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Introduction

Offshore wind energy is known to be a viable avenue to reduce greenhouse gas emissions, increase energy security, mitigate global climate change (Devine-Wright, 2011; Pasqualetti, 2011; Brownlee et al., 2015) and reduce (if not eliminate) disamenities associated with on-land wind turbines (Ladenburg, 2010). It is also a promising source of employment and revenues for local communities (Hattam et al., 2015). However, with the increasing global development of wind energy, optimal locations for offshore wind farms (OWFs) (i.e., locations that minimize the costs per kWh produced without altering the welfare of coastal communities and the economic attractiveness of coastal areas) have become more difficult to find (Brownlee et al., 2015; Hevia-Koch and Ladenburg, 2016). This situation has generated and still generates strong opposition movements. In some countries, such as France (Westerberg et al., 2013) and USA (Fooks et al., 2017), the construction of several offshore wind facilities has been delayed or even withdrawn due to protests. The drivers of the opposition to OWFs are visual impacts, noise and biodiversity losses (bird deaths) (Vechiato, 2014). Improvements in technology and collision risk models have substantially reduced noise and avian impacts (Vechiato, 2014). On the other hand, the potential negative impact that offshore wind facilities may have on coastal tourism or property values remains a major concern (Haggett, 2011; Hevia-Koch and Ladenburg, 2016). Consequently, most existing valuation research has focused on visual impacts of wind turbines (see Ladenburg and Lutzeyer, 2012; Hevia-Koch and Ladenburg, 2016; Mattmann et al., 2016).

The Government of Catalonia (Spain) is considering the use of offshore wind turbines to provide renewable energy as part of its Plan of Energy and Climate Change of Catalonia 2012 – 2020 (PECAC 2020). This plan aims at installing 5,153.6 MW of wind power by 2020 of which 570 MW will be generated by OWFs. With 580 km of coastline and about 221 beaches, Catalonia has a large offshore wind energy potential. At the same time, the coastal area substantially contributes to the economic attractiveness of the region and the welfare of the entire population (i.e., both residents and tourists). Any reduction in beach demand could lead to significant economic costs, both market costs (e.g., reduction in revenues for coastal activities) and nonmarket costs (i.e., welfare loss of the coastal communities). In this context, investigating the preferences of affected stakeholders is an important first step to a successful implementation of offshore wind energy policies.

The objectives of this paper are to (1) identify the factors affecting whether beach users (both residents and tourists) accept the potential OWF project in Catalonia; (2) identify the factors affecting whether they would change beach trip behaviour due to the project; (3) estimate the potential impact on their demand for trips. Particular emphasis is placed on the visual impacts of the project, measured through the density of turbines and their distance from the shore. For the third objective, we use a single-site travel cost (TC) model that combines actual and contingent beach trip data[1]. Combining TC and contingent behaviour (CB) data allows estimating the change in trip demand that might occur with changes in

[1] The TC method is commonly classified into two groups: single-site models and random utility maximisation (RUM) models (Parsons, 2017). The single-site TC model is used to estimate recreation demand functions. The RUM TC model is useful when the objective of the analysis is to identify how users make choices between substitute sites based on the attributes of those sites. This model, however, fails to account for the possibility of substitution across time periods in response to a short-term site closure or change in site quality (Parsons and Stefanova, 2011). Parsons and Stefanova (2011) addressed this concern through a combined RUM – contingent behaviour model in their study valuing short-term closures of beaches on the Texas Gulf coast.

attributes of the good (see Whitehead et al., 2008). This is particularly relevant, as policy makers require information on historical consumer demand and potential future demands to improve their basis for decision-making (Voltaire et al., 2017). The remainder of the paper is structured as follows: Section 2 provides a review of the literature on valuation studies related to OWFs. Section 3 describes the survey design and data collection. Section 4 summarizes the data. The econometric models used in the analysis are presented in Section 5. Results are discussed in Section 6, followed by concluding remarks in Section 7.

2. Previous literature

Several aspects related to wind power development have been analysed. In the field of non-market valuation, some studies investigated the visual impacts of turbines on residential property values using the hedonic pricing method (Jensen et al., 2014; Lang et al., 2014; Gibbons, 2015; Heintzelman and Tuttle, 2012; Hoen et al., 2015) and the choice experiment (CE) method (Krueger et al., 2011. Mariel et al., 2015). Other research examined their impacts on recreation and tourism using the CB method (Lilley et al., 2010), combined TC – CB method (Landry et al., 2012; Voltaire et al., 2017; Teisl et al., 2018 ; Parsons et al., 2019), contingent valuation method (McCartney, 2006), CE method (Ladenburg and Dubgaard, 2009; Landry et al., 2012; Westerberg et al., 2013; Lutzeyer et al., 2018) and a within-subject field experiment (Fooks et al., 2017).[2,3] There are also many empirical works on other external effects of wind power. Mattmann et al. (2016) conducted a meta-analysis of the

[2] Landry et al. (2012) gathered both TC – CB and CE data in the same survey.
[3] Teisl et al. (2018) was not a TC study per se in that no TC demand models were estimated. However, they collected revealed and contingent beach trips like in any combined TC-CB study.

stated-preference literature on the externalities generated by wind power (air pollution and climate change, fuel independence, biodiversity, and green policy, noise and visual impacts).

Of the studies mentioned above, ten examined the potential impacts of OWF projects on recreational beach use, paying particular attention to visual disamenities. Five come closest to our study in that they gathered TC – CB trip data (Table 1). From their results it emerges (among other things) that OWF projects are seen as visual disamenities, as respondents commonly state that they would cause them to reduce the frequency of their trips. In the short term, however, these projects could attract some curious visitors (Landry et al., 2012; Parsons et al., 2019).[4] It is also inferred that the placement of turbines further offshore could limit their visual impacts, thereby mitigating potential trip loss.[5]

(Table 1 about here)

These studies are not without limitations. For example, one underlying assumption is that visitors are homogenous in their preferences for beach recreation, implying that visitors with the same observed characteristics would have the same trip behaviour under OWF conditions. This assumption is unlikely to be valid if there is substantial unobserved heterogeneity in trip preferences. For example, consider two visitors A and B, with A having relatively stronger preferences for beach recreation, so that A takes more trips than B under status-quo conditions. Due to preference heterogeneity, it is conceivable that the installation of an OWF influences differently their beach trip demand, with A still taking

[4] Landry et al. (2012) and Parsons et al. (2019) found evidence of a curiosity trip effect among some respondents. Parsons et al. (2019), however, argued that such an effect can be expected to fall after the first generation of projects.

[5] These same conclusions also hold for studies focusing on coastal tourism and recreation using the CE method.

more trips than B. In other words, it is likely that the effect and/or the magnitude of the effect of the OWF on beach trip demand differ between A and B. Accounting for unobserved heterogeneity in trip preferences allows to better capture the effect and/or the magnitude of the effect of factors influencing the frequency of beach trips and to better estimate the welfare impacts caused by changes in beach attributes (Hynes and Greene, 2016).

Another limitation is specific to studies gathering TC – CB data on-site. An on-site sample is truncated at zero (i.e., no data are collected for individuals who took zero trips in the survey period, even though they may have taken trips in previous years, and may again in the future) and is endogenously stratified (i.e., frequent users are over-sampled) (Martínez-Espiñeira and Amoako-Tuffour, 2008; Hynes and Greene, 2013). Failure to account for these issues can result in biased and inconsistent parameter estimates (Shaw, 1988; Englin and Shonkwiler, 1995). Different econometric models have been developed to account for on-site sampling in combined TC – CB panel data count models. Hynes and Greene (2013) have introduced a Latent Class Negative Binomial (LCNB) model that applies to data where both revealed and stated trip data are truncated and endogenously stratified. This is typically the case when the CB scenario involves an improvement in site conditions. Under such conditions, individuals interviewed on-site rarely predict zero trips (Hynes and Greene, 2016). The other models adjusted for on-site sampling suit data where the revealed trip data are truncated and endogenously stratified, whereas the stated trip data are not. The CB scenario then commonly refers to a deterioration in site conditions. Under such conditions, some respondents often predict zero trips. These models include the Multivariate Poisson-log normal (MPLN) model (Egan and Herriges, 2006), seemingly unrelated negative binomial (SUNB) model (Egan and Herriges, 2006), random-effect Poisson gamma (REPG) model

(Beaumais and Appéré, 2010) and discrete factors method – generalized negative binomial (DFM – GNB) model (Nobel et al., 2019). To the best of our knowledge, there is no standard program available in statistical packages that allow to estimate such models. This may explain the reason why most studies using TC – CB trip data where only the revealed trip data are truncated and endogenously stratified ignored these problems (e.g., Simões et al., 2013; Voltaire et al., 2017)

The present paper compares the estimates of consumer surplus (CS) derived from correcting for unobserved heterogeneity in trip preferences to that from correcting for on-site sampling bias.[6] In addition, it extends the study by Voltaire et al. (2017) that investigated the impact of an OWF project on beach recreation demand from tourists using commercial accommodation in Catalonia. Contrary to their study, the target population here is all beach user groups, both residents and tourists (both those who use commercial and non-commercial accommodation during their stay). Bearing in mind that preferences of beach community residents for the development of offshore wind turbines facilities may be different from that of tourists (Fooks et al., 2017), this paper allows capturing potential heterogeneity in acceptance of and behavioural trip responses to the OWF project in Catalonia among beach users.

[6] To date, there is no econometric model that simultaneously controls for on-site sampling bias and unobserved heterogeneity with respect to slope parameters when only the revealed trip data are both truncated and endogenously stratified. Developing such a model is beyond the scope of this paper.

3. Survey design and data collection

The survey had four sections. The first section collected trip data on the beach where the respondent was approached – this beach – under current conditions. In particular, each respondent was asked the following questions: (Q_1) *During the last summer season (June – September 2011), how many trips have you taken to this beach?* (Q_2) *During this summer season (June – September 2012), (a) how many trips have you taken to this beach to date? (b) how many trips do you plan to take to this beach for the remainder of the season?* Responses to Q_1 referred to revealed data (RP_{2011}), whereas those to Q_2 referred to mixed revealed – stated data (MRS_{2012}).

The second section gathered travel cost expenditure data. Two approaches are typically used to estimate the travel cost. The first approach is based on researcher computation. The standard practice is to sum the direct costs of visiting the site (the round-trip distance to the site multiplied by a fixed cost per Km) and a proxy for the opportunity cost of time (a constant fraction of the respondent's wage rate). The second approach involves using the perceived costs as reported by the respondent. Because individuals base trip decisions in part on perceptions of cost, which may diverge from actual visitation costs, the second approach is considered to be the most likely to accurately reflect the costs affecting trip choice (Randall, 1994; Parsons, 2017). Accordingly, we elicited the travel costs by asking respondents to report all expenses on the beach trip taken on the day of the survey. The same approach was adopted in other studies (e.g., Prayaga et al., 2010; Alberini and Longo, 2006; Hynes et al., 2017). Items of expenditure included transport, meals, accommodation, equipment and other expenses. The third section collected trip data under OWF conditions.

It contained questions in relation to how respondents expected that their trip behaviour would change during the next summer season from their reported trips for the summer of 2012. The fourth section elicited socio-economic and demographic data.

(Figures 1, 2, 3 and 4 about here)

Two attributes pertaining to the OWF were selected: number of turbines and distance from the shore, with each attribute having two qualitative levels (Number of turbines: High/Low; Distance from the shore: Near/Far). The choice of qualitative levels was motivated by the absence of official data on the exact number of turbines that would be installed to generate 570 MW planned in the PECAC 2020 and the exact distance of these devices from the shore. The combination of attributes and levels resulted in four scenarios with different degrees of visual impact. In order to mitigate a likely heterogeneity bias in interpreting the attribute levels, each scenario was illustrated via simulated photos developed by a team from *Consejo Superior de Investigaciones Científicas* (CSIC) (https://www.csic.es/en) (Figures 1 – 4). Figure 1 describes an OWF scenario characterized by a high number of turbines placed far from the shore (High – Far scenario). Figure 2 depicts a low number of turbines placed far from the shore (Low – Far scenario). Figure 3 refers to a scenario with a high number of turbines placed near the shore (High – Near scenario). Figure 4 illustrates a low number of turbines placed near the shore (Low – Near scenario). Each respondent randomly received one scenario. After a careful description of the scenario, the respondent was asked the questions presented in Box 1. Thus, three trip responses were provided by each respondent: revealed trips for the summer of 2011 (time period 1); mixed revealed – stated trips for the summer of 2012 (time period 2) and stated trips for the next summer season under OWF conditions (time period 3).

