**Supplementary materials: Assessing the impact of management on sea anglers in the UK using choice experiments.**

# Hypothetical Bias

A much-debated issue in non-market valuation is that of hypothetical bias whereby responses to hypothetical experiments such as those used in choice experiments differ from real world decisions (Hausman 2012). Different strategies exist to minimize hypothetical bias and include ex-ante and ex-post options. In this study several measures were implemented to reduce hypothetical bias including estimating WTP rather than WTA (List and Gallet, 2001) and the use of a choice-based elicitation mechanism (Murphy et al., 2005). Ex-ante strategies include cheap talk, consequentially script, survey protocols and incentive compatible questions (Loomis, 2011, 2014; Penn and Hu, 2018; Amoah et al 2019) that aim at increasing the credibility of the contingent scenario, thereby reducing the chance that respondents overstate the benefits.

Before each choice card, respondents were reminded of their budgetary constraint such as “remember that taking any trip would cost the amount shown and so reduce your ability to make other purchases” as this has been shown to reduce hypothetical bias (Bateman and Langford, 1997). Additionally, in each choice card respondents were reminded that the results of the survey can influence the government management strategies introducing the consequentiality script that also prompts the importance of choices (Carson and Groves, 2007; 2011; Carson, 2012). Furthermore, the realism of the choice scenarios through explaining a plausible real-world mechanism through which the proposed management changes would be made was also ensured including policies and payment vehicle tested with respondents and experts (Johnson et al., 2017).

Ex-post treatments are mainly based on weighting or calibrating WTP responses (Champ and Bishop 2001; Champ et al., 2009; Weaver and Prelec, 2013). The calibration can be conducted by screening the data to control for “highly” abnormal responses (Loomis, 2014). This calibration was conducted in our study considering the attribute attendance responses and the willingness to contribute responses. The combination of these two information supports the analyst in sub-setting the sample to remove hypothetical biased responses. In the paper we adopted both ex-ante and ex-post treatments but there is no guaranteed that hypothetical bias is fully removed as in all stated preference studies (Whitehead and Cherry, 2007).

# Selection of Random Parameters

The selection of random parameters can be supported by the t-statistic test, the likelihood ratio (LR) test and the Lagrange multiplier (LM) test as suggested by Bimonte et al. (2016) and Hensher et al. (2005).

The t-statistic test requires the estimation of the mixed logit model including different combination of fixed and random parameters. The attributes that present significant t-statistic for the standard deviation coefficient are considered to be the most suitable to enter as random variables in the final model. The LR test involves estimation of the basic conditional logit model and the subsequent comparison of the maximum likelihood score with that of different mixed logit models with several combinations of random parameters. The mixed logit model with the highest LR statistic is the best to fit the data. Although previous tests are applicable, they require the estimation and comparison of multiple models and are often overlooked. The LM test represents the most applicable test as it requires just one expanded conditional logit model. McFadden and Train (2000) proposed the LM test as an effective alternative to randomness of parameters.

This test requires the specification of artificial variables $z\_{ij}$:

$$z\_{ij}=\frac{1}{2}\left(x\_{ij}-x\_{iC}\right)^{2}$$

and

$$x\_{iC}=\sum\_{C}^{}x\_{it}P\_{j}$$

where $i$ signals the parameter under investigation, $C$ is the set of alternatives being offered each time *t* and $P\_{j}$ is the conditional logit model choice probability for alternative $j$. The artificial variables $z\_{ij}$ are then included in a conditional logit model. If the null hypothesis of fixed parameters is rejected the parameter needs to be treated as random.

In order to select random parameters Table 1 below reports the results of the LM and t-test and the t-test values for only random selected factors.

**Table S1.** LM -test coefficient of the artificial variable zij and t-test results for the sea bass and cod estimation used to guide the selection of random parameters.

