what follows, though the survey specifically asked “how many separate days did you participate in bass angling in 2015?”

Table 1: Descriptive statistics of the variables included in the analysis

Variable	Description	Mean	Std. Dev.	Min	Max
Fishing_Days	Number of separate days participated in bass angling	30.757	28.443	0	140
Total_Catch	Total bass catch in Ireland in 2015	31.461	49.673	0	300
Trip_Cost	Average daily trip expenses on travel, food, drink, bait, lines, guides, etc €'000	0.048	0.097	0	1.30
Tackle_Inv	Annual expenditure on angling equipment. €'000	0.368	0.488	0	3.30
Session_length	Average length of a fishing session (hours)	4.300	1.358	2	6
Angler_bass	Angler targeting bass =1,0 otherwise	0.191	0.394	0	1
Angler_all	Angler targeting multiple species =1, 0 otherwise	0.283	0.451	0	1
Angler_sea	Reference category: A sea angler who occasionally catches or targets sea bass	0.521	0.501	0	1
Catch&Release	Engaged in 'catch & release' =1, 0 otherwise	0.848	0.360	0	1
Boatfishing	Regularly fished from a boat =1, 0 otherwise	0.152	0.360	0	1
Wexford	Mostly bass fished in Wexford =1, 0 otherwise	0.196	0.398	0	1
Waterford	Mostly bass fished in Waterford =1, 0 otherwise	0.174	0.380	0	1
Cork	Mostly bass fished in Cork =1, 0 otherwise	0.204	0.404	0	1
Kerry	Mostly bass fished in Kerry =1, 0 otherwise	0.204	0.404	0	1
Ireland	Living in Republic of Ireland =1, 0 otherwise	0.678	0.468	0	1
Employed	In full time employment =1, 0 otherwise	0.535	0.500	0	1
University	Holds university degree =1, 0 otherwise	0.322	0.468	0	1
Age55+	Aged 55 years or older =1, 0 otherwise	0.326	0.470	0	1

Barbier, 2009). The basic assumption of the model is that visitors are travel cost sensitive, meaning that the number of recreational trips or days decreases as the cost increases, reflecting microeconomic theory for which higher prices for goods lead to lower quantity consumed (Besanko and Braeutigam, 2011). The demand function usually incorporates individual, environmental and/or site-specific variables. The resulting demand curve models the number of trips to a recreational site as a function of the cost sustained for the travel, individual budget constraint and other relevant variables:

$$T = f_1(c, m, y; s, n) \tag{1}$$

where T is the number of trips or days made in a given timespan, c the financial costs incurred, m the composite price of all other goods, y the individual income, s is a vector of site-specific characteristics and n individual characteristics. Anglers' consumer surplus (CS) is derived by integrating (1) over price, with CS per day calculated as the negative inverse of the travel cost coefficient, β_c (Hellerstein and Mendelsohn, 1993):

$$CS = -\frac{1}{\beta_c} \tag{2}$$

2.3. Catch Function

Anglers' ability to catch a fish depends on the available fish stock, their capital (i.e. equipment) and effort (Englin et al., 1997; Massey et al., 2006). The number of fish caught, C, is modelled as a function of variables related to the site, to the investment on tackle and individual-specific characteristics in the following manner:

$$C = f_2(K, Z, A, Q) \tag{3}$$

where K is the angler's total capital stock (e.g. tackle, boats), Z is a vector of angler characteristics, fish abundance A and site-specific characteristics Q. Catch function models (CFM) are frequently estimated in the commercial fishing literature (see for example, Campbell, 1991) but in the context of recreation fisheries are less common. In the recreational angling literature a number of approaches have been used, including, modelling catch as a function of effort (Huszar et al., 1999) or specifically modelling CPUE (Sweke et al., 2015). Bio-economic models have also been used where catch is specified as a function of the fish stock and harvest quotas, i.e. 'catchability'(Olaussen and Skonhoft, 2008). Our modelling approach assumes that individual yearly catch, C, is a random Poisson process, with mean equal to the expected catch per trip.