(Box 1 about here)

The questionnaire was administered on-site in Catalan, Spanish and English via face-to-face interviews in the summer of 2012. Randomly selected individuals were interviewed at eight beaches (Table A in Supplementary Material). They were selected from a list of 221 beaches classified in terms of the geographical location (municipality), surface, water quality/visibility and surrounding environment. The beach sampling strategy was applied with the purpose of maximising the representativeness of the survey and ensuring that all beach activities were fully covered. Interviews were carried out in two distinct time frames (10:00 – 14:00 and 15:00 – 19:00), during both weekdays and weekends (14 June – 15 September), on the same days at the different survey sites, and using the itinerary method.[7]

4. Data summary

A total of 641 personal interviews were carried out with adult beach users (18 years of age or older), of whom 42.4% and 57.6% were residents and tourists, respectively. Summary statistics associated with these two shore audiences are provided in Table 2. One key factor thought to influence demand for trips to a site is the trip cost, taken as the implicit own-price. It includes all expenses required to make the trip possible (Parsons, 2017). As noted earlier, trip costs were elicited by asking the respondents to report all expenses (transport, meals, accommodation, equipment and other expenses) on the trip taken on the day of the survey. A large number of respondents, however, did not report their accommodation and food costs. Therefore, these costs were excluded from the trip cost estimates in order to

[7] For a presentation of the itinerary method, see Sardá et al. (2009)

improve the homogeneity of the data in terms of items of expenditure. In addition, consistent with studies using respondent – reported trip costs, the opportunity cost of time (both the travel time and on-site time) was ignored.[8] The trip cost per trip per person for the season of 2012 was calculated for residents and tourists, respectively, as follows:

$$Trip\ cost = t_{cost} + E_{cost} \tag{1}$$

$$Trip\ cost = \frac{(T_{cost} \times \delta) + E_{cost} + (L \times t_{cost})}{MRS_{2012}}, \qquad 0 < \delta \leq 1 \tag{2}$$

where t_{cost} is the travel cost reported by respondents from their main home to the beach or from their accommodation in Catalonia to the beach; E_{cost} is the total equipment costs related to beach activities; T_{cost} is the sum of travel costs reported by respondents from their place of residence to the Catalonian coast and back; L is the length of stay (in days); MRS_{2012} is the number of trips taken in the summer of 2012; and δ is a correction factor adjusting travel cost for multi-purpose trips. There is no standard approach to deal with the multi-purpose trip problem in the TC method (see Martínez-Espiñeira and Amoako-Tuffour, 2009). In this paper, the ratio between MRS_{2012} and L $\left({MRS_{2012}}/{L}\right)$ is used as a proxy for the degree of importance attached to beach activities; δ takes the value of one for tourists for whom the ratio is equal to or higher than one. For these tourists, this means that they go to

[8] The opportunity cost of time is typically estimated using a fraction of the respondent's wage rate. Underlying is the assumption that visitors have a flexible working arrangement and can substitute work time for leisure time at the margin (Parsons, 2017). In fact, this assumption fails for a large majority of visitors, as some are outside the formal labor market, others have fixed work schedules (Parsons, 2017) or (in particular for tourists) take trips during their holidays, paid vacation days or weekends (Bhat, 2003). For these people, there is no loss of income (Ward and Beal, 2000), since the trade-off is not between travelling and working, but rather between taking trips to a given site and engaging in other recreational activities (Voltaire et al., 2017). This is not to say that they do not have an opportunity cost of time, but simply that the labor-leisure trade-off-based approach is not appropriate to valuing their leisure time (for an alternative approach, see Lloyd-Smith et al., 2019).

the beach at least once a day during their stay in Catalonia. For tourists for whom $0 < \delta < 1$, this suggests that beach recreation is not the sole purpose of their trip, and therefore the travel cost from their place of residence to the Catalonian coast cannot be fully allocated to beach activities.

(Table 2 about here)

Overall, 21% of residents and 13.3% of tourists stated that they accepted the OWF project. The difference is significant (Pearson $\chi^2 = 6.547; p \leq 0.011$). Of these 21% of residents, the majority accepted Low – Far scenario (43.9%), followed by High – Far scenario (42.1%), High – Near scenario (8.8%) and Low – Near scenario (5.3%). For the 13.3% of tourists, the acceptance rates were somewhat similar across scenarios: 29.8% for High – Far scenario, 27.7% for High – Near scenario, 25.5% for Low – Far scenario and 17.0% for Low – Near scenario.

In terms of potential changes in beach trip behaviour due to the OWF project, no respondent claimed that they would take more trips. More than two-thirds of residents (68.8%) reported no trip change, 6.6% said that they would reduce the frequency of their trips (mostly a 50% drop) and 24.6% predicted no trips at all (Table B in Supplementary Material). In particular, the majority of residents predicted no change in their trip plans for Low – Far scenario (78.9%), followed by High – Far scenario (71.4%), Low – Near scenario (63.4%) and High – Near scenario (52.5%). The trend is similar for tourists, with 67.4% expecting no change in their trip plans, 5.4% reporting a reduction (mostly around 50%) and 27.2% claiming no trips at all (Table C in Supplementary Material). Specifically, the majority of tourists predicted no change in beach trips for Low – Far scenario (72.6%), followed by

Low – Near scenario (71.6%), High – Far scenario (69.2%) and High – Near scenario (57.3%). These results suggest that tourists were neither more nor less inclined than residents to change their future plans for trips if OWFs were built at the beaches where they were surveyed (Pearson $\chi^2 = 1.242; p \leq 0.265$). Among the respondents stating that they would take no trips, 95.2% of residents and 92.5% of tourists claimed that they would go to different beaches in Catalonia without a view of a farm. This suggests that the installation of an OWF would cause a shift in trips to other beaches in Catalonia without wind farms rather than to beaches outside of Catalonia.

On average, residents took 27.28 trips (range 0 – 120) during the 2011 summer season and 31.00 trips (range 1 – 120) during the 2012 summer season. The Wilcoxon rank-sum test indicates that the difference is significant ($Z = -3.689; p \leq 0.000$), suggesting that residents took significantly more trips in the summer of 2012 under similar beach conditions. Tourists took on average 15.72 trips (range 0 – 120) and 19.23 trips (range 1 – 120) in the summers of 2011 and 2012, respectively. The difference is also significant ($Z = -2.342; p \leq 0.019$). There are two plausible (and mutually exclusive) explanations for the discrepancies between the mean trips for RP_{2011} and MRS_{2012}. The first explanation refers to the fact that 26.1% of residents and 42.6% of tourists intercepted at surveyed beaches in the current summer season (i.e., summer of 2012) did not visit those beaches in the preceding summer season (i.e., summer of 2011). In other words, the RP_{2011} data contained zero trips, whereas the MRS_{2012} data did not. In this case, the mean trip for MRS_{2012} is logically higher than the mean trip for RP_{2011}. The second explanation refers to the potential existence of hypothetical bias in the MRS_{2012} data. Whitehead et al. (2000) argue that hypothetical bias exists when

stated preference trips (our MRS_{2012} data) exceed revealed trips (our RP_{2011} data) under similar benefit and cost conditions. This bias will be investigated in Section 5.

On average, residents would take 24.69 trips (range 0 – 120) under OWF conditions. This corresponds to a decrease by 20.3%, relative to their average number of trips in the 2012 summer season. The difference is significant ($Z = -8.057; p \leq 0.000$). A similar conclusion holds for tourists, with a 20.6% drop in their average planned number of trips (15.26 trips; range 0 – 120) ($Z = -9.790; p \leq 0.000$). The trip means under OWF conditions ($Trips_{OWF}$) were estimated as follows:

$$Trips_{OWF} = MRS_{2012}(1 - m), \qquad 0 \leq m \leq 1 \tag{3}$$

where m is the trip change percent stated by each respondent. It is equal to 0 for respondents who reported no change; in this case, $Trips_{OWF} = MRS_{2012}$. It is equal to 1 for respondents who reported no trips at all; hence $Trips_{OWF} = 0$. For any other value of m, $0 < Trips_{OWF} < MRS_{2012}$.

5. Empirical models

5.1. Modelling decisions whether to accept the OWF project and to change trip behaviour

Let us first focus on our objectives 1 (explaining the decision whether to accept the project) and 2 (explaining the decision whether to change trip behaviour due to the project). In both cases, the dependent variable is binary. One approach to modeling such decisions is to use

the binary logit model. The empirical specification takes the following functional form for individual i and for each decision j.

$$ln\left({P_{ij}}/{1-P_{ij}}\right) = \beta_0 + \beta_1 HF_{ij} + \beta_2 HN_{ij} + \beta_3 LN_{ij} + \cdots + \sum_n \beta_n X_{n_{ij}}, \quad (4)$$

where the left-hand side is the log of the ratio of the probability that the decision is taken to the probability that it is not taken; HF, HN, LN denote the scenarios High_Far, High_Near and Low_Near respectively (with Low_Far being the baseline); X_n are all other factors, presented in Table 2, affecting the decision in question. Equation 4 can be transformed into probability (P) as follows:

$$P_{ij} = {1}/{1 + e^{-\left(\beta_0 + \beta_1 HF_{ij} + \beta_2 HN_{ij} + \beta_3 LN_{ij} + \cdots + \sum_n \beta_n X_{n_{ij}}\right)}} \quad (5)$$

The predicted probability associated with each OWF scenario for an average respondent is estimated by substituting 1 into Equation 5 for the variable denoting the scenario under consideration, holding the variables denoting the other scenarios at 0 and all other variables at their sample means.

5.2. Modelling the demand for beach trips

Now consider our third objective (estimating the welfare impact of the OWF project). Count data models are a classic choice for explaining the occurrence of discrete events such as trip counts. Similar to Englin and Cameron (1996), Englin et al. (1997), Hanley et al. (2003), Huang et al. (2011) and Parsons et al. (2013), to name a few, revealed and stated trips taken

by each respondent to all selected beaches are combined in a single equation, generating a pseudo-panel trip data. The demand function for recreation trips for individual i during the simulated time period t is specified as follows:

$$V_{it} = f(M_{it}; \beta, \varepsilon_{it}) \tag{6}$$

where V is the number of trips taken by individual i in $t = 1,2,3$; M is the vector of factors reported in Table 2 thought to influence V; β is the vector parameters to be estimated, and ε is the error term. The starting point for our panel of trip data is to assume that V is drawn from a Poisson distribution with density:

$$Pr(V_{it} = n) = \frac{exp(-\lambda)\lambda^n}{n!}, \tag{7}$$

where λ is the mean of the assumed distribution.

A drawback of the Poisson model is that it constraints λ and the variance to be equal. For recreation demand data, however, the variance often exceeds the mean, a property known as overdispersion (Cameron and Trivedi, 1986). Overdispersion may arise from heterogeneity in the mean event rate of Poisson parameter λ (Holmes and Englin, 2010). We control for this through the negative binomial (NB) model, where a stochastic random variable ε is added to the index in the Poisson model (with log-gamma distribution) (Holmes and Englin, 2010). The probability density function for V is:

$$Pr(V_{it} = n) = \frac{\Gamma\left(n+\frac{1}{\alpha}\right)}{\Gamma(n+1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha}+\lambda}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda}{\frac{1}{\alpha}+\lambda}\right)^{n}, \tag{8}$$

where $\Gamma(.)$ is the gamma function and $1/\alpha$ is the overdispersion parameter.

5.2.1. Controlling for unobserved heterogeneity with respect to covariates

One limitation of the NB model developed above is that the vector of demand parameters (β) are assumed to be constant across individuals, failing to account for potential preference heterogeneity. We relax this restriction though the random parameters negative binomial (RPNB) model (Hynes and Greene, 2013; Hynes and Greene, 2016; Whitehead et al., 2018). This model generalizes the NB model by allowing the demand parameters to vary randomly across individuals. Under this model, a parameter for an explanatory variable is decomposed into a mean value and a deviation from the mean specific to each individual, which informs regarding the level of variability around the mean parameter. The estimable parameters are:

$$\beta' = \beta^* + \Gamma v, \tag{9}$$

where β^* is the fixed means of the distributions for the random parameters, Γ is a diagonal matrix of standard errors that scale the heterogeneity factors and v is a randomly distributed terms (e.g., a normally distributed term with mean 0 and variance 1). Estimation is by simulated maximum likelihoods (Hynes and Greene, 2013; Hynes and Greene, 2016).

5.2.2. Controlling for on-site sampling bias

As the trip data were collected on-site, our sample may not be representative of the broader population of residents and tourists in Catalonia. We follow the work of Egan and Herriges

(2006) to control for on-site sampling bias using a Multivariate Poisson log-normal. Let $V_i = (V_{i1}, V_{i2}, V_{i3})$ denote the vector of the number of trips taken by individual i over the time period $t = 1,2,3$ and M_{it} the vector of factors likely to influence V_i. We assume that there is an unobserved factor ϵ_{it} associated with the trips taken such that the vector $\epsilon_i = (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3})$ follows a multivariate normal distribution: $\epsilon_i \sim N(0, \Omega)$:

$$\Omega = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{pmatrix}$$

Each element V_{it} conditioned by the vector ϵ_i is Poisson distributed with parameter $\widehat{\lambda_{it}} = \lambda_{it}\, exp(\epsilon_{it})$, where $\lambda_{it} = exp\ (\beta' M_{it})$. The specification of Ω allows accounting for the overdispersion and the correlation between trip counts per individual. Specifically, σ_t^2 and σ_{tj} accounts for the overdispersion and correlation, respectively.

The probability density function of V_i is given by:

$$Pr(V_i|M_i) = \int \prod_{t=1}^{3} \frac{exp(-\lambda_{it} \exp(\epsilon_{it}))(\lambda_{it} \exp(\epsilon_{it}))^{n_{it}}}{n_{it}!} h(\epsilon_i) d\epsilon_i \qquad (10)$$

where the function h(.) is the multivariate normal density probability function and n_{it} is the number of trips taken.

Similar to Egan and Herriges (2006), the correction of on-site sampling bias is applied only to the trip data for the current summer season (i.e., MRS_{2012} data or $t = 2$). The corrected on-site probability density function of V_i can be shown as follow:

$$Pr\left(V_i|M_{i,}V_{i2} > 0\right) = \frac{V_{i2}}{\delta_{i2}} \int \prod_{t=1}^{3} \frac{exp(-\lambda_{it}\, exp(\epsilon_{it}))(\lambda_{it}\, exp(\epsilon_{it}))^{n_{it}}}{n_{it}!} h(\,\epsilon_i) d\epsilon_i \qquad (11)$$

where the δ_{i2} is the trip mean for individual *i* at $t = 2$. More details about the derivation of equations used in this subsection can be found in Egan and Herriges (2006).

5.3. Welfare measures

The consumer surplus (CS) per trip generated by a count data model is equal to the negative inverse of the parameter for the TC variable (Haab and McConnell, 2002). If the TC variable is specified as non-random or, in the case where it is specified as random, if the standard deviation parameter is not significant, then the CS estimated is a CS per individual per trip. On the other hand, if the standard deviation coefficient is significant, the CS estimated is the mean CS per individual per trip.

Predicted trip means based on the RPNB and MPLN models can be written, respectively:

$$E(V_{it}|M_{it}) = \lambda_{it} = exp(\beta' M_{it}) \qquad (12)$$

$$\delta_{it} = E(V_{it}|M_{it}) = \lambda_{it}\, exp(0.5 * \sigma_t^2) \qquad (13)$$

The CS per season estimated from RPNB and MPLM models is then given, respectively by:

$$CS = -{}^{\lambda_{it}}/_{\beta_{tc}} \quad \text{and} \quad CS = -{}^{\delta_{it}}/_{\beta_{tc}} \qquad (14)$$

The change in CS under OWF conditions, relative to that for the summer of 2012 ($t = 2$) is given by:

$$\Delta CS = {(\lambda_{i3}{}^{*} - \lambda_{i2})}/{\beta_{tc}} \quad \text{or} \quad \Delta CS = {(\delta_{i3}{}^{*} - \delta_{i2})}/{\beta_{tc}} \tag{15}$$

where $\lambda_{i3}{}^{*}$and $\delta_{i3}{}^{*}$ are the expected number of trips under OWF conditions estimated from the RPNM and MPLN models, respectively.