|  |  |  |
| --- | --- | --- |
|  | **Sea bass model** | **Cod model** |
| **Variables** | **LMZ score** | **T-Test (using all random parameters)** | **T-Test (using just LM z score > 1 as random** | **LM****Z score** | **T-Test (using all random parameters)** | **T-Test (using just LM z score > 1 as random** |
| **ZAsc** | -1.02 |  0.000 | 0.000 | -1.09 |  0.250 | 0.000 |
| **ZMls1** | NA | NA |  | NA | NA |  |
| **ZMls2** | NA | NA |  | -0.77 | 0.759 |  |
| **ZMls3** | NA | NA |  | -0.34 | 0.690 |  |
| **ZMls4** | -2.58 | 0.899 | 0.492 | -0.65 | 0.447 |  |
| **ZMls5** | 1.75 | 0.927 |  | NA | NA |  |
| **ZMls6** | 1.63 | 0.009 | 0.042 | NA | NA |  |
| **ZKeep2** | -0.78 | 0.111 |  | -2.10 | 0.550 | 0.662 |
| **ZKeep3** | -0.22 | 0.178 |  | 0.43 | 0.128 |  |
| **ZKeep4** | 0.26 | 0.001 |  | -0.22 | 0.541 |  |
| **Zdrelbl2** | -2.71 |  0.831 | 0.977 | -0.34 |  0.452 |  |
| **Zdrelbl3** | -2.72 |  0.837 | 0.399 | -0.01 |  0.456 |  |
| **Zdrelbl4** | -0.92 |  0.921 |  | 1.07 |  0.406 | 0.593 |
| **Zcost** | -1.45 |  0.000 | 0.000 | -0.92 |  0.413 |  |
| **Zdrelmls2** | 0.34 |  0.894 |  | -0.73 |  0.509 |  |
| **Zdrelmls3** | -0.70 |  0.954 |  | -1.16 |  0.345 | 0.008 |
| **Zdrelmls4** | 1.33 |  0.330 | 0.507 | 0.77 |  0.453 |  |
| **Zdoc2** | -0.93 |  0.394 |  | -1.18 |  0.588 | 0.138 |
| **Zdoc3** | 4.05 |  0.651 | 0.801 | -0.81 |  0.588 |  |
| **Zdoc4** | -2.78 |  0.703 | 0.014 | -0.50 |  0.671 |  |

**Table 2.** Conditional logit model for sea bass and cod (sea bass n = 4896, cod n = 1944). Coefficients and standard errors given in parenthesis.

|  |  |
| --- | --- |
| **Attributes**  | **Conditional logit** |
| **Sea Bass** | **Cod** |
|
| ASC  | 0.545 (0.335) | 0.497 (0.569) |
| Minimum Conservation Reference Size –46cm/39cm | -0.166 (0.165) | -0.021 (0.259) |
| Minimum Conservation Reference Size – 50cm/42cm | -0.033 (0.138) | 0.011 (0.233) |
| Minimum Conservation Reference Size – 55cm/46cm | -0.061 (0.162) | -0.066 (0.261) |
| Number of bass/cod sea bass caught and kept - One Fish   | 1.195 (0.180)\*\*\* | 0.924 (0.302)\*\*\* |
| Number of sea bass/cod caught and kept – Two Fish   | 1.310 (0.178)\*\*\* | 1.710 (0.303)\*\*\* |
| Number of sea bass/cod caught and kept – Three Fish   | 1.382 (0.183)\*\*\* | 1.948 (0.310)\*\*\* |
| Number of sea bass/cod caught and released due to the minimum landing size - One fish   | 0.292 (0.158)\* | 0.108 (0.262) |
| Number of sea bass/cod caught and released due to the minimum landing size - Two fish   | 0.458 (0.173)\*\*\* | 0.252 (0.277) |
| Number of sea bass/cod caught and released due to the minimum landing size - Three fish   | 0.505 (0.183)\*\*\* | 0.320 (0.299) |
| Number of sea bass/cod caught and released due to the bag limit – One fish   | 0.445 (0.166)\*\*\* | 0.206 (0.272) |
| Number of sea bass/cod caught and released due to the bag limit – Two fish   | 0.782 (0.194)\*\*\* | 0.517 (0.323) |
| Number of sea bass/cod caught and released due to the bag limit – Three fish   | 0.878 (0.172)\*\*\* | 0.680 (0.680)\*\* |
| Number of other fish (not cod or sea bass) caught and kept – One fish   | 0.471 (0.167)\*\*\* | 0.427 (0.270) |
| Number of other fish (not cod or sea bass) caught and kept – Two fish   | 0.762 (0.191)\*\*\* | 0.580 (0.314)\* |
| Number of other fish (not cod or sea bass) caught and kept – Three fish   | 0.986 (0.207)\*\*\* | 1.021 (0.344)\*\*\* |
| Cost    | -0.041 (0.005)\*\*\* | -0.040 (0.007)\*\*\* |
| Log likelihood Null model | -1792.9 | -711.91 |
| Log likelihood | -1511.24 | -565.899 |
| McFadden Pseudo R2  | 0.16 | 0.21 |

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