2.4. Model specification and estimation

The dependent variables in models (1) and (3) represented by the number of angling days per annum (*Fishing_Days*) and number of fish caught per annum (*Total_Catch*) are non-negative integers making count data models suitable for the analysis. The basic count regression model is the Poisson model, for which the probability that an individual i undertakes a certain number of fishing days t is (Cameron and Trivedi, 1986; Greene, 2003):

$$Pr[Fishing\ Days_i = t_i] = \frac{\exp^{-\mu_i} \cdot \mu_i^{t_i}}{t_i!} \tag{4}$$

where μ_i is the rate parameter, which is usually parametrized in a regression framework as an exponential function $\mu_i = exp(f_1) = exp(X_i\beta)$, in which X is a matrix of covariates in function f_1 and β is the vector of associated parameters to be estimated. A limitation of the Poisson model is that it assumes equi-dispersion, i.e. the mean of the distribution equals its variance (Cameron and Trivedi, 2013). This is a strong assumption and does not hold in many applications that comprise over-dispersed data, due to a small number of frequent visitors (Garrod and Willis, 1999). Overdispersion in a Poisson regression has similar consequences to heteroscedasticity in linear models. If data are not truncated or censored, the Poisson estimator is still consistent but non-efficient, thus resulting in very small standard errors and grossly inflated t-statistics (Cameron and Trivedi, 2005). A way to deal with overdispersion, is to use a Negative Binomial (NB) model. NB assumes that data generating process is Poisson but allows for overdispersion, by including an addition parameter to estimate (Cameron and Trivedi, 2013):

$$Pr[Fishing\_Days_i = t_i] = \frac{\Gamma(\alpha^{-1}+t)}{\Gamma(\alpha^{-1})\Gamma(t+1)} \times \left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu_i}\right)^{\alpha^{-1}} \times \left(\frac{\mu_i}{\alpha^{-1}+\mu_i}\right)^{t} \tag{5}$$

where Γ is the gamma function and α a parameter describing the over-dispersion of the data. In the special case in which the α parameter is equal to zero, the NB and Poisson models are the same (Cameron and Trivedi, 1986). There is an analogous model for the number of bass catch caught, $Pr[Total\_Catch_i = C_i]$, though in that instance we specify the rate parameter $\mu_i = exp(f_2) = exp(Y_i\theta)$ where Y is a matrix of covariates in function f_2 and θ is the vector of associated parameters to be estimated. In our analyses we tested the presence of overdispersion in the TCM and CFM models by means of a log-likelihood ratio test. In both cases, data were proved to be overdispersed, therefore further analyses were carried out only with the NB specification.[2]

To allow consistent results, we propose a joint estimation of the two equations, similar to the approach proposed by Englin et al. (1997), though we address the issue of over-dispersion by means of NB models. Our dataset was not on-site sampled, therefore corrections for truncation and endogenous stratification were not needed. In the first of the joint models, we include expected catch in the TCM specification. Let L_{CFM} be the NB log-likelihood function of the CFM model, determined by a vector of variables Y_i, and L_{TCM}

[2]The log-likelihood ratio test for α=0 returned a χ^2 value of 2766.02 (p-value = 0.000) in the TCM model, while the CFM model a χ^2 of 7818.66 (p-value = 0.000)

be the NB log-likelihood of the TCM model, affected by a vector of variables X_i, the joint log-likelihood function is given by:

$$LL_1 = L_{CFM}[Y_i\Theta] + L_{TCM}[(X_i; E[C_i])\beta] \quad (6)$$

where the covariates in the TCM model, X_i, include angler i's expected catch $E[C_i]$ from the CFM model. This model stems from the idea that individual catch may be a predictor of the number of trips, because it might be seen as a proxy for site quality but also for individual skills, which may be higher for anglers making a higher number of trips. From another perspective, the number of annual angling days is a measure of anglers' effort. For this reason, the number of annual angling days might be seen as a predictor of the catch. This relationship between catch and fishing days suggests the existence of feedback loops, which cannot be estimated in cross-sectional dataset (Eusebi, 2008). For this reason, we propose a second joint model, in which the expected value of the number of fishing days $E[T]$ enters the CFM function among the covariates, Y_i:

$$LL_2 = L_{CFM}[(Y_i; E[T_i])\Theta] + L_{TCM}[X_i\beta] \quad (7)$$

Using an instrumental variable would have represented an easier approach to address endogeneity but finding a suitable instrument is difficult. Therefore we decided to use a full structural model, which is also more convenient for assessing several factors affecting individual catch. Both models are estimated by maximum likelihood using the statistical package R, as well as separate standard TCM and CFM models for comparison (R Core Team, 2015).