6. Estimation results

6.1. Logistic regression

Results of separate binary logit models for residents and tourists are summarized in Tables 3 and 4.[9] Starting with the decision whether to accept the OWF project (Table 3), beach characteristics are key predictors as at least one of the associated estimated coefficients is significant in each model. Socio-economic and demographic factors are also significant determinants. In particular, the likelihood that residents accept the project is positively correlated with gender, age, household size and negatively related to income. For tourists, only the place of residence is significant, with local tourists (people who live in Catalonia and spend their holidays in another Catalan city) being more likely to accept the project than non-local tourists. The visual impacts of the wind power project play a major role,

[9] As some explanatory variables are specific to tourists (Local tourist and Paid_accom), we decided to estimate separate models for residents and tourists rather than estimating a pooled model with interaction terms. Furthermore, the likelihood ratio test supports the inclusion of these two variables in the regression models, in particular, in the logit model that explains the decision whether to change beach behaviour ($\chi^2 = 10.49; p \leq 0.005$). It also clearly rejects the pooled model in favour of separate ones at 5% level ($\chi^2 = 9.71$). The χ^2 theoretical value at 5% level is 7.815 for 3 degrees of freedom (the number of coefficients in the separate equations – the number of coefficients in the pooled equation).

particularly for residents, as reflected by the significance of estimated coefficients on dummy variables denoting the scenarios.

(Tables 3 about here)

Turning to the decision whether to change beach trip behaviour due to the project (Table 4), results show that the location of turbines matters. Bearing in mind that Castell and Golfet beaches (the base category) are labelled "natural" beaches, the negative sign of estimated coefficients on beach variables indicate that respondents would be less likely to reduce their trip frequency if an OWF was built at an urban or mixed beach. The variable Familiarity has a negative and substantial impact on the probability of changing trip behaviour for residents (the more familiar respondents are with the beach where they are interviewed, the lower the probability of reducing the trip frequency). The same is true of socio-economic factors, including age, household size and household income. For tourists, the place of residence and the feature of the accommodation used during their stay in Catalonia play a key role. The signs of the estimated coefficients on these variables suggest that local tourists are less likely to reduce their trip frequency than non-local tourists, and that tourists who stay in commercial accommodation are more likely to adopt such a behavior relative to those staying in non-commercial accommodation. Some estimated coefficients on OWF scenarios are also significant.

(Tables 4 about here)

Predicted probabilities associated with each scenario for an average respondent provide further insights regarding the visual impacts of the OWF project on the decisions (Table 5). The probability that residents accept the project is significantly higher with the 90%

confidence interval for scenarios where turbines are placed further offshore (High_Far scenario and Low_Far scenario), relative to scenarios where turbines are placed near the shore (High_Near scenario and Low_Near scenario), regardless of the number of turbines. This suggests that, of two attributes describing the OWF project, the distance from the shore is the main driver of its acceptance by residents. In other words, for residents, the visual impacts of the project are primarily attributable to the proximity of the farm to the shore, rather than the number of turbines. This result is consistent with Lutzeyer et al. (2018). For tourists, however, predicted probabilities are statistically similar across scenarios (since the 90% CI overlap), suggesting that no one single scenario is neither more nor less accepted than the others.

(Table 5 about here)

The probability that residents change their trip behaviour (i.e., reduce their trip frequency) is significantly higher for High_Near scenario, relative to Low_Far scenario or High_Far scenario. The outcome of the first paired comparison (High_Near scenario *vs* Low_Far scenario) suggests that switching from the scenario with the highest degree of visual impact (High_Near scenario) to the scenario with the lowest degree of visual impact (Low_Far scenario) significantly reduces the likelihood of changing trip behaviour. The outcome of the second paired comparison (High_Near scenario *vs* High_Far scenario) tells us that proximity of the farm to shore is likely to significantly reduce the frequency of trips only if a high number of turbines are installed. For tourists, paired comparisons of predicted probabilities reveal statistical differences only for High_Near scenario *vs* Low_Far scenario. This suggests that tourists are more inclined to reduce their trip frequency only when switching from the

scenario with the lowest degree of visual impact to the scenario with the highest degree of visual impact.

6.2. Count data regression

6.2.1. Accounting for unobserved heterogeneity with respect to covariates

Tables 6 and 7 provide the estimates of the RPNB model. The first specification includes a "composite" scenario variable, OWF, which refers to all scenarios combined (Table 6). The second specification includes the dummy variables denoting the four scenarios (Table 7). In the sample of tourists, we deleted 23 observations with missing travel cost information. As each respondent provided three trip responses, these models are estimated on a panel data set of 993 observations. For each sample, each model is estimated by specifying a normally distributed functional form of the parameter density function and using simulation-based maximum likelihood with 500 Halton draws, as in Whitehead et al. (2018). Because it is usually not known which parameters might exhibit statistically significant random variation (Holmes and Englin 2010), all explanatory factors are specified as random parameters, except for the constant term, beach variables (because they are included in the model only to control for demand shifts due to beach characteristics) and the RP variable. We also estimated the random effects panel NB model, referred to as the homogenous NB model. The estimates of this model are displayed in Supplementary Material (Table D). The RPNB model consistently fits the data better than the random effects NB model, as highlighted by the value of the log likelihood and the information criteria statistics. It also provides richer information about the impact of factors driving the decision to make beach trips, as the

estimated standard deviations for most parameters are significantly different from zero, suggesting significant level of preference heterogeneity across individuals.

As anticipated, trips decline with increases in trip cost (the higher the trip cost, the lower the probability of making a higher frequency of trips). All estimated coefficients on beach variables are statistically significant, suggesting that the effect of the OWF project on recreation demand is influenced by different types of beach environment (Voltaire et al., 2017). The RP dummy variable shifts the intercept significantly downwards. This indicates that the number of trips taken in the summer of 2011 is significantly lower than the number of trips taken in the summer of 2012 under similar status quo conditions. As previously mentioned, this could be because a large part of respondents approached at the surveyed beaches in the summer of 2012 did not visit those beaches in the summer of 2011 or could suggest hypothetical bias. Indeed, the MRS_{2012} data contain both a revealed part (the number of trips taken to a given beach to date) and a contingent part (the number of trips planned to take to the same beach for the remainder of the season). Hypothetical bias could arise if this contingent part is overstated by respondents. One way to investigate this point is to estimate the models on the sample of respondents who took trips in both the 2011 and 2012 summer seasons. The results are reported in Supplementary Material (Tables E and F). They show that the estimated coefficient on the variable RP is not significant for either residents or tourists, indicating that those respondents statistically took the same number of trips in the summers of 2011 and 2012 under status-quo conditions. Assuming no change in respondents' income from 2011 to 2012, this suggests that the MRS_{2012} data do not suffer from hypothetical bias (Whitehead et al., 2000). Therefore, the significant difference observed in the number of trips between 2011 and 2012 can be explained because a large

part of respondents intercepted at the surveyed beaches in 2012 were first-time users of these beaches. Based on this, we can argue that revealed trips for 2011 and mixed revealed – stated trips for 2012 are driven by the same demand function under similar benefit and cost beach conditions, and hence can be pooled for estimation purposes (Alberini et al., 2007; Hoyos and Reira, 2013).

(Tables 6 and 7 about here)

The negative and significant sign of the estimated coefficient on OWF indicates a downward shift of the demand function, suggesting that viewing an OWF from a recreational beach is a disamenity for both residents and tourists. The shift in beach demand differs across scenarios, as at least one of associated estimated coefficient is significant. In particular, a significant downward shift of the demand function is observed under scenarios High_Far, High_Near and Low_Near, relative to the scenario Low_Far for residents, and under scenarios High_Far and High_Near, relative to the same baseline scenario for tourists (RPNB_2). In addition, for residents, trips are positively correlated with the importance that respondents attach to swimming and nautical activities in the choice of this beach. Significant socioeconomic variables suggest that male respondents take fewer trips under both status quo and OWF conditions than female respondents, trips increase with age but decrease with household income. For tourists, local tourists take higher trips than non-local tourists, respondents staying in commercial accommodation make fewer trips than those using non-commercial accommodation, trips increase with age but decrease with household size.

Table 8 reports the distributions of parameters for factors specified as random parameters. The distributions of almost all the parameters have span both the negative and positive, suggesting that a positive or negative effect on recreation demand of variables in question does not apply to all respondents. For example, the standard deviation parameter for the estimated coefficient on the trip cost variable is significant for tourists. It is normally distributed with a mean of – 0.01575 and a standard deviation of 0.00828 (RPNBM_1) or with a mean of – 0.01114 and a standard deviation of 0.00810 (RPNB_2). This means that 97.1% of the distribution of respondents is below 0 and 2.9% is above 0 (RPNB_1) or 91.6% of the distribution is below 0 and 8.4% is above 0 (RPNBM_2). In other words, a negative trip cost effect does not apply to all respondents. Bearing in mind that we used perceived trip cost information, this finding could be due in part to the heterogeneity in the perceptions of trip cost across respondents. Note that a significant standard deviation for the trip cost variable was also obtained in studies using researcher-estimated costs (e.g., Hynes and Greene, 2016). The authors related this phenomenon to the hourly wage-based approach commonly used to value the opportunity cost of leisure time.

Regarding the visual impact of the project, a significant standard deviation is found for High_Near scenario for both residents and tourists. This suggests that moving from the scenario with the lowest degree of visual impact (Low_Far, the base category) to the scenario with the highest degree of visual impact (High_Near) would decrease trips for 76.1% of residents and increase trips for the remaining 23.9%, whereas it would decrease trips for 97.6% of tourists and increase trips for the remaining 2.4%.

(Table 8 about here)

6.2.2. Accounting for on-site sampling bias

Table 9 provides the estimates of the MPLN model corrected for truncation and endogenous stratification.[10] The estimates without the correction are displayed in Supplementary Material (Table G). The models were estimated using simulated maximum likelihood estimation approach with 1000 randomised Halton sequences, as in Egan and Herriges (2006). The corrected model produces a slightly higher log likelihood value (in absolute terms) than the uncorrected model. Egan and Herriges (2006) found somewhat similar results. The signs of the estimated coefficients are identical between corrected and uncorrected models, except for a few variables. On the other hand, notable differences in the value of some estimated coefficients exist. The biggest difference refers to the value of the estimated coefficient on the trip cost variable for tourists, which is much higher in the corrected model (in absolute terms). All the estimates σ_t's are significantly different from zero, indicating overdispersion in the data (Egan and Herriges, 2006). The same is true of $Cov(.)$, suggesting correlation between beach trip responses per individual. Consequently, jointly modelling RP_{2011}, MRS_{2012} and OWF trip data is appropriate.

(Table 9 about here)

6.2.3. Welfare estimates

Table 10 reports the estimates of CS per trip. The CS per trip derived from correcting for unobserved heterogeneity relates only to the current beach users. In contrast, the CS per trip derived from controlling for on-site sampling bias refers to the general population of

[10] We have developed a R code to estimate the model. It is provided in Supplementary Material.

residents and tourists in Catalonia. For example, the CS per trip for resident *i* and tourist *i* who currently visit the beaches in our survey area is €18.81 and €89.76, respectively, in RPNB_2 and MPLN_2 models. It is €11.54 and €74.66 for individual *i* in the general population of residents and tourists, respectively. Overall, the estimates of CS per trip corrected for unobserved heterogeneity exceed those corrected for on-site sampling bias by a factor ranging from 1.2 to 2.2.

(Table 10 about here)

The seasonal CS for individual *i* and variations in CS due to the potential OWF project are presented in Table 11. The MPLN models yield inflated estimates of trip demand, providing an unsuitable basis to compute the seasonal CS for individual *i* in the general population.[11] Therefore, only estimates of seasonal CS relating to the current beach users are reported in the table. They are derived from RPNB_2 as this model predicts the actual average trip for the 2012 summer season (our baseline) slightly more accurately than RPNB_1. Predicted average trips for the 2012 summer season and for each OWF scenario are estimated using the nonrandom parameters and the distribution of random parameters. The CS per person for the summer season of 2012 is €563 and €1,756 for residents and tourists respectively. If an OWF is installed, for residents, the seasonal CS is estimated to be reduced by from 3.17% under the scenario having the lowest visual impact (Low_Far) to 64.44% under the scenario having the highest visual impact (High_Near). For tourists, it is estimated to be reduced from 4.86% to 50.15% under the same scenarios.

[11] From Equation 13 it appears that the inflated measures of expected trip demand may stem from two sources, λ and $\exp(0.5\sigma_t^2)$. In our case, estimates of λ were of plausible magnitude as it lied below on-site sample counts. On the other hand, estimates of $\exp(0.5\sigma_t^2)$ were substantially large, in particular for RP_{2011} and $Trip_{OWF}$ data. We also estimated the seemingly unrelated negative binomial model adjusted for on-site sampling, an alternative to the MPLN model. We found somewhat similar results.

(Table 11 about here)

The aggregate welfare loss (AWL) under each OWF scenario is uncertain as no official data is available on (1) the number of wind farms required to generate 570 MW planned in the PECAC 2020, (2) the distance of these devices from the shore, and (3) the proportion of the Catalan coastline that would be affected. However, Voltaire et al. (2017) made a rough estimation of these three factors. Based on the literature review, the authors assumed that wind farms have negative visual impact if they are located no more than 24 km from the shore, and within a horizontal angle of 135 degrees. With this in mind and using trigonometry, they estimated that wind farms located 3 km, 5 km, 10 km, 15 km and 20 km away from the coastline generate a visual impact that is extended to 14.5 km, 24.1 km, 43.6 km, 37.5 km and 26.5 km of the shoreline, respectively.[12] In addition, they considered two options to estimate the number of wind farms necessary to generate 570 MW. The first option was based on an experimental project, labelled ZÈFIR, launched in Catalonia in 2010 with the purpose of generating 70 MW (http://www.zefirteststation.com/ca/), but finally withdrawn due to vigorous opposition from stakeholders, including tourism operators.[13] They estimated that about 8 wind farms would be required. The second option referred to the average size of OWFs in Europe. This figure was 337.9 MW in 2015 (European Wind Energy Association, 2015), which lead the authors to argue that about 2 OWFs would be required. Combining these factors, they then determined the number of kilometers of the

[12] Visual impact is not a linear function of distance to the shore because wind farms that are installed close to the coastline will be far out in the periphery if seen from a distance of 24km whereas wind farms that are installed far from the coastline will be visible only along a relatively short segment of the coastline.
[13] It was partially funded by The Government of Spain. The wind park should be used as a research and testing platform for offshore wind turbines in deep waters. However, stakeholders opposed the project by pointing out the potential negative impact on the landscape.

shoreline that will be visually impacted by 570 MW offshore wind power installations (Table H in Supplementary Material)

At this stage, we can roughly estimate the total expected welfare loss associated with the generation of 570 MW offshore wind power for residents and tourists. According to the Catalan government, 263.7 million trips were made to Catalan beaches in 2012 including residents and tourists (Nunes et al., 2015). Based on our survey data for the 2012 summer season, it is known that: (1) the average number of adults in a beach recreation party is 3.15; (2) the average number of trips is 25.11; (3) 42.4% and 57.6% of the respondents are residents and tourists respectively. Combining these statistics, it can be inferred that our target beach user population consists of 1,413,575 residents (263,700,000 ÷ 3.15 ÷ 25.11 × 0.424) and 1,920,328 tourists (263,700,000 ÷ 3.15 ÷ 25.11 × 0.576). The total welfare loss associated with each OWF is then estimated as follows:

$$AWL = P * CS_{baseline} * \Delta CS_{OWF_i} * VI \tag{16}$$

where P is the size of the target population, $CS_{baseline}$ is the CS for the 2012 summer season, ΔCS_{OWF_i} is the change in CS due to OWF i relative to 2012 and VI is the percentage of coastline with visual impact under each OWF.[14] Table 12 reports the welfare loss estimates caused by 570 MW offshore wind power installations. They range from €77.1 to €150 million per season for residents and from €338.2 to €760 million per season.

