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Using angling logbook data to inform fishery management decisions

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Abstract: *With the sustainability of fish resources threatened across many locations globally, decisions on fishery management are often based on inadequate information. This paper presents a methodology that uses fishery data collected for the purpose of administering and monitoring harvest quotas in a recreational fishery to give additional insights into effectiveness of various fishing methods, and expected catch rates associated with different licence types. The empirical application is based on the Atlantic salmon (Salmo salar) recreational fishery in Ireland but the statistical analysis is easy to replicate and the models are flexible enough to allow different specifications applicable to other fisheries. The output of the analysis facilitates a better understanding of the factors associated with recreational catches, which in turn provides supplementary information to inform the regulation and management of recreational fisheries.*

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1. Introduction

Fish provide important ecosystem services not only for food but also for habitat stability and regulation. From a cultural perspective fish have a strong historical relationship with humans' economic activity and recreation (AAAS, 1997). At present fish stocks are subject to manifold anthropogenic stresses such as pollution, invasion of exotic species, river fragmentation and habitat loss that are threatening the sustainability of the stock resources (Carpenter et al., 2017; Cambray, 2003). At the same time fish stocks are seriously affected by overfishing (i.e. excessive harvest resulting in depleting fish stocks) as one of the main drivers of declining populations (Camp et al., 2017). For this reason a sustainable management of a fishery involves constant monitoring of catch rates. This is important for commercial fishing activities, however recreational angling has also a relevant impact on fish stocks, although it is often overlooked.

Recreational angling has raised interest in economic terms because it represents a source of income for local communities that are frequently located in remote and relatively poor areas (Cookie and Cowx, 2005; Curtis et al., 2017; Lawrence, 2005; Toivonen et al., 2004), as well as its impact on environmental sustainability (Ready et al., 2018; Gagne et al., 2017). It is estimated that 11% of the world population practice fishing as a social and leisure activity (Arlinghaus et al., 2015). Therefore, even if the individual impact of one recreational angler is small, the cumulative effect of all anglers becomes extremely important for sustainability. Cooke and Cowx (2006) reported that recreational angling is responsible for about 12% of the total catches worldwide. Zarauz et al. (2015) argue that in the Basque Country recreational landings were found to be higher than expected after a monitoring period, accounting for roughly half of the total harvest. For some popular species, such as Largemouth bass (*Micropterus salmoides*), Rainbow Trout (*Oncorhynchus mykiss*), Sockeye Salmon (*Oncorhynchus nerka*) and Yellow Perch (*Perca flavescens*), the impact of recreational landings is estimated to exceed commercial volumes (Lewin et al., 2006). McPhee et al. (2002) argue that recreational fishing is not sustainable in the long term without constant monitoring and control. For example, Schroeder et al. (2002) find large differences in fish species density and specimen size in comparable adjacent areas, one of which is subject to recreational fishing and the other a fishery reserve.

Fisheries are complex systems and their dynamics are always subject to a certain degree of uncertainty (Dayton, 1998) plus management failures may be due to poor decisions and inadequate or erroneous scientific information (Maunder et al., 2006). In some cases fish might be overexploited before scientists and managers have the necessary data to realize the decline in populations. Systematic monitoring of recreational angling activity and the volume of fish harvesting is necessary for sustainable management, as there is evidence that overexploited fisheries rarely recover after collapse (Hutchings, 2000). Effective management is fundamental when a fish species shows declining stocks, as the case of salmonids in Ireland. Salmon in Irish waters have been heavily exploited for many years. In an attempt to tackle the situation and assure a viable salmon population, commercial salmon fishing was curtailed in the early 2000s and a drift net ban was introduced in 2007. Recreational angling for salmonids is also well regulated, with a licence required for salmon (*Salmo salar*) or sea trout (*Salmo trutta*) fishing, unlike other target species within Ireland, plus anglers are subject to both daily and season bag limits. Anglers must report their catch via logbook returns. The use of such logbooks is quite common to record data for many fish species and for several angling activities, not only in Ireland but in several other part of the world.

The main advantage of a logbook scheme is the possibility to monitor the fishery at a relatively low cost (Pollock et al., 1995) and there are many practical applications (e.g. Prince et al., 2002; Mosindy and Duffy, 2007; Kerr, 2007). Logbook returns are often used to estimate catch per unit (CPUE) (Jansen et al., 2013; Stephens and MacCall, 2004) or for assessing anthropogenic pressure on fish stocks (Jankovskỳ et al., 2011; van der Hammen et al., 2015). In Ireland logbook return data from recreational salmon anglers, in particular river-specific weight data, have been used to develop river scale biological reference points, which are used to set conservation limits above which a harvest fishery is allowed (White et al., 2016). The approach developed by White et al. (2016) is judged to be a significantly improved method of assessing conservation limits and is a major development for the conservation and management of salmon stocks on a river-by-river basis. The empirical analysis in this paper utilises the same logbook return data and provides insight into another aspect of river specific management guidance – the efficacy of various fishing methods. The modelling approach used allows management to assess the potential impact of limiting the method of fishing used in different river systems on catch rates thereby providing valuable information that can be used to influence CPUE.

A parametric approach is proposed to analyse logbook data and identify the extent to which angling-specific variables are associated with successful catch. Unlike previous research, we do not estimate CPUE but focus on factors associated with probability of catch, as our dataset contains no information on fishing effort. The primary objective of the analysis is to provide fishery managers information on the most successful methods of fishing controlling for differences across fisheries and anglers. This information may aid fishery management decisions when sustainability of fish stocks are threatened. A secondary analysis is undertaken with respect to licence types, which vary by duration and geographical location. The type of licence purchased will reflect an angler's needs, e.g. 1-day versus season long licence, however, the logbook returns data enable the assessment of the ex-post expected value for money of licence types, i.e. expected catch per licence unit cost, which is information that should be useful for the administration of the licensing system. This contrasts with the standard approach to economic valuation of angling, which usually entails estimating an angling demand function and calculating consumer (angler) surplus (Curtis, 2002; Englin et al., 1997; Hynes et al., 2017; Grilli et al., 2018; Morey and Waldman, 1998).

The remainder of the paper is organized as follows. Section 2 briefly reviews the state of salmon angling in Ireland. Section 3 then presents the methodology used in the analysis. Section 4 presents the results. Section 5 then discusses how the information generated from the modelling approach used is useful to in terms of regulation and management of recreational fisheries. It also includes a discussion of the policy implications related to the model findings. Finally, Section 6 offers some conclusions.