3. Results

3.1. Econometric models

Results of the econometric models are shown in Table 2. Model-1 is the standard or baseline model for the CFM, which includes the number of angling days simply as an independent variable. Model-2 is the baseline model for the TCM, including the annual catch as covariate. Model-3 is the structural model in which the expected catch, $E[C_i]$, enters the TCM model as predictor, while Model-4 is the structural model in which the expected number of angling days, $E[T_i]$, enters in the catch model as a covariate. The estimated coefficient for the negative binomial over-dispersion parameter, α, across all the estimated models is significant, suggesting that over-dispersion matters for our data and thus confirming the likelihood ratio tests.

Though not included in the final specification we examined including income as an explanatory variable in the TCM model. Income was an item non-response for almost 18% of observations, which we attempted to address by assigning the median income value to those observations as well as adding a dummy to control for missing income data (equal to one if data on income was missing and zero otherwise), as previously used in the TCM literature (e.g. Martinez-Espineira and Amoako-Tuffour, 2008). However, the income variable was not significant, while the missing income dummy variable was, suggesting people not declaring income were different from the average. The inclusion of the missing income variable contributed to instability of the model, as some of the coefficients changed significantly (including *Trip_Cost*, probably due to high correlation). Therefore, the income variables were excluded. We calculated the Variance Inflation Factor (VIF) to quantify the severity of multicollinearity. A VIF higher than 10 generally indicates severe multi-collinearity (Gujarati, 2009), whereas in our estimates the maximum value was 2.01 (mean VIF 1.33) suggesting that collinearity is not a serious problem for our models.

Table 2: Results of the econometric models

	Model - 1	Model - 2	Model - 3		Model - 4	
	CFM	TCM	CFM	TCM	CFM	TCM
Total_Catch		0.008***				
		(0.001)				
Fishing_Days	0.031***					
	(0.005)					
Session_length	-0.272		1.032**		0.113*	
	(0.57)		(0.416)		(0.068)	
Session_length^2	0.049		-0.122**			
	(0.069)		(0.05)			
Tackle_Inv	0.697***	0.21*	0.422***		1.092***	
	(0.23)	(0.12)	(0.115)		(0.225)	
Angler_bass	0.449*	0.318**	0.652***		0.81***	
	(0.251)	(0.135)	(0.18)		(0.252)	
Angler_all	-0.296		-0.679***		-0.289	
	(0.252)		(0.202)		(0.228)	
Boatfishing	0.539**		0.491**		0.577**	
	(0.239)		(0.201)		(0.265)	
Wexford	0.73**	0.182	1.092***		1.301***	
	(0.292)	(0.167)	(0.273)		(0.299)	
Waterford	1.041***	0.282*	1.123***		1.39***	
	(0.287)	(0.169)	(0.279)		(0.311)	
Cork	0.88***	-0.093	0.886***		1.256***	
	(0.27)	(0.164)	(0.267)		(0.29)	
Kerry	0.787***	0.313*	1.218***		1.408***	
	(0.3)	(0.164)	(0.28)		(0.298)	
$E[C]$				0.017***		
				(0.005)		
$E[T]$					0.112***	
					(0.024)	
Trip_Cost		-2.664***		-3.21***		-3.54***
		(0.875)		(1.025)		(0.832)
Ireland		0.34**		0.412**		0.084
		(0.16)		(0.178)		(0.087)
Catch&Release		0.145		0.112		-0.008
		(0.15)		(0.158)		(0.065)
Employed	-0.208	-0.088		-0.141		-0.084
	(0.247)	(0.122)		(0.134)		(0.06)
University	-0.151	-0.302***		-0.281**		-0.094
	(0.247)	(0.116)		(0.131)		(0.07)
Age55+	0.132	0		0.108		0.031
	(0.253)	(0.158)		(0.18)		(0.08)
Constant	1.205	2.665***	0.193	2.718***	3.572***	-2.507***
	(1.155)	(0.211)	(0.836)	(0.257)	(0.117)	(0.798)
α	1.319***	0.525***	1.892***	0.632***	0.761***	1.613***
	(0.133)	(0.052)	(0.176)	(0.061)	(0.071)	(0.158)
LL	-895.0	-965.9				
combined LL			-1923.4		-1927.1	
Observations	230	230	230		230	