(Table 12 about here)

[14] AWL under an OWF installed at 10 km from the shore is calculated using the change in CS due the composite OWF scenario.

7. Discussion and conclusions

OWF projects gain ground in several European countries. Opposition to such projects often relates to their potential negative impact on coastal recreation demand. This study explored this issue as part of the potential installation of 570 MW offshore wind power in Catalonia. Several points about the results presented above are worth noting. First, preferences of beach users for the OWF project depend on the specific place of location offshore. This suggests that decision-makers could enhance the public's support and mitigate the potential negative impact on beach trips by carefully selecting the policy sites. For example, residents and tourists would be more prone to accept the offshore wind power project and less prone to reduce their trip frequency if wind farms were built at urban or mixed urban/natural beaches than at natural beaches (i.e., Golfet and Castell beaches, our base category).

Second, although the majority of respondents claimed that they would not change their trip plans in response to the implementation of the project, a significant proportion (34.03%) stated the opposite. This suggests that these respondents perceive the OWF project as a visual disamenity. However, the size of the trip loss depends on the OWF scenario considered, and therefore on its degree of visual impact. In particular, residents and tourists are more likely to reduce their trip frequency under a scenario with a high density of turbines placed near the shore (High_Near scenario) than under a scenario with a low density of turbines placed far from the shore (Low_Far). Third, the impact of factors affecting beach visitation is heterogenous in the population as most parameters have both positive and negative signs. One example includes the binary variables denoting the OWF scenarios. Beach trips significantly fall when switching from the scenario with the lowest

visual impact (Low_Far, the base category) to the scenario with the highest visual impact (High_Near). However, this downward shift in beach demand does not apply to all respondents. Fourth, implementing the OWF project would lead to a welfare loss to a greater or lesser extent depending on the degree of visual disamenities from the OWF scenario considered. Specifically, the welfare loss caused by the implementation of 570 MW in line with the ZÈFIR investment program would be from €77.1 to €150 million per season for residents and from €368.2 to €760.2 million per season for tourists.

However, it should be recalled that about 90% of respondents (both residents and tourists) who said that they would reduce their trip frequency if an OWF was built at the beach where they were surveyed reported a re-allocation of trips across beaches without wind farms within Catalonia rather than outside Catalonia. This suggests that beach demand could be expected to increase in Catalan coastal localities not concerned by the project. Consequently, at regional level, the estimated negative economic impacts could be moderate.[15] This finding clearly calls for the design and implementation of redistributive instruments to offset the negative impacts in areas where the wind farms would be located.

We should also note that the welfare loss reported above relates to the current beach users only. The analysis in this paper showed that correcting for on-site sampling yields smaller estimates of CS per trip, relative to correcting for unobserved heterogeneity in trip preferences (less than €7 – €17 depending on the individual is a resident or a tourist). The CS per trip corrected for on-site sampling both includes the use value attached to the beaches

[15] Of course, this is true if and only if beach users in the localities not concerned by the project do not change their trip behaviour in response to an increase in the number of beach users.

by current users and accounts for the option to use the beaches by potential users who currently are non-users (Englin and Shonkwiler, 1995). The question that then arises is how likely current non-users become users of beaches with wind farms. When a public policy refers to an improvement in the quality of a site, a significant part of non-users could be expected to become users. In our case, however, (1) none of the respondents predicted in increase in their beach demand under OWF conditions; (2) the composite OWF variable has a significant negative impact on beach demand and its impact is constant across individuals (since the corresponding standard deviation is not significant). All these points taken together suggest that an OWF is seen as an unfavorable change to the current beach conditions by the vast majority of respondents. Therefore, it is unlikely that a large part of current non-users become users of beaches with wind farms in the future, and so a decision-making based on estimates of welfare loss for the entire population of residents and tourists could be flawed.

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References

Alberini, A., Longo, A., 2006. Combining the travel cost and contingent behavior methods to value cultural heritage sites: Evidence from Armenia. Journal of Cultural Economics 30, 287-304.
Alberini, A., Zanatta, V., Rosato, P., 2007. Combining actual and contingent behavior to estimate the value of sports fishing in the Lagoon of Venice. Ecological Economics 61, 530-541.
Anne, N., Sebastien, L., Nele, W., François, R., Robert, M., 2019. The impact of wildfires on the recreational value of heathland: A discrete factors approach with adjustment for on-site sampling, 24th Annual Conference of the European Association of Environmental and Resource Economists, Manchester, UK, p. 54.
Beaumais, O., Appéré, G., 2010. Recreational shellfish harvesting and health risks: A pseudo-panel approach combining revealed and stated preference data with correction for on-site sampling. Ecological Economics 69, 2315-2322.
Bhat, M.G., 2003. Application of non-market valuation to the Florida Keys marine reserve management. Journal of environmental management 67, 315-325.
Brownlee, M.T., Hallo, J.C., Jodice, L.W., Moore, D.D., Powell, R.B., Wright, B.A., 2015. Place attachment and marine recreationists' attitudes toward offshore wind energy development. Journal of Leisure research 47, 263-284.
Cameron, A.C., Trivedi, P.K., 1986. Econometric models based on count data. Comparisons and applications of some estimators and tests. Journal of Applied Econometrics 1, 29-53.
Devine-Wright, P., 2011. Place attachment and public acceptance of renewable energy: A tidal energy case study. Journal of Environmental Psychology 31, 336-343.
Egan, K., Herriges, J., 2006. Multivariate count data regression models with individual panel data from an on-site sample. Journal of Environmental Economics and Management 52, 567-581.
Englin, J., Cameron, T.A., 1996. Augmenting travel cost models with contingent behavior data. Environmental and resource economics 7, 133-147.
Englin, J., Lambert, D., Shaw, W.D., 1997. A structural equations approach to modeling consumptive recreation demand. Journal of Environmental Economics and Management 33, 33-43.
Englin, J., Shonkwiler, J.S., 1995. Estimating social welfare using count data models: an application to long-run recreation demand under conditions of endogenous stratification and truncation. The Review of Economics and Statistics 77, 104-112.
European Wind Energy Association, 2015. The European offshore wind industry - key trends and statistics 2015, p. 24.
Fooks, J.R., Messer, K.D., Duke, J.M., Johnson, J.B., Li, T., Parsons, G.R., 2017. Tourist Viewshed Externalities and Wind Energy Production. Agricultural and Resource Economics Review 46, 224-241.
Gibbons, S., 2015. Gone with the wind: Valuing the visual impacts of wind turbines through house prices. Journal of Environmental Economics and Management 72, 177-196.
Haab, T.C., McConnell, K.E., 2002. Valuing environmental and natural resources: the econometrics of non-market valuation. Edward Elgar Publishing.
Haggett, C., 2011. Understanding public responses to offshore wind power. Energy Policy 39, 503-510.
Hanley, N., Bell, D., Alvarez-Farizo, B., 2003. Valuing the benefits of coastal water quality improvements using contingent and real behaviour. Environmental and resource economics 24, 273-285.
Hattam, C., Hooper, T., Papathanasopoulou, E., 2015. Understanding the Impacts of offshore wind farms on well-being. The Crown Estate, 77.
Heintzelman, M.D., Tuttle, C.M., 2012. Values in the wind: a hedonic analysis of wind power facilities. Land Economics 88, 571-588.
Hevia-Koch, P., Ladenburg, J., 2016. Estimating preferences for wind turbine locations-a critical review of visualisation approaches.

Hoen, B., Brown, J.P., Jackson, T., Thayer, M.A., Wiser, R., Cappers, P., 2015. Spatial hedonic analysis of the effects of US wind energy facilities on surrounding property values. The Journal of Real Estate Finance and Economics 51, 22-51.
Holmes, T.P., Englin, J.E., 2010. Preference heterogeneity in a count data model of demand for off-highway vehicle recreation. Agricultural & Resource Economics Review 39, 75.
Huang, J.-C., Parsons, G.R., Poor, P.J., 2011. Combined conjoint-travel cost demand model for measuring the impact of erosion and erosion control programs on beach recreation, in: Whitehead, J.C., Haab, T., Huang, J.-C. (Eds.), Preference Data for Environmental Valuation: Combining Revealed and Stated Approaches. Routledge, pp. 115-138.
Hynes, S., Gaeven, R., O'Reilly, P., 2017. Estimating a total demand function for sea angling pursuits. Ecological Economics, 73-81.
Hynes, S., Greene, W., 2013. A panel travel cost model accounting for endogenous stratification and truncation: a latent class approach. Land Economics 89, 177-192.
Hynes, S., 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, 348-367.
Jensen, C.U., Panduro, T.E., Lundhede, T.H., 2014. The vindication of Don Quixote: The impact of noise and visual pollution from wind turbines. Land Economics 90, 668-682.
Krueger, A.D., Parsons, G.R., Firestone, J., 2011. Valuing the visual disamenity of offshore wind projects at varying distances from the shore. Land Economics 87, 268-283.
Ladenburg, J., 2010. Attitudes towards offshore wind farms—The role of beach visits on attitude and demographic and attitude relations. Energy Policy 38, 1297-1304.
Ladenburg, J., Dubgaard, A., 2009. Preferences of coastal zone user groups regarding the siting of offshore wind farms. Ocean & Coastal Management 52, 233-242.
Ladenburg, J., Lutzeyer, S., 2012. The economics of visual disamenity reductions of offshore wind farms—Review and suggestions from an emerging field. Renewable and Sustainable Energy Reviews 16, 6793-6802.
Landry, C.E., Allen, T., Cherry, T., Whitehead, J.C., 2012. Wind turbines and coastal recreation demand. Resource and Energy Economics 34, 93-111.
Lang, C., Opaluch, J.J., Sfinarolakis, G., 2014. The windy city: Property value impacts of wind turbines in an urban setting. Energy Economics 44, 413-421.
Lilley, M.B., Firestone, J., Kempton, W., 2010. The effect of wind power installations on coastal tourism. Energies 3, 1-22.
Lloyd-Smith, P., Abbott, J.K., Adamowicz, W., Willard, D., 2019. Decoupling the value of leisure time from labor market returns in travel cost models. Journal of the Association of Environmental and Resource Economists 6, 215-242.
Lutzeyer, S., Phaneuf, D.J., Taylor, L.O., 2018. The amenity costs of offshore wind farms: Evidence from a choice experiment. Energy Economics 72, 621-639.
Mariel, P., Meyerhoff, J., Hess, S., 2015. Heterogeneous preferences toward landscape externalities of wind turbines–combining choices and attitudes in a hybrid model. Renewable and Sustainable Energy Reviews 41, 647-657.
Martinez-Espineira, R., Amoako-Tuffour, J., 2008. Recreation demand analysis under truncation, overdispersion, and endogenous stratification: An application to Gros Morne National Park. Journal of environmental management 88, 1320-1332.
Martínez-Espiñeira, R., Amoako-Tuffour, J., 2009. Multi-destination and multi-purpose trip effects in the analysis of the demand for trips to a remote recreational site. Environmental Management 43, 1146-1161.
Mattmann, M., Logar, I., Brouwer, R., 2016. Wind power externalities: A meta-analysis. Ecological Economics 127, 23-36.
McCartney, A., 2006. The social value of seascapes in the Jurien Bay Marine Park: an assessment of positive and negative preferences for change. Journal of Agricultural Economics 57, 577-594.