2. Background - salmon angling in Ireland

The Atlantic salmon is a native Irish fish. The salmon fishing season open on the majority of Irish rivers on various dates in February, March, April and May. For a small number the start date is January 1st. The majority of rivers close to salmon fishing on September 30th. The bigger fish known as 'Springers' tend to run in the early months of the year and weigh an average of nine pounds Angling Ireland (2018). The biggest run of salmon occur in the summer months although many Irish rivers also have large runs of salmon at the beginning of the autumn. Large-scale commercial salmon fishing ended in Ireland in 2007 with the introduction of a mixed-stock drift net ban. Recreational anglers are now the primary users of Ireland's wild salmon resources. The best salmon rivers are generally located on the western and southern coasts in areas where angling related employment is an important income source in what is often rural locations with limited employment opportunities.

When fishing for salmon and sea trout in Ireland a State licence is required. At present there are several different types of licences that anglers can choose from, differing by time and geographical location:

- Annual, all-districts
- Annual, district-specific (one only of 17 fishery districts/regions)
- Annual, juvenile (below 18 years old), all districts
- 21 day, all-districts
- 1 day, all-districts
- Special licence for the Foyle river[1]
- Other special local licences

A fishing permit or club membership may also be required at some locations. Salmon and sea trout angling is subject to the 'Wild salmon and sea trout tagging scheme' administered by Inland Fisheries Ireland (IFI). The main objective of this scheme is to collect accurate information on nominal catch and estimate stock exploitation in order to develop adequate management strategies for the long-term sustainability of salmonid fisheries. When an angler purchases a licence they also receive a logbook and 'gill tags'. Anglers must attach a gill tag to all salmon and sea trout harvested (the minimum size for a fish to be retained is 40 cm) and record all details of the catch in the logbook. All released fish must also be recorded, not just harvested fish. Information recorded in the logbook includes date and location, length and weight of the fish, the species (salmon or sea trout), fishing method (i.e. type of bait), and whether the fish was released or not. While returning logbooks at the end of the season is mandatory, approximately 30% of logbooks are not returned. The majority of non-returned logbooks are associated with 1-day licences where catches are relatively few due to low effort and possibly angler inexperience, or where no catch is recorded. The logbook return data is consequently confined to anglers with positive catch.

3. Methods

3.1. Data preparation and statistical analysis

Our analysis relates to logbook returns for the 2016 salmon angling season. The initial dataset had 22,954 observations, each representing a fish caught. We excluded records related to sea trout, totalling 1,145 observations, i.e. less than 5% of the total, as our focus is on salmon. Observations with missing data (e.g. unknown fishing method or location) were also excluded. The data was then organised as a panel of anglers by fishing method and by river system such that each row of the panel recorded the number of fish caught by an angler in one river system with a specific fishing method. For example, if an angler caught fish in two rivers with the same method, then his catch is recorded as two rows in the dataset. If an angler caught fish in just one river but using two different fishing methods his catch is also recorded in two rows of the dataset. The final dataset had 6,811 observations grouped by 4,662 anglers, which is an unbalanced panel of anglers across rivers and methods. Descriptive statistics of the sample are shown in Table 1.

[1]The Foyle river represents the boundary between the Republic of Ireland and Northern Ireland. This licence allows anglers to fish from both river banks.

Table 1: Catch rates conditional on positive catch by fishing method, licence type and angler origin for 2016 season

Conditional average catch per angler for 2016 season			3.08			
Standard deviation			(3.67)			
By fishing method per angler:		Shrimp	Spinners	Worms	Fly	
(one river)						
Conditional average catch		3.81	3.02	2.7	3.22	
Standard deviation		(4.48)	(3.54)	(2.83)	(3.95)	
Frequency (%)		9	30	22	39	
By licence type per angler :	Annual	District	Juvenile	1 day	21 day	Foyle ext.
(one fishing method and one river)						
Conditional average catch	3.30	3.42	2.24	2.22	1.22	2.34
Standard deviation	(4.12)	(3.82)	(2.26)	(2.16)	(0.83)	(2.30)
Frequency (%)	38	40	3	14	1	4
By angler country of origin per angler:	Ireland	N. Ireland	Great Britain	Europe	America	Australasia
(one fishing method and one river)						
Conditional average catch	3.26	2.67	2.65	2.47	2.16	3.00
Standard deviation	(3.95)	(2.40)	(3.37)	(2.08)	(1.99)	(3.39)
Frequency (%)	76.2	8.2	6.5	8.5	0.4	0.2

Source: 2016 IFI logbook returns

For anglers that did not return logbooks we have no information on the fishing location (i.e. river system) nor the fishing methods used. Also, as the logbook returns are limited to positive catches the sample is truncated at zero and the average catch per angler in Table 1 is conditional on positive catch. The sample annual average catch per angler, conditional on positive catch is 3.08 (std. err 3.67) salmon. A histogram of catches is presented in Figure 1. The maximum number of salmon caught by an angler using a single method in one river was 68 and with an annual bag limit of 10 fish almost all of these fish were released. The average catch across all anglers, including those with zero catch, is lower. The most prolific fishing methods per angler in a single river are spinners and fly fishing (39% and 30% of the catch, respectively), followed by worms (22%) and shrimps (9%). Of the 4662 anglers in the dataset 32% held a annual-all districts licence, 43% held an annual district-only licence, 18% held a 21-day licence, with the remaining 8% holding other licence types. Catch by single fishing method and single river system categorised by licence type and angler country of origin are also reported in 1.

3.2. *Statistical Model*

The variable of interest is the number of fish caught by river-fishing method combination, which was illustrated graphically in Figure 1. The distribution of this count variable covers positive integer values, which is typically modelled by Poisson and negative binomial (NB) distributions that are defined over non-negative integers. Under the Poisson distribution the probability an individual i in river r, using fishing method m catches t salmon is given by (Greene, 2003):

$$Pr[T = t] = \frac{\exp^{-\mu} \cdot \mu^{t_{irm}}}{t_{irm}!} \quad \mu > 0, t \in \mathbb{N} \tag{1}$$

where μ is the rate parameter and equal to the mean of the Poisson distribution. In a regression framework μ is usually parametrised with an exponential function $\mu = exp(X'\beta)$. Incorporating the X matrix facilitates the introduction of heterogeneity within the model, while defining μ with an exponential functional form

Table 2: Most prolific rivers for salmon in Ireland

River Name	Salmon catch 2016
Blackwater(Munster)	4836
Moy	4565
Laune	3123
Corrib	2223
Lee	2029
Suir	1466
Feale	1423
Ballysadare	1200
Drowes	1124
Bandon	1000
Nore	599
Owenduff	590
Owenea	585
Ilen	354
Shannon(Mulkear)	333
Waterville/Cummeragh/Currane	332

Source: Table 10, IFI (2017)