Standard errors of coefficient estimates are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Model-1, the coefficient for *Fishing_Days* is positive, suggesting that the likelihood of catching more fish is positively related to the number of fishing days. Conversely, the average length of an angling session is non-significant. Anglers specifically targeting bass are on average more successful than other anglers. There is a positive coefficient in each of the four south coast counties, indicating that there is a higher likelihood of catching more fish Kerry, Cork, Waterford and Wexford compared to other counties, *ceteris paribus*. Sea bass catch is not influenced by socio-demographic characteristics. Age, education and employment do not affect the likelihood of catching fish, which is unsurprising as these attributes would not necessarily impact on angler skill levels.

In the TCM baseline model, Model-2, the level of annual catch (*Total_Catch*) positively affects the number of fishing days, suggesting that the number of fishing days increases as more sea bass are caught. Both dedicated bass anglers (*Angler_bass*) and those with higher investment in tackle (*Tackle_Inv*) have a greater number of fishing days. In terms of fishing location, anglers make more trips to fish in Kerry compared to other counties. The coefficient for the variable *Trip_Cost* is as expected negative, indicating decreasing marginal utility of price. As the unit cost per trip increases, the number of fishing days per annum decreases. The number of fishing days is not significantly different between those engaged in 'catch and release' practices compared to others, which indicates that the 1-fish bag limit is not adversely impacting on angling trip frequency. As one would expect anglers living in Ireland are more frequent anglers for bass in Ireland, while anglers with a university degree take fewer trips than other anglers. Age and employment status do not significantly impact on trip frequency.

We now move to the structural models. In Model-3 there is a general improvement of the parameters' statistical significance compared to the baseline models. The coefficient for *Session_length* in the CFM part of the model is positive and now statistically significant, indicating that the likelihood of catching more fish increases as the average angling session increases in length, as one might expect. We also included a quadratic term for the session length, whose coefficient is negative. Based on these parameter estimates average catch increases as session length increases up to approximately 4 hours. Beyond a 4 hour session length average catch levels do not increase further. Similar to the baseline model dedicated bass anglers (*Angler_bass*) and those with higher investment in tackle (*Tackle_Inv*) generally are more frequent anglers, while anglers targeting multiple species (*Angler_all*) have a lower likelihood of catching more fish compared to others. Anglers fishing from a boat have a higher likelihood of catching more fish. Also similar to the baseline CFM model catch levels are higher for anglers fishing in the four southern coastal counties. Interestingly, the CFM constant is not significant in Model-3, possibly indicating that the included variables have a good explanatory power for modelling individual annual catch.

The expected value of catch ($E[C]$) in the TCM model in Model-3 is positive and statistically significant, meaning that more successful anglers undertake more angling trips per annum, all else equal. The coefficient estimate on *FullEmployed* becomes significant compared to the baseline model; with the negative sign indicating fewer trips. Those in full-time employment may have less time for leisure activities or alternatively work schedules might not always be compatible with the most productive bass fishing times, which are often during the evening into darkness.