Nunes, P.A., Loureiro, M.L., Piñol, L., Sastre, S., Voltaire, L., Canepa, A., 2015. Analyzing beach recreationists' preferences for the reduction of jellyfish blooms: Economic results from a stated-choice experiment in Catalonia, Spain. PloS one 10, e0126681.
Parsons, G.R., 2017. The travel cost model, in: Champ, P.A., Boyle, K.J., Brown, T.C. (Eds.), A primer on nonmarket valuation. The Economics of Non-Market Goods and Resources, 2nd Edition ed. Kluwer Academic Publishers, Dordrecht, pp. 269-329.
Parsons, G.R., Chen, Z., Hidrue, M.K., Standing, N., Lilley, J., 2013. Valuing beach width for recreational use: Combining revealed and stated preference data. Marine Resource Economics 28, 221-241.
Parsons, G.R., Firestone, J., Toussaint, J., Yan, L., 2019. The effect of offshore wind power projects on recreational beach use: A contingent-behavior study on the East Coast of the United States, in: Delaware, U.o. (Ed.), p. 44.
Parsons, G.R., Stefanova, S., 2011. Gauging the value of short-term site closures in a travel-cost rum model of recreation demand with a little help from stated preference data, in: Whitehead, J.C., Haab, T., Huang, J.-C. (Eds.), Preference Data for Environmental Valuation: Combining Revealed and Stated Approaches. Routledge, pp. 239-251.
Prayaga, P., Rolfe, J., Stoeckl, N., 2010. The value of recreational fishing in the Great Barrier Reef, Australia: a pooled revealed preference and contingent behaviour model. Marine Policy 34, 244-251.
Randall, A., 1994. A difficulty with the travel cost method. Land Economics 70, 88-96.
Sardá, R., Mora, J., Ariza, E., Avila, C., Jimenez, J.A., 2009. Decadal shifts in beach user sand availability on the Costa Brava (Northwestern Mediterranean Coast). Tourism Management 30, 158-168.
Shaw, D., 1988. On-site samples' regression: Problems of non-negative integers, truncation, and endogenous stratification. Journal of Econometrics 37, 211-223.
Simões, P., Barata, E., Cruz, L., 2013. Joint estimation using revealed and stated preference data: An application using a national forest. Journal of Forest Economics 19, 249-266.
Teisl, M.F., Noblet, C.L., Corey, R.R., Giudice, N.A., 2018. Seeing clearly in a virtual reality: Tourist reactions to an offshore wind project. Energy Policy 122, 601-611.
Vecchiato, D., 2014. How do you like wind farms? Understanding people's preferences about new energy landscapes with choice experiments. Aestimum, 15.
Voltaire, L., Lévi, L., Alban, F., Boncoeur, J., 2017. Valuing cultural world heritage sites: an application of the travel cost method to Mont-Saint-Michel. Applied Economics 49, 1593-1605.
Voltaire, L., Loureiro, M.L., Knudsen, C., Nunes, P.A., 2017. The impact of offshore wind farms on beach recreation demand: Policy intake from an economic study on the Catalan coast. Marine Policy 81, 116-123.
Ward, F.A., Beal, D.J., 2000. Valuing nature with travel cost models: A manual. Edward Elgar Cheltenham.
Westerberg, V., Jacobsen, J.B., Lifran, R., 2013. The case for offshore wind farms, artificial reefs and sustainable tourism in the French Mediterranean. Tourism Management 34, 172-183.
Whitehead, J.C., Haab, T., Larkin, S.L., Loomis, J.B., Alvarez, S., Ropicki, A., 2018. Estimating Lost Recreational Use Values of Visitors to Northwest Florida due to the Deepwater Horizon Oil Spill Using Cancelled Trip Data. Marine Resource Economics 33, 000-000.
Whitehead, J.C., Pattanayak, S.K., Van Houtven, G.L., Gelso, B.R., 2008. Combining revealed and stated preference data to estimate the nonmarket value of ecological services: an assessment of the state of the science. Journal of economic surveys 22, 872-908.

Figure 1 The Phase solubility profile of β-CD and TH in water.

Figure 2 FESEM images of a) β-CD b) TH c) PM d) KN e) CP f) MW.

Figure 3 FTIR spectra of a) β-CD, TH and PM b) KN, CP and MW.

PXRD pattern of c) β-CD, TH and PM d) KN, CP and MW

e) DSC thermograms of β-CD, MF, PM, KN, CP and MW.

f) Thermal stability of TH, PM, KN, CP and MW.

g) 3D structures of β-CD and TH and inclusion of TH inside the cavity of β-CD.

Figure 4(a-l) FESEM images of CH-GEL HPN (MW) at (a) first; (b) second; (c) third stages of biodegradation using soil-burial method.

FESEM images of CH-GEL-β-CD HPN (MW) at (d) first; (e) second; (f) third stages of biodegradation using soil-burial method.

FESEM images of CH-GEL HPN (MW) at (g) first; (h) second; (i) third stages of biodegradation using composting method.

FESEM images of CH-GEL-β-CD HPN (MW) at (j) first; (k) second and (l) third stages of biodegradation using composting method.

Figure 5(a-d) FTIR of (a) CH-GEL HPN (MW); (b) CH-GEL-β-CD HPN (MW) soil-burial method and (c) CH-GEL HPN (MW) and (d) CH-GEL-β-CD HPN (MW) using composting method at different stages of biodegradation.

Figure 6 (a-g) Drug release profile of **a)** TH from CH-GEL-β-CD: TH (MW) and CH-GEL-TH (MW).

b) Drug release profile of TH through CH-GEL-β-CD: TH (MW) at pH 2, 7 and 7.4.

c), d), e) Drug release kinetics of TH through CH-GEL-β-CD: TH (MW).

f) Plot of relaxation to the Fickian contribution (R/F) with the fraction of drug release for the CH- GEL- β-CD: TH (MW).

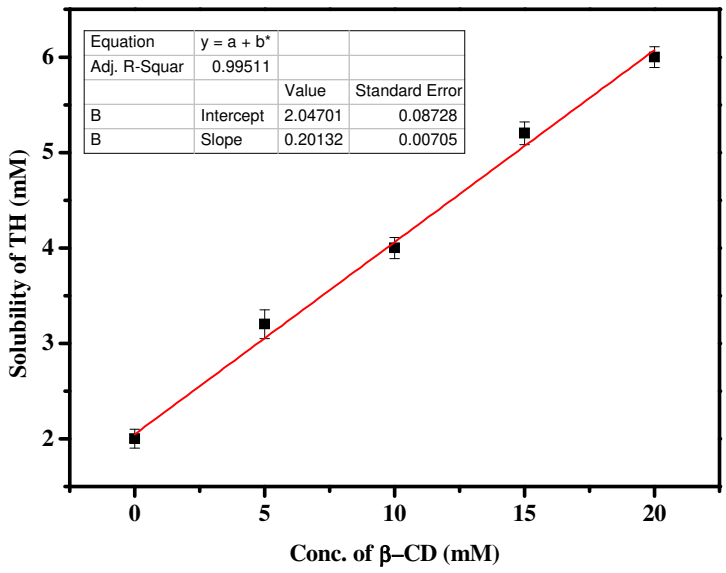

Equation
y = a + b*
Adj. R-Squar
0.99511
Value
Standard Error
B
Intercept
2.04701
0.08728
B
Slope
0.20132
0.00705
Solubility of TH (mM)
Conc. of β–CD (mM)
0
5
10
15
20
2
3
4
5
6

Figure 1

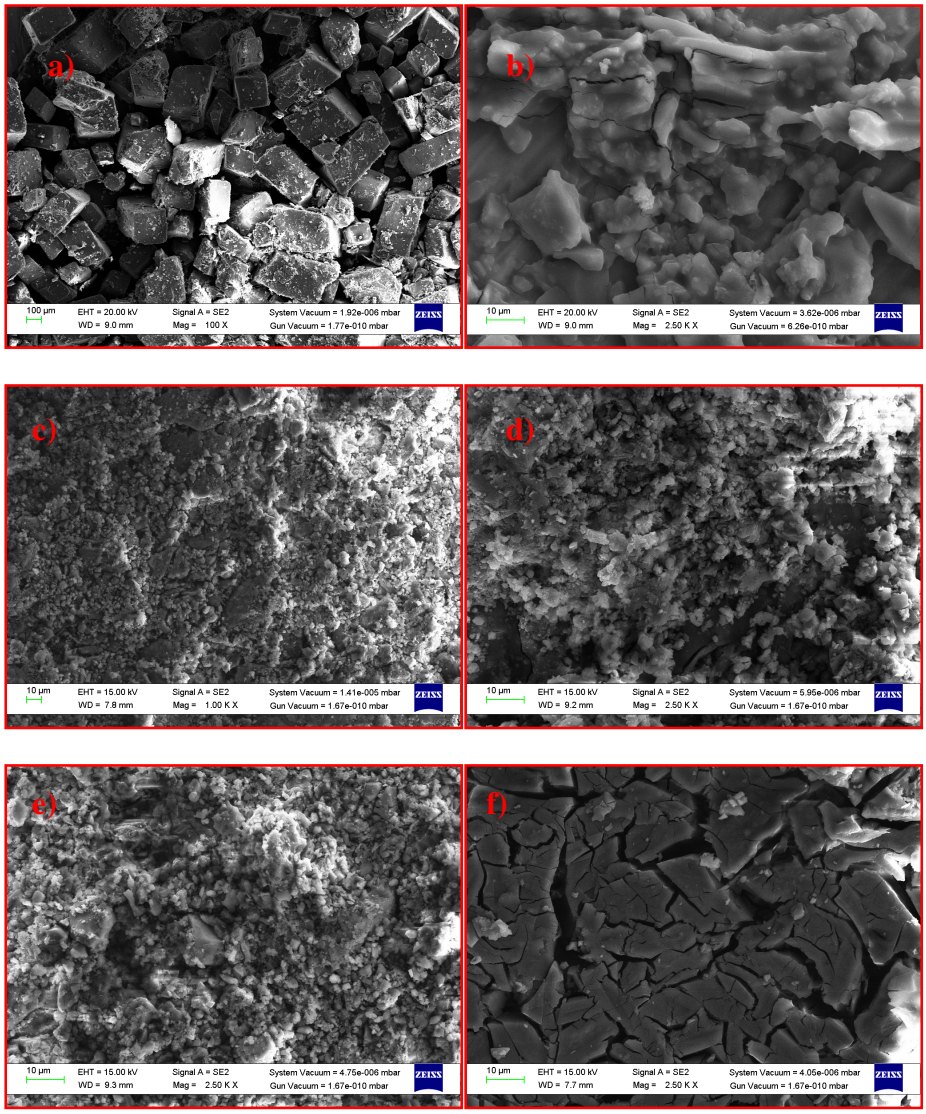
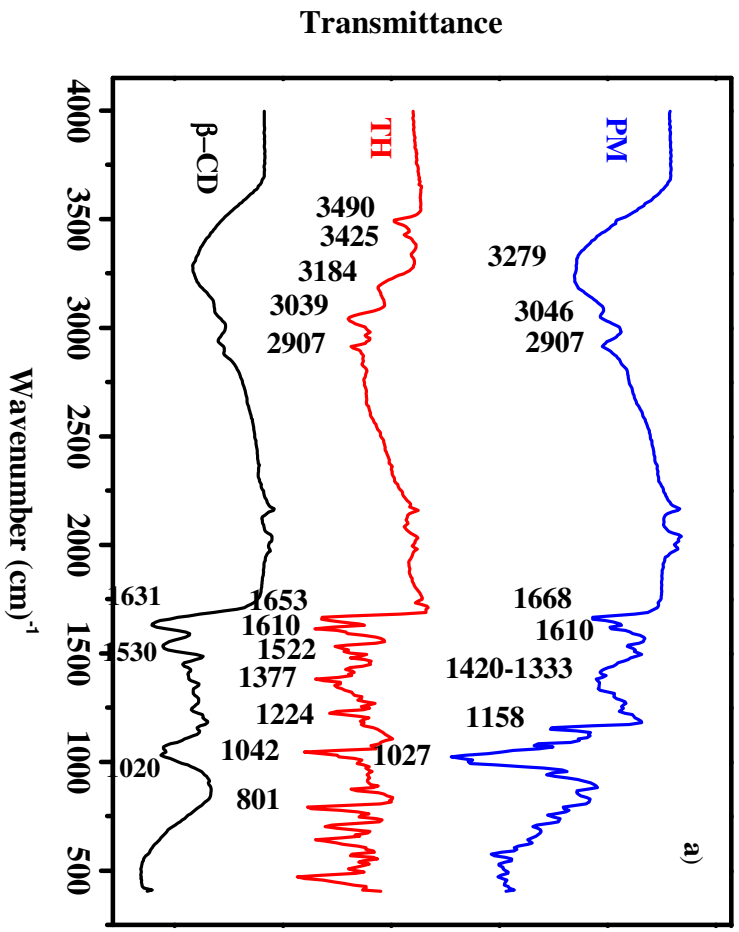
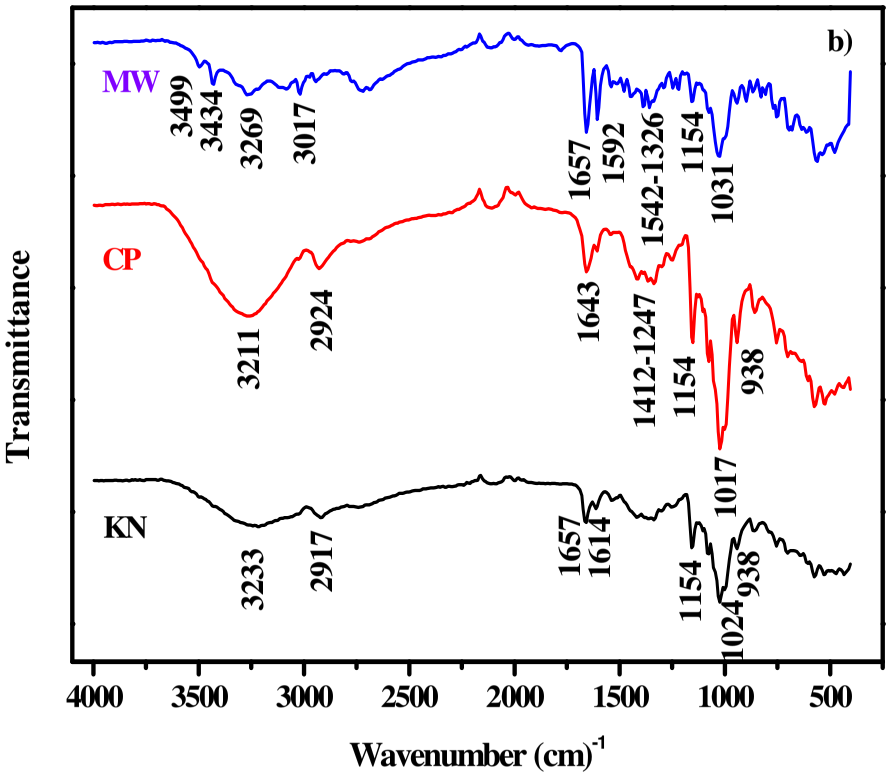
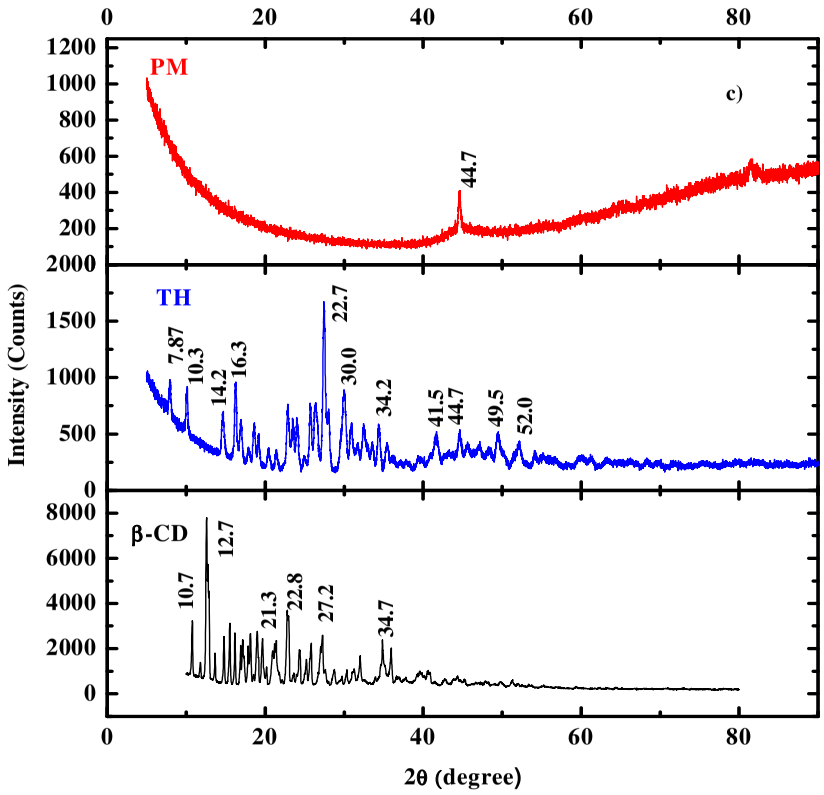
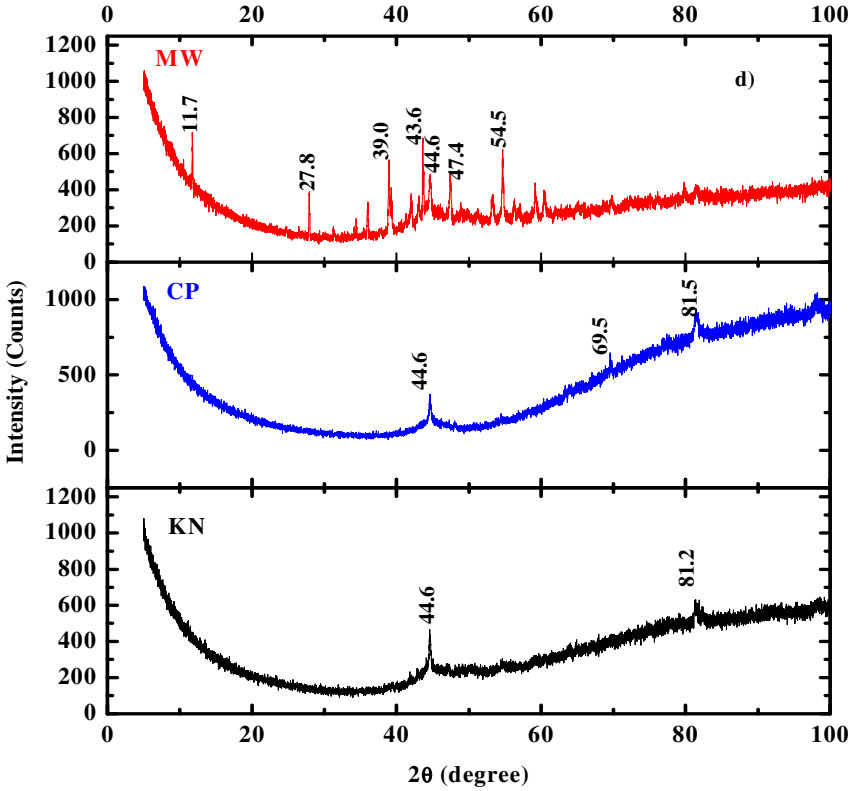