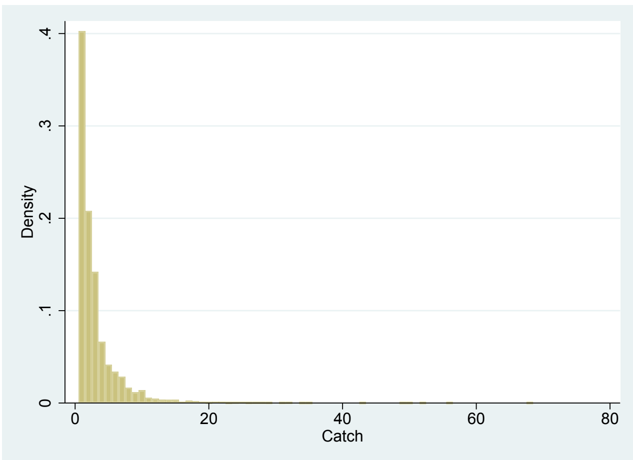


Figure 1: Histogram: number of salmon caught per angler (by river-method combination)

ensures $\hat{\mu} > 0$. The logbook returns data is truncated at zero, because we have no information on anglers that did not catch at least one salmon during the season. The Poisson model conditioned for truncation at zero has the following likelihood function (Hilbe, 2011):

$$Pr[T = t] = \frac{\exp^{-\mu} \cdot \mu^{t_{irm}}}{t_{irm}!}\left[\frac{1}{1 - e^{-\mu}}\right] \tag{2}$$

A well recognised shortcoming of the Poisson model in empirical applications is the imposition of equality of mean and variance. This assumption is often violated and many datasets show over-dispersed data, i.e. variance larger than the mean. Overdispersion occurs when a few anglers catch a very larger number of fish compared to the average, boosting the variance of the distribution. This has similar consequences to heteroscedasticity in linear regression models and in non-truncated samples leads to biases in standard error estimates. However, in a truncated sample over-dispersion leads to inconsistent estimates, therefore corrections are needed for a valid model. The negative binomial (NB) distribution, which includes an extra parameter to account for overdispersion, is often used as an alternative to the Poisson. The truncated NB model has the following log-likelihood function:

$$Pr[T = t] \ = \frac{\Gamma(\alpha^{-1} + t_{irm})}{\Gamma(\alpha^{-1})\Gamma(t_{irm} + 1)}(\alpha\mu)^{y}(1 + \alpha\mu)^{-(y+\alpha^{-1})}\left[\frac{1}{1 - (1 + \alpha\mu)^{\alpha^{-1}}}\right] \tag{3}$$

where α represents the over-dispersion parameter and Γ indicates the gamma function that distributes t_{irm} as a gamma random variable. 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).

Nominally our dataset is a panel of anglers but estimating a panel regression, such as a fixed effects model, though feasible is not practically useful as policy relevant angler-invariant variables (e.g. licence type, angler country of origin) are dropped during estimation (Baltagi, 2013). While this feature does not occur in random effects models, random effects assume exogeneity of all the regressors (i.e. X) with the model's random individual effects (Mundlak, 1978), which is not a reasonable assumption in this application. Variables such as licence type or angler country of origin are likely to be correlated with the error term. The estimation approach taken here is a least squares dummy variables (LSDV) count model, which is a pooled regression model that provides parameter estimates equivalent to the fixed effects model but additionally includes parameter estimates associated with variables normally dropped from the fixed effects model (Baltagi, 2013). The dropped variables in a regular fixed effects panel framework are usually described as 'time-invariant' but in the context of this panel are observations that do not vary within angler groups. In the current dataset the dropped observations would relate to all anglers with just one observation, i.e. they only catch salmon by one method from one river, and represent 48% of anglers in the dataset. Following the LSDV approach means that the information from these anglers is not lost. However, during estimation it is important to account for the fact that observations from the same angler are related. For instance, more skilled anglers are likely to catch higher numbers of salmon irrespective of fishing methods or the river compared to less skilful anglers. Consequently, to allow for angler heterogeneity during estimation we cluster standard errors at the angler level (Cameron and Miller, 2015). We also estimate a weighted regression model, where the inverse of the number of observations per angler is used as a weight.

The estimated parameter vector, $\hat{\beta}$, reflects how the probability of fish caught is associated with the explanatory variables, X, but the parameter values themselves are not of direct policy relevance. To consider the practical implications of the model estimates we calculate predicted mean catch, $\hat{\mu}$, and conditional predicted mean catch, $\hat{\mu}_c$, which is conditional on specific values of the independent variables, X_c. For example, predicted mean catch conditional on fishing method or licence type.

$$\hat{\mu}_c = exp(X_c'\hat{\beta}) \tag{4}$$

4. Results and Discussions

4.1. Econometric models

Table 3 shows results of four regression models, (1)–(4). The first two are truncated Poisson and negative binomial models, with standard errors clustered at angler level. The third is a weighted truncated NB model, as described earlier, while the fourth model additionally includes some interaction terms between fishing methods and the river.[2] We first consider model fit and preferred model across the four models estimated. We calculated the variance inflation factor coefficient (VIF) to check whether the explanatory variables were collinear. A VIF higher than 10 for one variable is usually an indication that the variable is collinear with another and should be dropped to allow stability in the model (Greene, 2003). In our case the maximum VIF is 3.52 and the average across all explanatory variables is 1.15 so multicollinearity is not a serious problem for the data. There is also consistency across the estimated models with only changes in magnitude rather than sign of the estimated coefficients between models. The presence of overdispersion in the data was tested by a log-likelihood ratio test on the dispersion coefficient α in the NB models. For instance, in the first NB model the test returned a $\chi^2_{(1)}$ value of 6992.75 (p-value = 0.000) indicating that overdispersion is important and that the NB model is more appropriate to model the data. This conclusion is also supported by significant coefficients for α in both NB models and the much lower statistics for the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The weighted NB model (model 3) has the lowest scores for AIC and BIC and was selected as the preferred model. The subsequent discussion of the results refers to model 3 unless otherwise stated.

The first analysis of the coefficients concerns fishing methods, with shrimp as a reference category. All the other methods have a negative coefficient, which suggests that all are less effective compared to shrimp as a bait for salmon angling. In particular, fishing with spinner is the method providing the lowest probability of catch, followed by worms and fly fishing. This ranking is the same across models, which is an additional indication of consistency of this analysis. This result was expected, as shrimp are considered a very effective bait for salmon and many local bye-laws either prohibit or curtail the use of shrimp as bait.

We include licence types to examine how catch rates vary across licences with the annual licence covering all districts as a reference category. The type of licence anglers buy may influence the catch because it may reflect how often and where anglers fish. The annual district-only licence has a positive coefficient, meaning that catch with this licence is more prolific than the annual geographically-unrestricted licence. This suggests that anglers who only fish in one district have a deeper knowledge and experience of angling sites and that is reflected in higher catches. Anglers fishing across several districts (i.e. Annual, all districts licence) may have lower levels of local knowledge, which is reflected in lower catches. Anglers with a juvenile licence catch less than anglers with a standard licence. A juvenile licence is for anglers under 18 years old and they are therefore less expert than anglers fishing for many years. Licences with 1 or 21

[2] The model with interaction terms included a large number of coefficients. For space and legibility reasons only main coefficients are included in Table 3. Interaction terms are briefly discussed in the next section and reported in appendix Table A1.