In Model-4 the expected number of trips ($E[T]$) estimated in the TCM equation is used as a covariate in the CFM equation and has a positive and statistically significant effect on catch. A greater number of fishing days increases the likelihood of catching more fish. Generally the same coefficients are statistically significant compared to both Model-3 and the baseline models. There are a few notable exceptions. In the CFM equation in Model-3 anglers primarily targeting sea bass have a higher likelihood of catching more sea bass than the reference angler category, *Angler_sea*; and that all round anglers have a lower likelihood of catching more sea bass than other sea anglers. The latter is not the case in Model-4 with the coefficient on *Angler_all* being insignificant. The estimates in Model-3 seem practically more likely as it is more conceivable that an all round angler (incl. inland waterways) is less likely to catch sea bass than the reference angler category that fishes in salt waters. In the TCM equation in Model-3 anglers from Ireland have a higher likelihood of taking more trips than anglers from overseas, which is as one would anticipate. The coefficient on *Ireland* in Model-4 is not significant, which is contrary to expectations. However, many overseas anglers spend a high number of days fishing for sea bass in Ireland, with 36 overseas anglers from the sample spending 20 or more days bass fishing in Ireland up to a maximum of 130 days in one instance.

In comparing between models the coefficient estimates of particular interest are *Fishing_Days* and *Total_Catch* from the baseline models versus $E[C]$ and $E[T]$ from the structural equation models. The coefficient estimates are all statistically significant but they differ substantially in magnitude between models. Consequently, the estimated feedback effects between catch on fishing days and vice versa will be substantially different between models, which in turn could potentially impact on policy conclusions. The marginal effects are reported in Table 3 and calculated as the product of the predicted value of the dependent variable, e.g. catch, and the estimated coefficient on the relevant covariate, e.g. fishing days. The marginal effect of catch on number of fishing days per annum is 0.52 in Model-3, which is double the estimate from the baseline model. For every two additional sea bass caught the number of days sea bass fishing per annum increases by one. Bilgic and Florkowski (2007) also calculate marginal impacts of catch on sea bass trips in southeastern United States. In elasticity terms they estimate that a 1-percent change in the number of fish caught increases the number of bass fishing trips by 0.06 percent. The comparable estimate for Model-3 is 0.51 (s.e. 0.15). Angling frequency among bass anglers is influenced by catch rates to a much larger extent in Ireland than in the US. One explanation for the large difference might be that while bass species are popular among anglers in both areas, US anglers have a greater variety of alternative target species. The marginal effect of fishing days on annual catch from Model-4 is 3.78, which is 7-times the estimate from the baseline model. For each additional fishing days the annual catch increases by almost 4 fish.

Table 3: Marginal effects: fishing days and catch

Model-1	Model-2	Model-3	Model-4
Marginal effect of catch on fishing days			
–	0.26	0.52	–
	(0.04)	(0.15)	
Marginal effect of fishing days on catch			
0.53	–	–	3.78
(0.08)			(0.82)

Standard errors in parentheses

Table 1 reported the sample mean fishing days per annum and annual bass catch at approximately 31.5 in both cases. Table 4 reports the model predictions for both variables. Model-1 is relatively poor at predicting annual catch, whereas both structural equation models provide satisfactory estimates. In the case of Model-4 this possibly reflects the greater estimated marginal effect of angling days on catch. The baseline

TCM model predicts a mean of 33 angling days per annum, which is a reasonable estimate and within 7% of the sample mean, whereas the estimates from both structural equation models are substantially closer to the sample mean. While we cannot draw general conclusions based solely on this particular dataset, the structural equation models are better at within sample prediction of these two key variables of policy interest.

Price elasticity estimates from the TCM equations are also reported in Table 4 and were calculated as the product of the estimated coefficient on the variable $Trip\_Cost$ and mean value for $Trip\_Cost$. The estimates are broadly similar ranging from -0.13 – -0.17, with the estimates from the structural equation model estimates slightly less inelastic. Bass anglers are quite price sensitive; a one-percent change in trip costs diminishes number of bass fishing days by approximately 0.15 percent, ceteris paribus. This is in line with several previous elasticity estimates for angling in Ireland, though these are the first estimates specifically for sea bass angling (Curtis, 2002; Curtis and Stanley, 2016; Curtis and Breen, 2017). The price elasticity for sea angling from Hynes et al. (2017) is an exception, where the implied elasticity is -0.6. However, Hynes et al. (2017) model annual trip demand rather than annual days demanded, with mean trip length exceeding 4 days. Consequently the estimates are not directly comparable. While Hynes et al. (2017) model all sea angling trips they find that anglers targeting sea bass undertake a higher number of angling trips than other anglers. The price elasticity estimates here are also in line with estimates for sea bass anglers in the southeastern United States, where Bilgic and Florkowski (2007) estimate a price elasticity -0.02.