a)
100 µm
EHT = 20.00 kV
WD = 9.0 mm
Signal A = SE2
Mag = 100 X
System Vacuum = 1.92e-006 mbar
Gun Vacuum = 1.77e-010 mbar
ZEISS
b)
10 µm
EHT = 20.00 kV
WD = 9.0 mm
Signal A = SE2
Mag = 2.50 K X
System Vacuum = 3.62e-006 mbar
Gun Vacuum = 6.26e-010 mbar
ZEISS
c)
10 µm
EHT = 15.00 kV
WD = 7.8 mm
Signal A = SE2
Mag = 1.00 K X
System Vacuum = 1.41e-005 mbar
Gun Vacuum = 1.67e-010 mbar
ZEISS
d)
10 µm
EHT = 15.00 kV
WD = 9.2 mm
Signal A = SE2
Mag = 2.50 K X
System Vacuum = 5.95e-006 mbar
Gun Vacuum = 1.67e-010 mbar
ZEISS
e)
10 µm
EHT = 15.00 kV
WD = 9.3 mm
Signal A = SE2
Mag = 2.50 K X
System Vacuum = 4.75e-006 mbar
Gun Vacuum = 1.67e-010 mbar
ZEISS
f)
10 µm
EHT = 15.00 kV
WD = 7.7 mm
Signal A = SE2
Mag = 2.50 K X
System Vacuum = 4.05e-006 mbar
Gun Vacuum = 1.67e-010 mbar
ZEISS

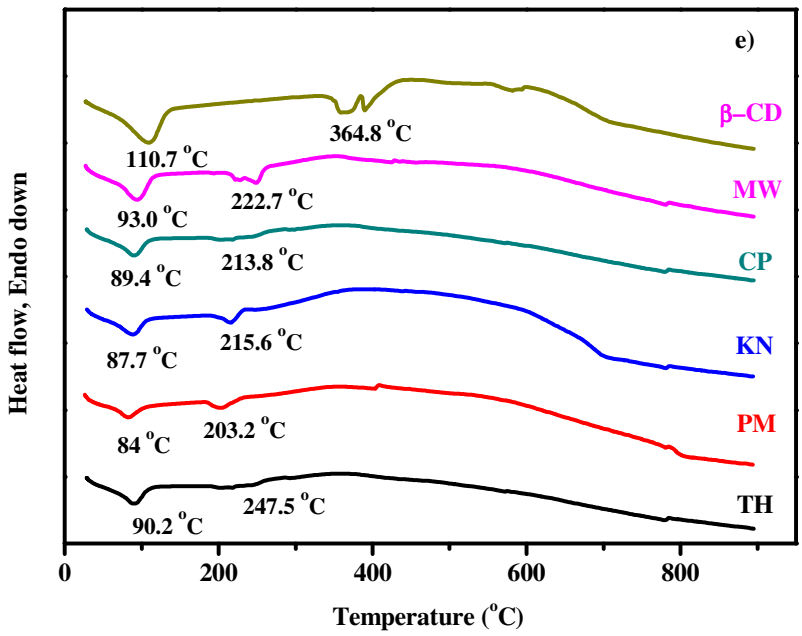
Figure 2

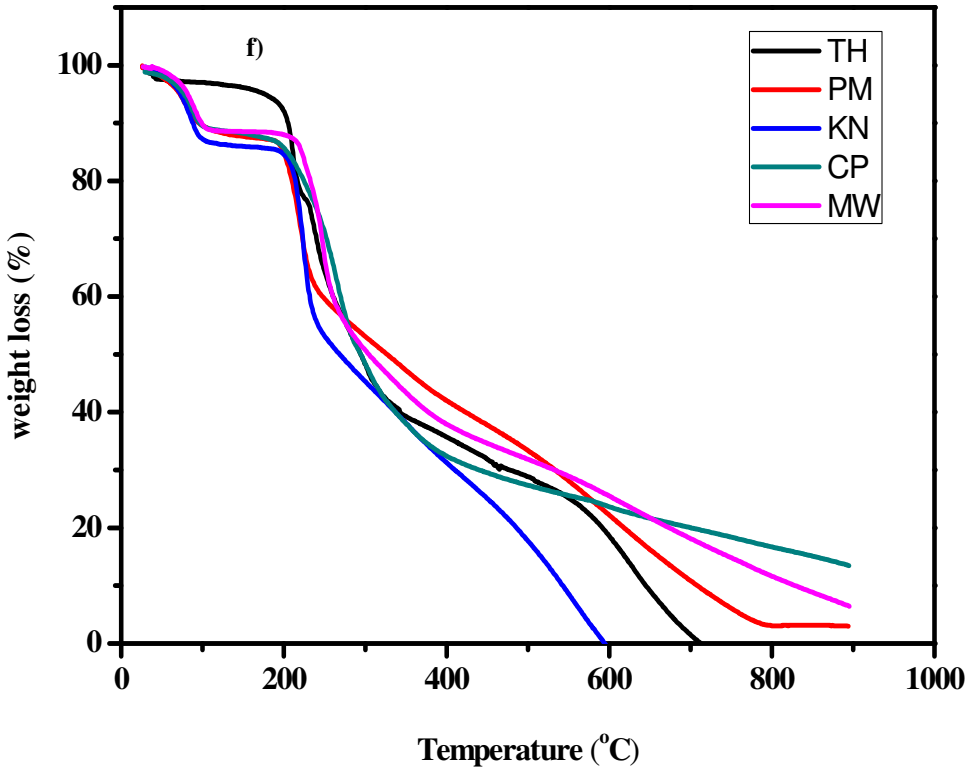

a)
PM
TH
β–CD
Transmittance
Wavenumber (cm)-1
4000
3500
3000
2500
2000
1500
1000
500
3279
3046
2907
1668
1610
1420-1333
1158
1027
3490
3425
3184
3039
2907
1653
1610
1522
1377
1224
1042
801
1631
1530
1020


b)
MW
3499
3434
3269
3017
1657
1592
1542-1326
1154
1031
CP
3211
2924
1643
1412-1247
1154
938
1017
KN
3233
2917
1657
1614
1154
1024
938
Transmittance
4000
3500
3000
2500
2000
1500
1000
500
Wavenumber (cm)-1


c)
PM
44.7
TH
7.87
10.3
14.2
16.3
22.7
30.0
34.2
41.5
44.7
49.5
52.0
β-CD
10.7
12.7
21.3
22.8
27.2
34.7
Intensity (Counts)
2θ (degree)


d)
MW
11.7
27.8
39.0
43.6
44.6
47.4
54.5
CP
44.6
69.5
81.5
KN
44.6
81.2
Intensity (Counts)
2θ (degree)


e)
β–CD
364.8 °C
110.7 °C
MW
222.7 °C
93.0 °C
CP
213.8 °C
89.4 °C
KN
215.6 °C
87.7 °C
PM
203.2 °C
84 °C
TH
247.5 °C
90.2 °C
Heat flow, Endo down
Temperature (°C)


f)
TH
PM
KN
CP
MW
weight loss (%)
Temperature (°C)
0
20
40
60
80
100
0
200
400
600
800
1000

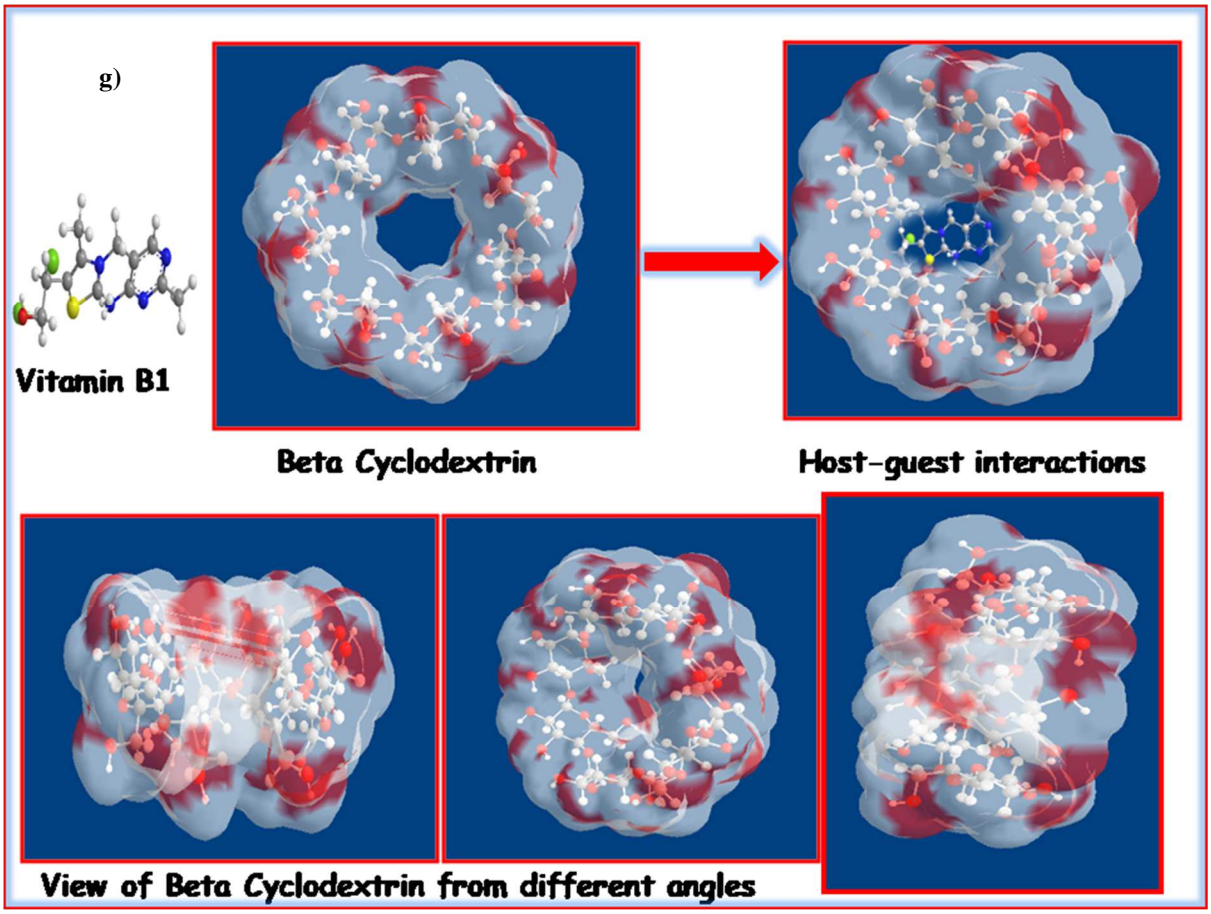

g)
Vitamin B1
Beta Cyclodextrin
Host-guest interactions
View of Beta Cyclodextrin from different angles