Table 3: Results of the econometric models

	(1) Truncated Poisson	(2) Truncated NB	(3) Truncated NB†	(4) Truncated NB w\interactions†
Methods (reference category: shrimp)				
Spinner	-0.287***	-0.395***	-0.416***	-0.483***
	(0.0590)	(0.0770)	(0.0733)	(0.165)
Worms	-0.297***	-0.351***	-0.282***	-0.634***
	(0.0559)	(0.0757)	(0.0772)	(0.184)
Fly fishing	-0.174***	-0.222***	-0.210***	-0.446***
	(0.0596)	(0.0775)	(0.0725)	(0.158)
Licence types (reference category: annual, all districts)				
District	0.0680	0.110**	0.136***	0.119**
	(0.0420)	(0.0526)	(0.0494)	(0.0483)
Juvenile	-0.442***	-0.619***	-0.535***	-0.572***
	(0.105)	(0.129)	(0.125)	(0.118)
21 day	-0.601***	-0.835***	-0.823***	-0.819***
	(0.0749)	(0.101)	(0.0982)	(0.0968)
1 day	-2.001***	-2.491***	-2.448***	-2.427***
	(0.387)	(0.408)	(0.415)	(0.417)
Foyle-extended licence	-0.314***	-0.350**	-0.347**	-0.358**
	(0.116)	(0.157)	(0.144)	(0.140)
Anglers' country of origin (reference category: Republic of Ireland)				
Northern Ireland	-0.0594	-0.0874	-0.0190	-0.0420
	(0.0614)	(0.0854)	(0.0833)	(0.0831)
UK	0.233**	0.360***	0.397***	0.323***
	(0.0940)	(0.125)	(0.126)	(0.123)
Europe	0.112*	0.261***	0.282***	0.281***
	(0.0664)	(0.0951)	(0.0963)	(0.0947)
America	-0.125	-0.209	-0.578	-0.610
	(0.203)	(0.303)	(0.410)	(0.405)
Australasia	0.372	0.668	0.752	0.769
	(0.397)	(0.551)	(0.513)	(0.489)
Constant	1.189***	0.338***	0.353***	0.622***
	(0.0737)	(0.106)	(0.107)	(0.159)
α		2.999***	2.612***	2.359***
		(0.350)	(0.272)	(0.227)
Pseudo R-squared	0.08	0.025	0.029	0.033
AIC	32711.5	25402.1	17245.0	17245.9
BIC	32916.3	25613.7	17456.6	17710.1
Log-likelihood	-16325.7	-12670.1	-8591.5	-8555.0
Observations	6811	6811	6811	6811

Robust standard errors clustered at individual level in parentheses
† Weighted regression, as described in section 3.2
*p<0.10 ** p<0.05 *** p<0.01

Table 4: Results of the econometric models - river system variables only

	(1) Truncated Poisson	(2) Truncated NB	(3) Truncated NB†	(4) Truncated NB w\interactions†
River systems (reference category: all other river systems)				
Blackwater	0.271***	0.386***	0.426***	0.0782
	(0.0708)	(0.0923)	(0.0788)	(0.216)
Moy	0.0140	0.0443	0.0758	-0.120
	(0.0506)	(0.0683)	(0.0671)	(0.192)
Laune	-0.211***	-0.265***	-0.221**	-0.674
	(0.0749)	(0.101)	(0.110)	(0.411)
Corrib	0.111*	0.159*	0.210***	0.131
	(0.0607)	(0.0816)	(0.0795)	(0.187)
Lee	0.168*	0.263**	0.337**	-0.216
	(0.0986)	(0.132)	(0.152)	(0.326)
Suir	1.180***	1.582***	1.675***	1.611***
	(0.0999)	(0.126)	(0.130)	(0.174)
Feale	-0.281**	-0.332**	-0.346**	-0.302*
	(0.120)	(0.158)	(0.166)	(0.172)
Ballysadare	0.210***	0.304***	0.439***	-0.0460
	(0.0725)	(0.0967)	(0.103)	(0.409)
Drownes	0.123	0.164	0.181	-0.195
	(0.0781)	(0.109)	(0.111)	(0.284)
Bandon	0.258***	0.381***	0.427***	-0.0124
	(0.0937)	(0.124)	(0.164)	(0.295)
Nore	0.640***	0.926***	0.848***	0.845***
	(0.144)	(0.193)	(0.207)	(0.300)
Owenduff	-0.218	-0.298	-0.265	-0.232
	(0.154)	(0.198)	(0.220)	(0.222)
Owenea	0.263**	0.362**	0.439**	0.438*
	(0.131)	(0.179)	(0.182)	(0.244)
Ilen	0.331***	0.469***	0.619***	-0.587
	(0.123)	(0.164)	(0.167)	(0.411)
Shannon	0.795***	1.068***	1.098***	1.188***
	(0.132)	(0.175)	(0.192)	(0.251)
Waterville	-0.549***	-0.673***	-0.624***	0.448***
	(0.154)	(0.203)	(0.189)	(0.149)

Robust standard errors clustered at individual level in parentheses
† Weighted regression, as described in section 3.2
*p<0.10 ** p<0.05 *** p<0.01

day duration have considerably lower probability of catching fish, which most likely reflects lower effort compared to anglers with season long licences. In particular, anglers with a daily licence have a very large and negative coefficient in absolute value. These short duration licences, i.e. 1 and 21 day licences, are frequently purchased by tourist and novice anglers, whose expertise in salmon fishing is likely to be lower than other salmon anglers.

Angler country of origin is the only demographic variable available from the logbooks. Catches by anglers visiting from Great Britain and elsewhere in Europe are higher compared to those from the Republic of Ireland, whereas catches by anglers from Northern Ireland or elsewhere are not statistically different from Irish anglers. It is not clear why anglers from the Great Britain and Europe have higher catches. It may reflect higher relative skill levels of visiting anglers but the predominant fisheries where Great Britain and European anglers catch salmon are the two most prolific fisheries, the river Moy and the Munster Blackwater. Visiting anglers tend to concentrate on the premier salmon fisheries, whereas anglers living in the Republic of Ireland fish across all the salmon rivers. Visiting anglers might also be expected to be more likely to use the services of a gilly, which should increase their chances of catching a higher number of salmon, all else being equal.