Table 4: Model Predictions and price elasticity

	Model-1	Model-2	Model-3	Model-4
Predicted catch	17.49	–	30.27	33.82
	(1.48)		(2.82)	(7.49)
Predicted fishing days		33.00	31.02	30.61
	–	(1.65)	(0.42)	(0.02)
Price elasticity	–	-0.13	-0.15	-0.17
		(0.04)	(0.05)	(0.04)

Standard errors in parentheses

3.2. *Welfare estimates*

Results of the welfare analysis are shown in Table 5, with consumer surplus (CS) per day calculated using equation 2. Willingness to pay for a day's sea bass angling is the summation of consumer surplus and mean trip costs from Table 1. Though mean CS estimates across all three models are broadly similar in the range €276–369, the estimate from the baseline TCM Model-2 is at least 20% higher than the estimates from the structural equation models. A difference of that magnitude could be sufficiently large to materially alter management or policy conclusions. The CS estimates are somewhat higher than comparable estimates from the literature. For example, Bilgic and Florkowski (2007) estimate mean CS of $161 for bass angling in the southeastern United States, while Hynes et al. (2017) estimate a CS for sea angling in Ireland of €242–261. Lawrence (2005), using a choice experiment methodology, find that English anglers are willing to pay more for additional catches of sea bass compared to cod, mackerel, or other species. In that context the CS estimates from the structural equation models could be considered in line with Hynes et al.'s estimates.

Table 5: Consumer surplus and willingness to pay

	Model-1	Model-2	Model-3	Model-4
Consumer surplus		€375	€311	€282
		(123)	(99)	(66)
Willingness to pay		€423	€359	€330
		(123)	(100)	(66)

Standard errors in parentheses

4. Discussion

In terms of model performance, the structural models predicted an average number of angling days and catch very close to the sample means, while baseline models were less precise. The baseline CFM model was particularly poor at modelling angler catches. The structural equation models, at least in this instance, contribute to a better understanding of recreational activity. The structural equation models also produce more conservative CS estimates compared to the baseline TCM model. While neither the baseline nor the structural equation approach can be considered the ‘right’ one, acknowledging that catch and effort (i.e. angling days) are endogenous to each other favours the structural equation approach.

Previous applications of the structural equation model in fishing and hunting applications have assumed feedback between catch and effort flows in one direction, similar to Model-3 here (Englin et al., 1997; Huszar et al., 1999; Pang, 2017). In Model-4 we also allow for feedback in the opposite direction with predicted angling days entering the catch model as a measure of effort. There are only small differences between Model-3 and Model-4 across the main variables of policy interest, including the welfare estimates, as outlined in Tables 4 and 5. While, further research is necessary to draw more general conclusions, the estimates here suggest that either approach is useful for policy application. The choice of model to estimate may depend on either the availability of data or the objective of the research.

Understanding the factors that influence anglers’ catches are among the critical inputs to effective stock management. Sustainable stock management also underpins socio-economic benefits, including angler satisfaction and the contribution to the local economy. Recreational catches are broadly determined by two factors: anglers’ effort and catch efficiency, i.e. CPUE. With the objective of sustainable stock management it follows that fishery managers can attempt to manage recreational harvests by either controlling angler effort or CPUE. The low price elasticity estimates indicate that using a price mechanism, such as a permit or licence fee, to control effort is unlikely to be particularly successful in managing angling effort. This result reinforces the existing management approach that controls effort through regulations. Although sea bass anglers are price sensitive they derive a high benefit from their activity, which also reflects that sea bass are a prized and popular target species among sea anglers in Ireland. The relatively high consumer surplus of approximately €300/day, combined with a conservative estimate of some 11,000 sea bass anglers (IFI, 2015) fishing an average of 31.5 days per annum illustrates the high value to recreational anglers of the sea bass fishery. This value of the recreational sea bass fishery, which exceeds €100 million, is not a financial value as the economic contribution is substantially lower and derived from sea bass anglers’ expenditures associated with their fishing activities (e.g. bait, equipment, travel, accommodation). Nonetheless, the high value of the recreational fishery provides support for the continued closure of the commercial sea bass fishery in Irish waters.