Figure 3

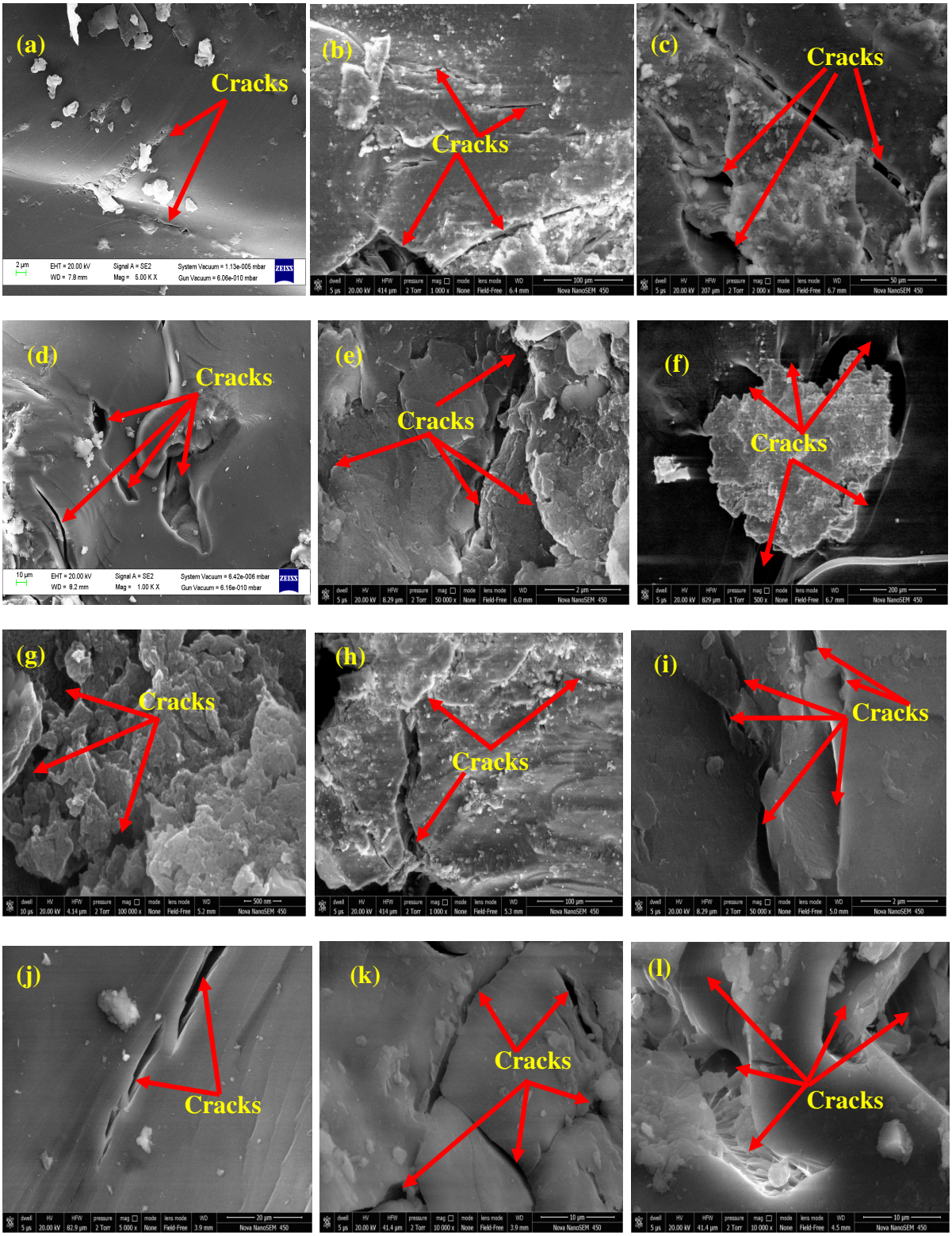
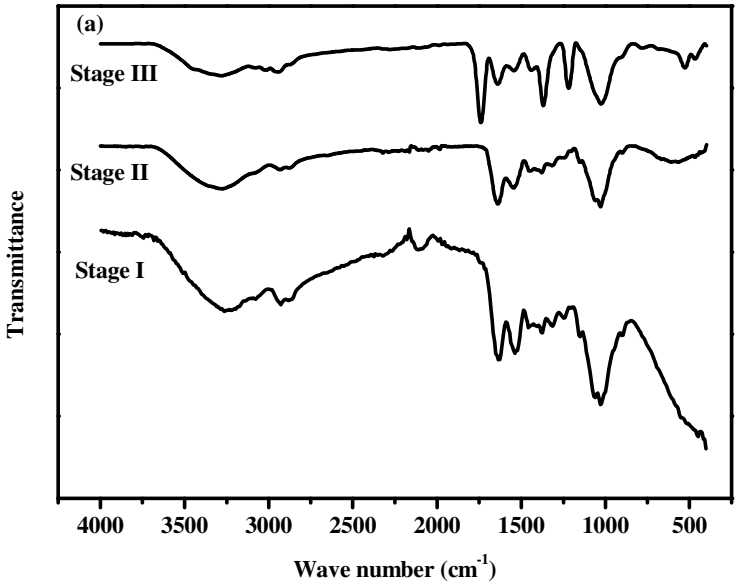
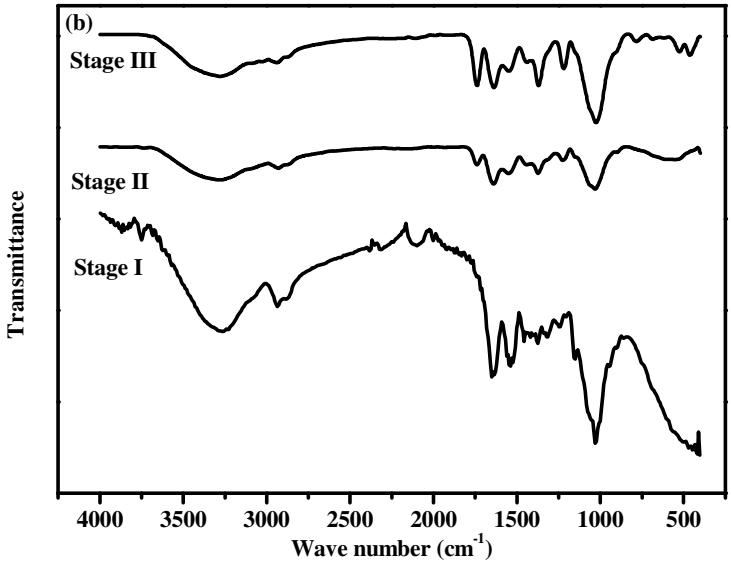
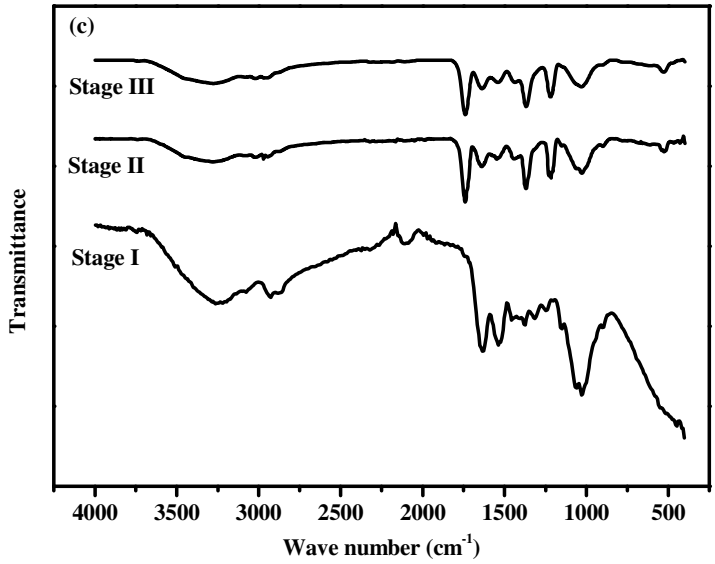

(a)
Cracks
(b)
Cracks
(c)
Cracks
(d)
Cracks
(e)
Cracks
(f)
Cracks
(g)
Cracks
(h)
Cracks
(i)
Cracks
(j)
Cracks
(k)
Cracks
(l)
Cracks

Figure 4


(a)
Stage III
Stage II
Stage I
Transmittance
4000
3500
3000
2500
2000
1500
1000
500
Wave number (cm-1)


(b)
Stage III
Stage II
Stage I
Transmittance
4000
3500
3000
2500
2000
1500
1000
500
Wave number (cm-1)


(c)
Stage III
Stage II
Stage I
Transmittance
4000
3500
3000
2500
2000
1500
1000
500
Wave number (cm-1)

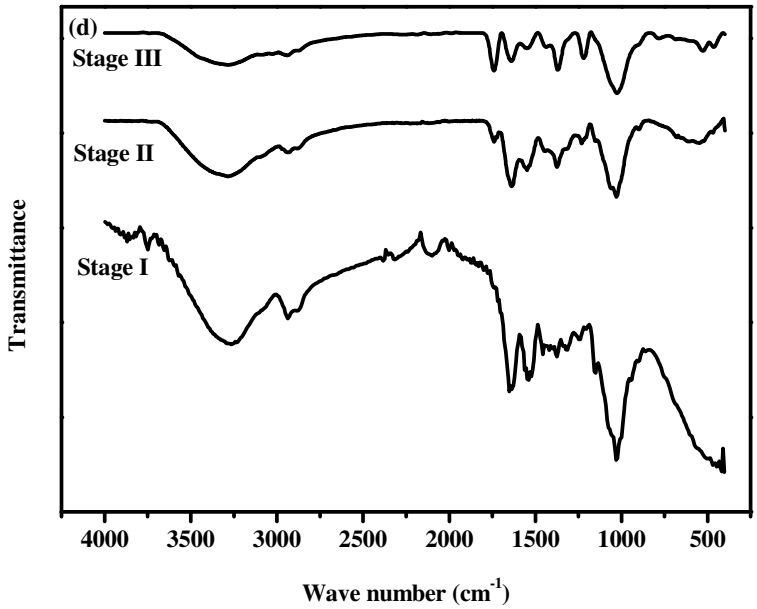
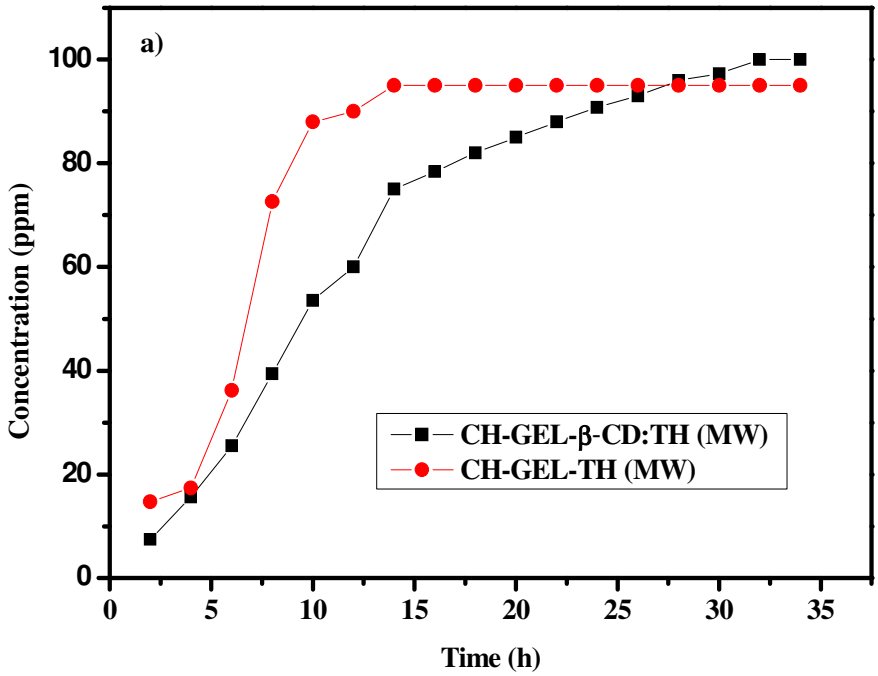
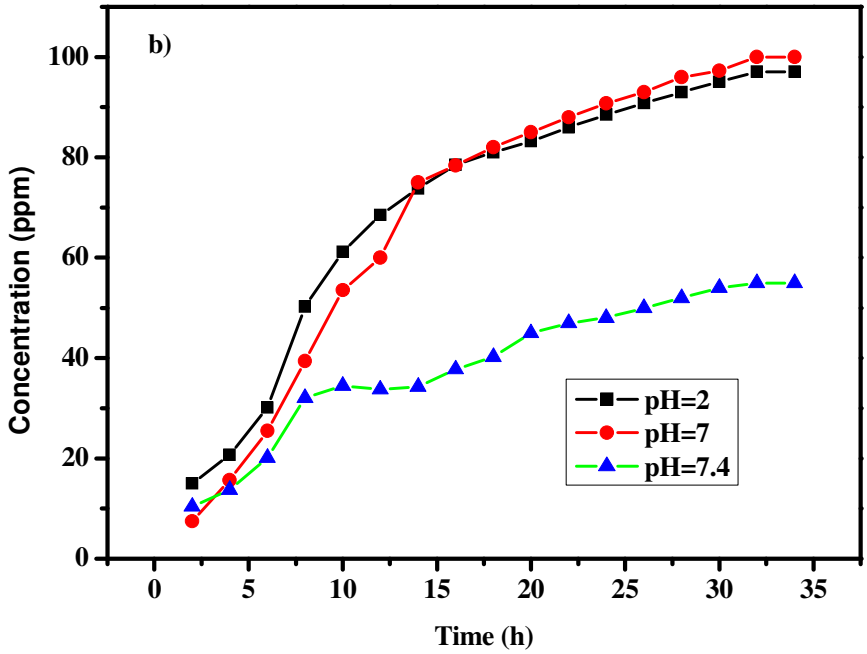
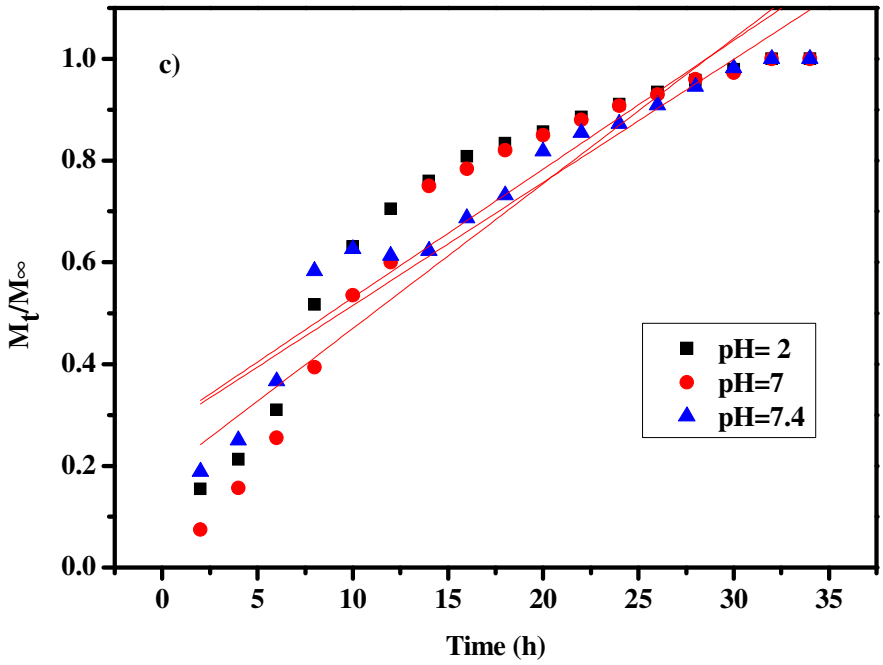
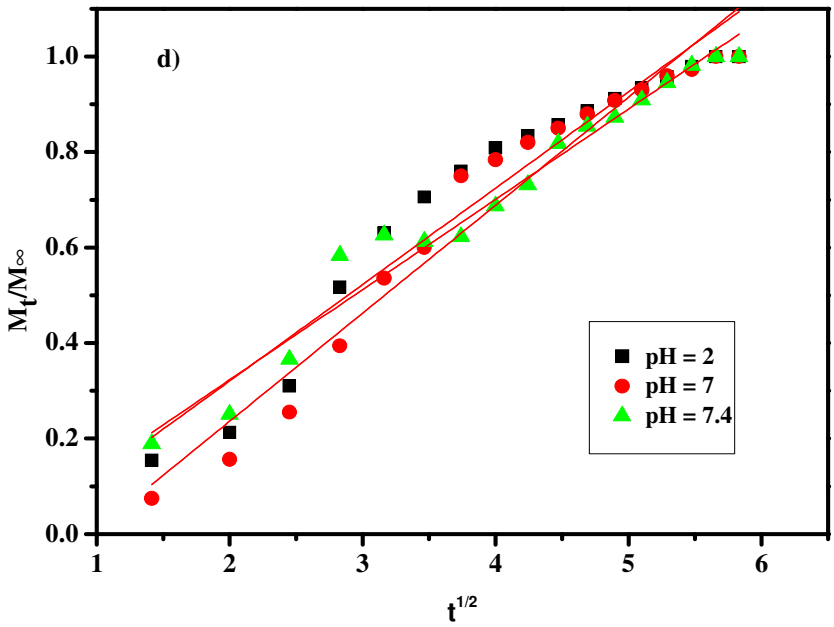