In the regression models we included dummy variables for river systems to control for differences in salmon stocks, habitat quality and water pollution across sites. The logbook database covers 92 separate river systems and for tractability in the regression model output we included dummy variables for the 16 most prolific river systems in 2016 each with annual catches exceeding 300 fish, as illustrated in Table 2. These 16 river systems accounted for 81% of the total recreational catch for the 2016 season. The reference category is the remaining river systems. Although the dummy variables represent the most prolific fisheries compared to the reference category, it is not necessary for the estimated coefficients to be always positive, as the model is estimating catch per angler by river and method. The most prolific river systems also have the highest number of anglers so average catch per angler is not necessarily higher on the most prolific river systems. We report the regression coefficients for these dummy variables separately in Table 4. Controlling for the other explanatory variables in the model the results in Table 4 indicate average catch rates on the river Moy, the second most prolific river in the country, are not statistically different than the reference category, while mean angler catch on the Blackwater is higher and lower on the river Laune compared to the reference category. The Suir river system has the highest coefficient estimate at 1.675. Controlling for fishing method, licence type, as well as angler country of origin, the river Suir has the highest mean catch per angler, though the coefficient itself cannot be interpreted directly as a number of fish. From the logbook returns mean catch per angler on the Suir using a fly as a fishing method is 8.7 salmon compared to 3.9 fish on the Blackwater. In general, the statistical significance of almost all river system coefficients highlights a high explanatory power for these variables and suggests that catch is site-specific, therefore angling location is an important factor.

Model (4) included interaction terms between fishing methods and rivers, on the premise that there may be non-linearities in the catch rates associated with particular river and fishing method combinations. Though model (4) is not the preferred model, its AIC score and log-likelihood values are similar in magnitude to the preferred model (3). The interaction terms are reported separately in the appendix Table A1. Just 9 of the 38 reported parameter estimates are statistically different than zero at the 5% level suggesting little added value from this model in terms of using the estimates to inform angling pressure or stock assessment at specific river level. However, collectively the 38 interaction terms are highly statistically significant with a $\chi^2_{(38)}$ = 176.5 suggesting that the association between catch rates and river-fishing method combinations are non-linear. Consequently, in Table A1 we have also reported mean predicted catch rates for the 16 top river systems associated the different fishing methods.

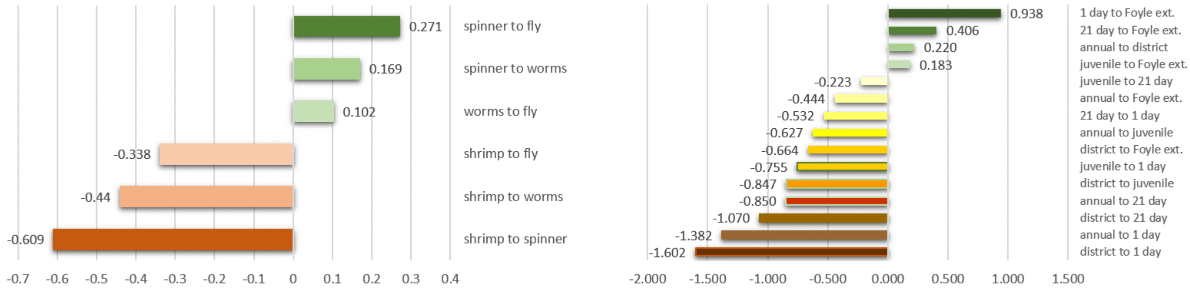
4.2. Postestimation and marginal effects

Table 5 shows model predicted mean catch rates associated with variables of policy interest, i.e. methods and licence types, calculated based on the preferred model 3 specification. The information that can be retrieved from these indicators is the predicted catch associated with the fishing method or licence type controlling for all other covariates, such as river systems. First, the overall model unconditional mean predicted catch is 1.37 salmon, which contrasts with the mean of 3.08 conditional on positive catch from Table 1. Table 5 shows how the unconditional mean catch varies by fishing method or licence type. Anglers using shrimp as a fishing method have a model mean catch of 1.79 salmon for the 2016 season, which is the highest of the four fishing methods, while those using a spinner as bait have the lowest mean catch of 1.18 salmon. With regard to licence types, as outlined earlier, anglers purchasing a district licence have the highest catch, estimated at 1.73 salmon in our preferred model specification, all else held equal. The annual licence is associated with the second largest bag, i.e. 1.51 salmon per season. The higher predicted catch for anglers with a district licence may be related to the degree of local knowledge of anglers frequently fishing in the same district rivers, compared to anglers with an annual licence covering all districts but who may not have the same in-depth experience at all fishing locations. Juvenile and time-limited licences show the lowest return in terms of catch, which is reasonable due to the likely lower degree of expertise or potentially lower fishing effort, particularly with the short duration licences. It is also feasible to calculate predicted mean catches associated with a combination of fishing methods or river systems. In the previous section we noted that the river Suir has the highest mean catch per angler. The model predicted mean catch rate for district licence holders, flying fishing on the river Suir is 7.1 (s.e. 0.94) salmon compared to a comparable angler on the Blackwater of 2.0 (s.e. 0.18).

Table 5: Unconditional predicted mean catch by fishing method and licence type

	Predicted mean catch	Standard Error
Overall	1.37***	(0.09)
By fishing method:		
Shrimp	1.79***	(0.16)
Spinner	1.18***	(0.09)
Worms	1.35***	(0.10)
Fly	1.45***	(0.10)
By licence type:		
Annual	1.51***	(0.11)
District	1.73***	(0.11)
Juvenile	0.89***	(0.12)
21 day	0.66***	(0.07)
1 day	0.13**	(0.05)
Foyle Ext.	1.07***	(0.16)

*p<0.10 ** p<0.05 *** p<0.01



(a) Fishing methods

(b) Licence types

Figure 2: Pairwise comparison of marginal effects

Figure 2 presents these results visually, where catch associated with licences types and fishing methods are evaluated as pairwise comparisons. In this case the general interpretation of the bars indicate the increase (or decrease) in the predicted mean catch when switching from one method or licence to another. With respect to fishing methods, switching from shrimp to spinners is associated with the largest decrease in the average catch of approximately 0.6 fish less on average, a switch from shrimp to worms or flies decreases in the bag of 0.45 and 0.32, respectively. Swapping spinners with fly fishing is associated with an average increase of 0.3 fish per season, while replacing spinners with worms is associated with an increase in mean catch of almost 0.2 fish per season. With respect to licences the largest difference in mean seasonal catch occurs between a district licence and the 1 or 21 days licences.

5. Discussion

The complexity of water ecosystems require considerable efforts to assure a sustainable and long-lasting habitat for fish and the other species living in the water. A critical factor for effective conservation policies is the availability of data, which are not always available in a timely manner. Mandatory logbooks for recreational anglers provide detailed data to help managers sustainably manage fishery resources. Information retrieved from angler logbooks is already being used to establish river specific conservation limits (White et al., 2016) and assess whether recreational harvesting is permitted. The models estimated here based on the same logbook data provides additional information useful for the regulation and management of recreational fisheries, including informing decisions on the regulation of fishing methods, catch and release, river-specific policies, licence types and costs.