The second lever to control angler harvests is via CPUE, which is outside the scope of this research. However, two findings are pertinent to any management decisions attempting to manage stocks. Current regulations permit a bag limit of 1 fish per day from July through December with a size limit of 42cm and a catch and release policy otherwise. Across all the models estimated the catch and release variable had an insignificant coefficient estimate, indicating that anglers who engage in catch and release practices fish the same number of days per annum as anglers who do not, *ceteris paribus*. There is no basis for an argument that the catch and release regulation curtails recreational activity and consequently the economic contribution of that activity. In Ireland there is evidence that a large proportion of sea bass anglers are conservation oriented and therefore a catch and release type of fishing would be broadly accepted. The second finding pertinent to decisions on stock management relate to the marginal effects reported in Table 3. Higher catches, irrespective of size or whether they are harvested, result in a higher number of bass angling days. Managing stocks to increase average catch rates will obviously benefit anglers but it also has an indirect economic impact through additional angler expenditures. Zwirn et al. (2005) argue that catch and release fisheries can contribute both to conservation targets as well as economically via angling tourism. However, there is evidence that a mandatory catch and release policy can lead to sharp declines in angler participation, which can have a detrimental economic impact (Johnston et al., 2011).

It is worth repeating that the survey on which the analysis is based is potentially subject to bias. We are unable to determine the nature of the bias but it is likely that more avid bass anglers are over-represented in the sample simply because they are more likely to be aware of and self-select into the survey. This means that the model results are not representative of all bass anglers. Nonetheless the results have relevance for decision makers in fisheries management. A better understanding of the harvest and conservation practices of frequent anglers is particularly useful for stock management.

5. Conclusions

Sea bass are a popular target species among sea anglers in Ireland. Due to its biological characteristics and life-cycle traits the species is vulnerable to over-fishing. Although the species is closely managed to ensure sustainable stocks, there is relatively little research on angling activity. In the academic literature Bilgic and Florkowski (2007) is the only paper identified that specifically models demand for bass angling. This paper makes two contributions to the literature. In the context of sea bass fishing in Irish waters the paper provides new insights on angler demand, in particular anglers' responsiveness to catch as well as to angling costs. The paper also considers a methodological issue with respect to the feedback relationship between catch and effort. In many applications of the TCM model catch is either unknown or treated as an exogenous explanatory variable. Ideally a panel dataset where catch and effort are observed over time is necessary consider the the reciprocal nature of the feedback. But where catch is recognised as endogenous within the context of cross-sectional data, the approach adopted has been to assume a feedback loop in one direction (e.g. Englin et al., 1997). We investigate the feedback between catch and effort in both directions, estimating two structural equation models where predicted catch enters the effort equation in one and predicted effort enters the catch model in the other. We find that the two structural equation models produce similar estimates, and perform better at predicting anglers' catch and effort than the standard baseline models. While, further research is necessary to draw more general conclusions, the estimates here suggest that either approach is useful for policy application.

While sea bass is recognised as a popular and valuable recreational resource, the analysis here provides estimates of the benefit anglers derive from the resource, as well as expenditure levels associated with sea bass angling. Aggregate angler consumer surplus exceeds €100 million, though expenditure associated with sea bass angling is substantially less. The high benefit to anglers from the recreational fishery provides support for the continued closure of the commercial sea bass fishery in Irish waters. However, demand for sea bass angling is quite inelastic, which limits the opportunity for fishery managers to share some of the benefits enjoyed by anglers. An important component of sea bass management in Irish waters is that it is managed as a catch and release fishery beyond the 1 fish bag limit. We find no evidence that the catch and release regulation curtails the level of fishing activity. Finally, we find that higher catches, irrespective of size or whether they are harvested, result in a higher number of bass angling days. While some anglers may specifically target specimen sized fish there is a case based on the indirect economic impact that stocks should be managed to increase average catch rates.

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