5.1. Angling regulation

Angling regulation aimed at control of fishing method could be used to influence both number of anglers and their catch rate. As seen in the model results, shrimp as a bait has the highest predicted catch and fishing by spinner has the lowest. Across all four fishing methods considered, the mean predicted catch is between 1–2 salmon per angler, per season, over all river systems. So, on average across all salmon rivers there is not a substantial difference between fishing methods. And on this basis one could conclude that fishing methods have been regulated in such a manner that no single fishing method, averaging across anglers and the entire season, is substantially more successful in catching salmon than any others. But averages obscure the distribution of outcomes on specific rivers. For example, there is a difference of 3 fish between the highest angler catch per method (shrimp, 8.7 fish) and and the lowest (spinner, 5.7 fish) on the river Suir. On the Blackwater river the difference is less than 1 fish, with mean catch by shrimp at 2.5 fish compared to mean catch by spinner at 1.6 fish. The estimated model can be used to compare mean catch rates by fishing methods both within and between river systems for the purpose of reviewing regulations pertaining to specific rivers or fishing methods.

5.2. *Licences*

Information on licence types may be important from several perspectives. The relative comparison of catch by licence type highlights that annual and district licences are those associated with the highest average catch per season, while time-constrained licences are less prolific on average. With this information fishery managers can assess in near real-time recreational angling pressure on fish stocks based on the number and types of licences sold. This information is also useful to compare the catch (or return) per unit cost of a licence, i.e. the ratio of average catch by licence type to licence cost, as illustrated in Table 6. For instance, an annual all-districts licence costs €100 and the mean catch of anglers with that licence is 1.51 salmon. The mean licence cost per fish caught is €66.10. Contrast that with the 1-day licence, the annual licence is five times the 1-day licence cost but the mean catch is over 11 times higher. The mean licence cost per fish caught for the 1-day licence is €152.95. Across the adult licences, the district licence has the lowest mean licence cost per fish caught at €33.32. District licence holders, on average, enjoy the best value or returns in terms of the cost of their licence fee. The juvenile licence has the lowest cost per fish caught, which no doubt reflects a policy measure by fishery managers to encourage participation in recreational angling by young people.

Table 6: Marginal catch, cost and cost per fish for different licences

Licence type	Predicted mean catch	Cost (€)	€ per fish
Annual	1.51	100	66.10
District	1.73	56	32.32
Juvenile	0.89	10	11.29
21 day	0.66	40	60.33
1 day	0.13	20	152.95
Foyle ext.	1.07	80	74.84

5.3. *River systems*

Rivers are very different from each other and finding interventions suitable for all can be difficult. For this reason diversified policies based on river characteristics are often successful for conservation. Our models account for site specific effects reported in Table 4, while model 4 allows interaction effects between fishing methods and rivers systems, which are reported in Table A1. A couple of examples are provided to illustrate the diversity of research findings. The consequent implications for the management of these fisheries ultimately depends on the viability of the stocks in these rivers. These examples highlight which fishing methods are the most effective within a given fishery. Taking the river Ilen it is noticeable that fly fishing and the spinner are the particularly effective. Spinners, fly and worms are substantially less effective in Waterville compared to the shrimp as a bait. On the river Bandon fly fishers have a higher probability of catch while those using worms are less likely to reach the average bag. Interactions enrich the informative potential of this analysis and identify the most and least effective methods by river, so that specific policies can be tailored if conservation is in danger.

6. Conclusions

Fishery managers are increasingly concerned about the environmental impacts caused by recreational anglers and attempt to avert negative outcomes through regulation. There is therefore an increasing need to monitor anglers' activity given the wide evidence of environmental impact cause by recreational fishing. Currently, the tools available for managing recreational fisheries tend to place restrictions on individual anglers, such as daily catch limits and bag size limits. However, the effectiveness of these methods to restrict recreational catch have been questioned as they may not effectively limit the total harvest (Chan et al., 2018; Cox et al., 2002). Also, ecosystem impacts are caused by both the number of anglers and their catch; policies usually aim to reduce one or the other. Limiting the number of anglers might have negative economic consequences so reducing fish harvest is often preferred. In this contribution we proposed a method to identify a ranking of fishing methods for salmon based on catch effectiveness, controlling for river specific characteristics such as habitat conditions and stocks. We argue that the analysis of logbook data to estimate the impact of fishing methods on catch rates provides valuable information to fishery management. This information should facilitate the better protection of fish stocks by allowing managers to consider fishing method restrictions as a means of limiting catch rates in threatened fisheries.

This contribution discussed the mandatory logbook scheme operating in Ireland and proposed a methodology to analyse the data in a simple and at the same time informative manner. A major advantage of the approach suggested is that collecting data from logbooks is efficient and cheap, both in terms of money and time. Self-compiled logbooks allow surveying the full population of anglers without the need of interviewers or costly surveys. The statistical analyses that we proposed are quite simple to replicate and models are flexible enough to allow different specifications based on the objective of the study. As already highlighted possible improvement of the models could be collecting additional variables and identify other causal effects of anglers' characteristics on catch. In addition, this procedure is flexible and may be applied to many endangered fish species and also to different recreational activities involving pressure on natural stocks, e.g. hunting.

The methodology employed in the paper has some limitations to consider when interpreting our results and to improve the method in future applications. Firstly, and as discussed in the methodology section, we have ignored the panel nature of the data in the model estimation. If the catch rate is affected by unobservable variables that systematically vary across river-method in the panel, then the coefficient on any variable that is correlated with this variation will be biased. The cluster-adjusted standard error used in the chosen models to allow us to account for the fact that observations from the same angler are related but an area for future research is to consider the use of a panel count model along the lines of Hynes and Greene (2016). Another important factor to note is that it is not possible to control for IUU (illegal, unreported and unregulated fishing). The accuracy of the results also depends on the reliability of logbooks, which is in turn determined by anglers' environmental consciousness and enforcement levels. Another limitation of the dataset was the absence of information on effort levels, e.g. the number of fishing days, as well as observations representing persons that did not catch at least one salmon.

A recommendation therefore for fisheries management is to collect additional information via the logbook, specifically to collect information on angling effort, as well as on those fishers who have a zero catch rate. Incorporating this information should lead to a more accurate estimation of the causal effects of anglers' characteristics on catch. The assessment of the ex-post expected value for money of licence types highlighted the fact that the cost per fish caught is highest for the 1-day licence at a cost per fish of €153 (a 1 day licence costs €20 but the expected catch is just 0.13). Therefore, a further recommendation to fishery managers would be to consider the introduction of a special "come and try it" 1 day licence for beginners at a cost below the current 1 day licence if the goal is to try and encourage new participants in the sport of salmon angling.

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8. References

AAAS (1997). Ice age communities may be earliest known net hunters. *Science*, 277(5330):1203–1204. http://doi.org/10.1126/science.277.5330.1203.

Angling Ireland (2018). Salmon fishing in Ireland. http://www.fishinginireland.info/salmon/salmon.htm. Last accessed 21/7/2018.

Arlinghaus, R., Tillner, R., and Bork, M. (2015). Explaining participation rates in recreational fishing across industrialised countries. *Fisheries Management and Ecology*, 22(1):45–55.

Baltagi, B. (2013). *Econometric analysis of panel data*. John Wiley & Sons, Chichester, United Kingdom, 5th edition.

Cambray, J. A. (2003). Impact on indigenous species biodiversity caused by the globalisation of alien recreational freshwater fisheries. *Hydrobiologia*, 500(1-3):217–230.

Cameron, A. C. and Miller, D. L. (2015). A practitioners guide to cluster-robust inference. *Journal of Human Resources*, 50(2):317–372. https://doi.org/10.3368/jhr.50.2.317.

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. https://doi.org/10.1002/jae.3950010104.

Camp, E. V., Larkin, S. L., Ahrens, R. N., and Lorenzen, K. (2017). Trade-offs between socioeconomic and conservation management objectives in stock enhancement of marine recreational fisheries. *Fisheries research*, 186:446–459.

Carpenter, S. R., Brock, W. A., Hansen, G. J., Hansen, J. F., Hennessy, J. M., Isermann, D. A., Pedersen, E. J., Perales, K. M., Rypel, A. L., Sass, G. G., et al. (2017). Defining a safe operating space for inland recreational fisheries. *Fish and Fisheries*, 18(6):1150–1160.

Chan, M. N., Beaudreau, A. H., and Loring, P. A. (2018). Evaluating the recreational fishery management toolbox: Charter captains perceptions of harvest controls, limited access, and quota leasing in the guided halibut fishing sector in alaska. *Marine Policy*, 91:129–135. https://doi.org/10.1016/j.marpol.2018.02.013.

Cooke, S. J. and Cowx, I. G. (2006). Contrasting recreational and commercial fishing: searching for common issues to promote unified conservation of fisheries resources and aquatic environments. *Biological conservation*, 128(1):93–108. https://doi.org/10.1016/j.biocon.2005.09.019.

Cookie, S. and Cowx, I. (2005). The role of recreational fishing in global fish crisis. *Bioscience*, 54:857–9.

Cox, S. P., Beard, T. D., and Walters, C. (2002). Harvest control in open-access sport fisheries: hot rod or asleep at the reel? *Bulletin of Marine Science*, 70(2):749–761.

Curtis, J., Breen, B., O'Reilly, P., and O'Donoghue, C. (2017). The economic contribution of a recreational fishery in a remote rural economy. *Water Resources and Rural Development*, 10:14–21. https://doi.org/10.1016/j.wrr.2017.11.001.

Curtis, J. A. (2002). Estimating the demand for salmon angling in Ireland. *Economic and Social Review*, 33(3):319–332. http://hdl.handle.net/2262/59840.

Dayton, P. K. (1998). Reversal of the burden of proof in fisheries management. *Science*, 279(5352):821–822.

Englin, J., Lambert, D., and Shaw, W. D. (1997). A structural equations approach to modeling consumptive recreation demand. *Journal of Environmental Economics and Management*, 33(1):33–43. https://doi.org/10.1006/jeem.1996.0976.

Gagne, T. O., Ovitz, K. L., Griffin, L. P., Brownscombe, J. W., Cooke, S. J., and Danylchuk, A. J. (2017). Evaluating the consequences of catch-and-release recreational angling on golden dorado (salminus brasiliensis) in Salta, Argentina. *Fisheries research*, 186:625–633.

Greene, W. H. (2003). *Econometric Analysis*. Pearson Education India.

Grilli, G., Curtis, J., Hynes, S., O'Reilly, P., et al. (2018). Sea bass angling in ireland: A structural equation model of catch and effort. *Ecological Economics*, 149(3):285–293.

Hilbe, J. M. (2011). *Negative binomial regression*. Cambridge University Press.

Hutchings, J. A. (2000). Collapse and recovery of marine fishes. *Nature*, 406(6798):882.

Hynes, S., Gaeven, R., and O'Reilly, P. (2017). Estimating a total demand function for sea angling pursuits. *Ecological Economics*, 134:73–81. https://doi.org/10.1016/j.ecolecon.2016.12.024.

Hynes, S. and Greene, W. (2016). Preference heterogeneity in contingent behaviour travel cost models with on-site samples: A random parameter vs. a latent class approach. *Journal of Agricultural Economics*, 67(2):348–367. https://doi.org/10.1111/1477-9552.12143.

IFI (2017). Wild salmon and sea trout fisheries statistics report 2016, IFI/2017/1-4374. *Inland Fisheries Ireland, Citywest, Dublin*. https://www.fisheriesireland.ie/extranet/fisheries-management-1/1461-wild-salmon-and-sea-trout-statistics-report-2016/file.html.

Jankovskỳ, M., Boukal, D., Pivnička, K., and Kubečka, J. (2011). Tracing possible drivers of synchronously fluctuating species catches in individual logbook data. *Fisheries Management and Ecology*, 18(4):297–306.

Jansen, T., Arlinghaus, R., Als, T. D., and Skov, C. (2013). Voluntary angler logbooks reveal long-term changes in a lentic pike, esox lucius, population. *Fisheries Management and Ecology*, 20(2-3):125–136. https://doi.org/10.1111/j.1365-2400.2012.00866.x.

Kerr, S. J. (2007). Characteristics of ontario muskellunge (esox masquinongy) fisheries based on volunteer angler diary information. *Environmental Biology of Fishes*, 79(1-2):61–69.

Lawrence, K. (2005). Assessing the value of recreational sea angling in South West England. *Fisheries Management and Ecology*, 12(6):369–375. https://doi.org/10.1111/j.1365-2400.2005.00465.x.

Lewin, W.-C., Arlinghaus, R., and Mehner, T. (2006). Documented and potential biological impacts of recreational fishing: insights for management and conservation. *Reviews in Fisheries Science*, 14(4):305–367. https://doi.org/10.1080/10641260600886455.

Maunder, M. N., Sibert, J. R., Fonteneau, A., Hampton, J., Kleiber, P., and Harley, S. J. (2006). Interpreting catch per unit effort data to assess the status of individual stocks and communities. *Ices Journal of marine science*, 63(8):1373–1385.

McPhee, D. P., Leadbitter, D., and Skilleter, G. (2002). Swallowing the bait: is recreational fishing in Australia ecologically sustainable? *Pacific Conservation Biology*, 8(1):40–51. https://doi.org/10.1071/PC020040.

Morey, E. R. and Waldman, D. M. (1998). Measurement error in recreation demand models: the joint estimation of participation, site choice, and site characteristics. *Journal of Environmental Economics and Management*, 35(3):262–276. https://doi.org/10.1006/jeem.1998.1029.

Mosindy, T. E. and Duffy, M. J. (2007). The use of angler diary surveys to evaluate long-term changes in muskellunge populations on lake of the woods, ontario. *Environmental Biology of Fishes*, 79(1-2):71–83.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society*, pages 69–85. https://www.jstor.org/stable/1913646.

Pollock, K. H., Jones, C. M., and Brown, T. L. (1995). Angler survey methods and their application in fisheries management. *Reviews in Fish Biology and Fisheries*, 5(3):378–380. https://doi.org/10.1007/BF00043009.

Prince, E. D., Ortiz, M., and Venizelos, A. (2002). A comparison of circle hook and" j" hook performance in recreational catch-and-release fisheries for billfish. In *American Fisheries Society Symposium*, pages 66–79. American Fisheries Society.

Ready, R. C., Poe, G. L., Lauber, T. B., Connelly, N. A., Stedman, R. C., and Rudstam, L. G. (2018). The potential impact of aquatic nuisance species on recreational fishing in the great lakes and upper mississippi and ohio river basins. *Journal of environmental management*, 206:304–318.

Schroeder, D. M., Love, M. S., et al. (2002). Recreational fishing and marine fish populations in california. *California Cooperative Oceanic Fisheries Investigations Report*, pages 182–190.

Stephens, A. and MacCall, A. (2004). A multispecies approach to subsetting logbook data for purposes of estimating cpue. *Fisheries Research*, 70(2-3):299–310.

Toivonen, A.-L., Roth, E., Navrud, S., Gudbergsson, G., Appelblad, H., Bengtsson, B., and Tuunainen, P. (2004). The economic value of recreational fisheries in nordic countries. *Fisheries Management and Ecology*, 11(1):1–14.

van der Hammen, T., de Graaf, M., and Lyle, J. M. (2015). Estimating catches of marine and freshwater recreational fisheries in the Netherlands using an online panel survey. *ICES Journal of Marine Science*, 73(2):441–450. https://doi.org/10.1093/icesjms/fsv190.

White, J., Ó Maoiléidigh, N., Gargan, P., de Eyto, E., Chaput, G., Roche, W., McGinnity, P., Crozier, W. W., Boylan, P., Doherty, D., et al. (2016). Incorporating natural variability in biological reference points and population dynamics into management of Atlantic salmon (Salmo salar l.) stocks returning to home waters. *ICES Journal of Marine Science*, 73(6):1513–1524.

https://doi.org/10.1093/icesjms/fsw015.
Zarauz, L., Ruiz, J., Urtizberea, A., Andonegi, E., Mugerza, E., and Artetxe, I. (2015). Comparing different survey methods to estimate european sea bass recreational catches in the Basque Country. *ICES Journal of Marine Science*, 72(4):1181–1191. https://doi.org/10.1093/icesjms/fsv054.

9. Appendix

Table A1: Model parameter estimates for interaction terms from Model (4) and associated mean predicted catch rates

Method	River	parameter estimate, β Model (4)	Standard error	Predicted mean catch, μ_c	Standard Error
Shrimp	Moy	†		1.57	0.22
Shrimp	Ballysadare	†		1.69	0.65
Shrimp	Drownes	†		1.46	0.37
Shrimp	Corrib	†		2.02	0.27
Shrimp	Nore	†		4.11	1.11
Shrimp	Blackwater	†		1.91	0.32
Shrimp	Laune	†		0.90	0.35
Shrimp	Waterville	†		2.77	0.16
Shrimp	Lee	†		1.42	0.42
Shrimp	Bandon	†		1.75	0.46
Shrimp	Ilen	†		0.98	0.38
Spinner	Owenea	-0.008	0.382	1.68	0.48
Spinner	Moy	-0.113	0.224	0.86	0.09
Spinner	Ballysadare	0.440	0.523	1.62	0.52
Spinner	Drownes	0.630	0.332	1.69	0.29
Spinner	Corrib	-0.203	0.268	1.02	0.19
Spinner	Shannon	-0.326	0.372	2.58	0.70
Spinner	Suir	0.034	0.259	5.65	1.02
Spinner	Nore	0.237	0.376	3.22	1.03
Spinner	Blackwater	0.006	0.24	1.19	0.11
Spinner	Feale	-0.110	0.318	0.72	0.19
Spinner	Laune	0.447	0.441	0.87	0.14
Spinner	Waterville	-0.962	0.32	0.65	0.18
Spinner	Lee	0.498	0.404	1.45	0.33
Spinner	Bandon	0.400	0.335	1.61	0.27
Spinner	Ilen	1.336	0.458	2.31	0.46
Worms	Owenea	-0.418	0.518	0.96	0.42
Worms	Moy	0.481	0.23	1.35	0.11
Worms	Ballysadare	0.565	0.439	1.58	0.20
Worms	Drownes	0.510	0.402	1.29	0.35
Worms	Corrib	0.249	0.25	1.37	0.18
Worms	Blackwater	0.379	0.325	1.48	0.33
Worms	Feale	-2.424	1.021	0.06	0.06
Worms	Laune	0.674	0.458	0.94	0.16
Worms	Waterville	-0.989	0.337	0.55	0.16
Worms	Lee	-0.256	0.451	0.58	0.17
Worms	Bandon	-0.831	0.439	0.40	0.12
Worms	Ilen	0.809	0.462	1.17	0.22
Fly fishing	Owenea	†		1.75	0.43
Fly fishing	Owenduff	†		0.90	0.19
Fly fishing	Moy	0.162	0.225	1.18	0.13
Fly fishing	Ballysadare	0.604	0.438	1.98	0.31
Fly fishing	Drownes	0.143	0.311	1.07	0.16
Fly fishing	Corrib	0.102	0.223	1.43	0.17
Fly fishing	Shannon	†		3.71	0.92
Fly fishing	Suir	†		5.67	0.93
Fly fishing	Nore	-0.687	0.360	1.32	0.26
Fly fishing	Blackwater	0.636	0.249	2.31	0.26
Fly fishing	Feale	†		0.84	0.14
Fly fishing	Laune	0.056	0.462	0.61	0.13
Fly fishing	Waterville	-1.179	0.309	0.55	0.15
Fly fishing	Lee	0.722	0.395	1.88	0.41
Fly fishing	Bandon	0.811	0.406	2.52	0.69
Fly fishing	Ilen	1.816	0.542	3.87	1.35

Note: Other parameter estimates from model (4) were reported in Tables 3 and 4
† Interaction term not estimated.

Year	Number	Title/Author(s)
2018		
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