(d)
Stage III
Stage II
Stage I
Transmittance
4000
3500
3000
2500
2000
1500
1000
500
Wave number (cm-1)

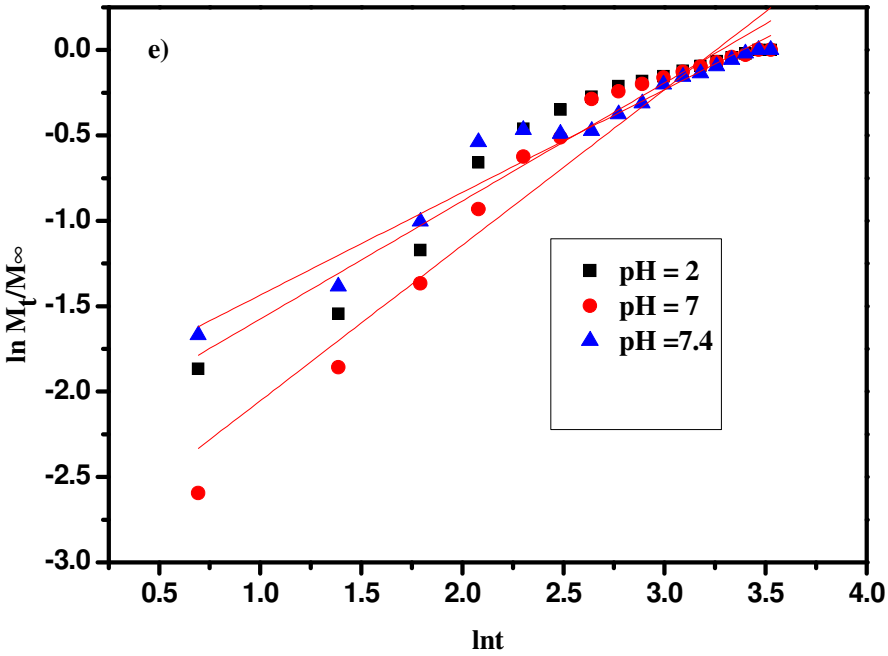
Figure 5


a)
Concentration (ppm)
Time (h)
CH-GEL-β-CD:TH (MW)
CH-GEL-TH (MW)
0
20
40
60
80
100
0
5
10
15
20
25
30
35


b)
Concentration (ppm)
Time (h)
pH=2
pH=7
pH=7.4
0
20
40
60
80
100
0
5
10
15
20
25
30
35


c)
1.0
0.8
0.6
0.4
0.2
0.0
M_t/M_∞
0
5
10
15
20
25
30
35
Time (h)
pH= 2
pH=7
pH=7.4


d)
1.0
0.8
0.6
0.4
0.2
0.0
M_t/M_∞
1
2
3
4
5
6
$t^{1/2}$
pH = 2
pH = 7
pH = 7.4


e)
0.0
-0.5
-1.0
-1.5
-2.0
-2.5
-3.0
ln M_t/M_∞
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
lnt
pH = 2
pH = 7
pH =7.4

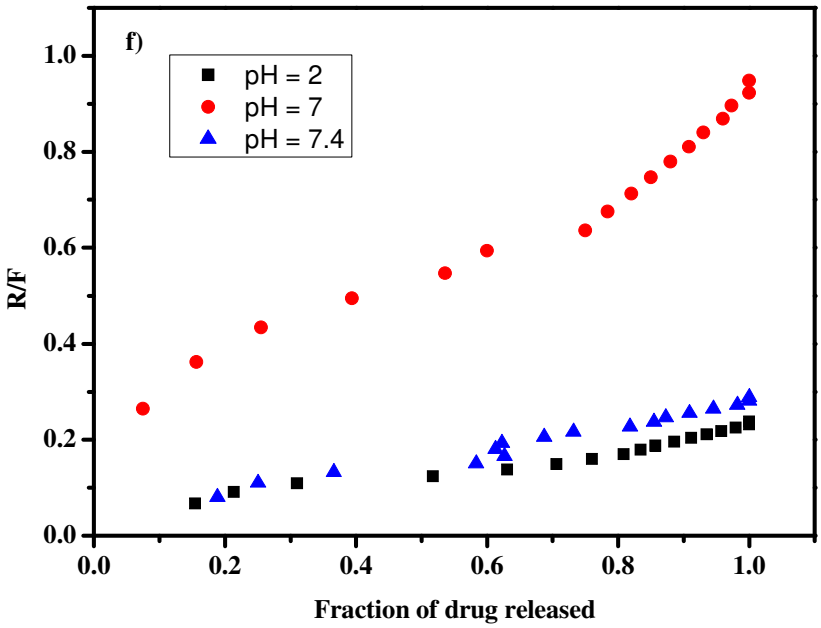

f)
1.0
0.8
0.6
0.4
0.2
0.0
R/F
0.0
0.2
0.4
0.6
0.8
1.0
Fraction of drug released
pH = 2
pH = 7
pH = 7.4

Figure 6

Table 1. Studies applying the combined TC – CB method to the issue of OWF

Authors (year)	Target population and survey mode	OWF project	Use of visual aids	Accounting for on-site sampling bias	Accounting for unobserved heterogeneity	Main results
Lilley et al. (2010)	Tourists surveyed on-site in Delaware (USA)	Projects located at 4 distances offshore: 1.5km, 10km, 22km and out of sight	Yes (static aids)	No	No	Almost one-quarter would switch beaches if the project was located 10 km from the shore. The reported avoidance effect diminished with greater distance from the shore.
Landry et al. (2012)	Telephone survey data collected over coastal residents in North Carolina (USA)	100 turbines, standing about 400 feet high, located 1 mile offshore	No	Not necessary given the used survey mode	No	Little impact on aggregate recreational visitation, with a loss in consumer surplus of about $17 under OWF conditions
Voltaire et al. (2017)	On-site survey over tourists using commercial accommodation in Catalonia (Spain).	Four OWF scenarios with different degrees of visual impact generated by varying both the number of turbines and their proximity to shore	Yes (static aids)	No	No	Respondents would change their trip behavior if an OWF was build. Welfare loss to Catalonia's beach visitors estimated to range between €67.3 and €203 million per season
Teisl et al. (2018)	Tourists surveyed on-site in Monhegan Island (USA)	6 MW floating deep-water offshore wind turbine prototypes placed about 2.9 miles from the Island	Yes (virtual reality or dynamic wind turbines)	No	No	The type of visual aids affect beach trip behavior, with respondents receiving the dynamic visual aid reporting fewer trips compared to those receiving the static photo.
Parsons et al. (2019)	Internet-based data collected from beach users in 20 states from Massachusetts to South Carolina (USA).	Wind power projects located at different distances offshore (2.5 to 20 miles) in clear and hazy conditions and at night	Yes (static aids)	Not necessary given the used survey mode	No	At 2.5-miles offshore, 29% of respondents claimed that they would take fewer trips compared to 5% at 20-miles offshore. Welfare effects for a project at 12.5 miles offshore were about $5 million per year.

Table 2. Descriptive statistics

		Residents		Tourists
Variables	**Description**	**Mean (std. dev.)**		**Mean (std. dev.)**
Dependent variables				
RP_{2011}	Trips taken during the 2011 summer season	27.28 (36.560)		15.72 (25.862)
MRS_{2012}	Mixed revealed – stated trips taken for the 2012 summer season	31.00 (32.87)		19.23 (24.587)
$Trips_{OWF}$	Trips the respondents would take under OWF conditions	24.69 (31.999)		15.26 (24.168)
Independent variables				
RP	1 if revealed trip behaviour during the 2011 summer season	0.33 (0.472)		0.33 (0.472)
MRS	1 if both revealed and planned trip behaviour during the 2012 summer season	0.33 (0.472)		0.33 (0.472)
OWF	1 if contingent trip behaviour under the offshore wind farm scenarios	0.33 (0.472)		0.33 (0.472)
High_Far scenario	1 if contingent trip behaviour under the scenario High_Far	0.28 (0.451)		0.27 (0.447)
High_Near scenario	1 if contingent trip behaviour under the scenario High_Near	0.22 (0.413)		0.27 (0.444)
Low_Near scenario	1 if contingent trip behaviour under the scenario Low_Near	0.15 (0.358)		0.20 (0.402)
Low_Far scenario	1 if contingent trip behaviour under the scenario Low_Far	0.35 (0.478)		0.25 (0.436)
TC	Travel cost per person for the 2012 summer season (in euro)	2.66 (5.276)		15.56 (54.289)
Local_tourist	1 if the respondent was a local tourist			0.62 (0.487)
Paid_accom	1 if the respondent stays in a paid accommodation			0.42 (0.494)
Length_stay	The length of stay of the respondent in Catalonia			16.06 (22.950)
Barceloneta	1 if the respondent was interviewed in the beach “Barceloneta”	0.26 (0.438)		0.08 (0.270)
Bogatell	1 if the respondent was interviewed in the beach “Bogatell”	0.20 (0.400)		0.04 (0.195)
Sabanell	1 if the respondent was interviewed in the beach “Sabanell”	0.08 (0.273)		0.19 (0.390)
Blanes	1 if the respondent was interviewed in the beach “Blanes”	0.10 (0.300)		0.10 (0.298)

Gran de Palamos	1 if the respondent was interviewed in the beach “Gran de Palamos”	0.10 (0.304)		0.16 (0.363)
Fosca	1 if the respondent was interviewed in the beach “Fosca”	0.10 (0.304)		0.14 (0.346)
Castell	1 if the respondent was interviewed in the beach “Castell”	0.11 (0.318)		0.13 (0.337)
Golfet	1 if the respondent was interviewed in the beach “Golfet”	0.04 (0.206)		0.17 (0.378)
Imp_swimming	Rating of the importance of swimming/bathing activity in the respondent’s decision to go this beach (from 0 not at all important to 4 fully important)	3.30 (0.944)		3.47 (0.828)
Imp_nautical activity	Rating of the importance of nautical activity in the respondent’s decision to go this beach (from 0 not at all important to 4 fully important)	1.00 (1.093)		1.32 (1.000)
Familiarity	1 if 0 trip taken in 2011; 2 if 0 – 5 trips taken; 3 if 5 – 20 trips taken; 4 if more than 20 trips taken	2.68 (1.226)		2.02 (0.916)
Men	Dummy indicating whether the respondent is a male	0.46 (0.499)		0.50 (0.500)
Age	Age of the respondent, in years	42.04 (13.580)		43.32 (13.55)
Household size	The number of people living in the house	2.65 (1.212)		3.00 (1.218)
Household income	Mid-point of income bracket	2588.55 (4066.057)		5015.50 (9263.65)

Table 3. Results of the logistic regression models explaining the decision whether to accept the OWF project

	Residents	**Tourists**
Constant	$-3.891\ (1.080)\ ***$	$-4.000\ (1.286)\ ***$
Barceloneta	$1.293\ (0.555)\ **$	$1.857\ (0.746)\ **$
Bogatell	$1.227\ (0.590)\ **$	$2.240\ (0.785)\ ***$
Sabanell	$1.172\ (0.677)\ *$	$1.100\ (0.559)\ **$
Blanes	$0.490\ (0.732)$	1.275 (0.610) **
Gran de Palamos	$-0.597\ (0.784)$	$0.993\ (0.613)$
Fosca		$0.797\ (0.672)$
Golfet & Castell	$Reference$	$Reference$
High_Far scenario	$0.072\ (0.366)$	$0.009\ (0.446)$
High_Near scenario	$-1.512\ (0.544)\ ***$	$-0.067(0.457)$
Low_Near scenario	$-1.568\ (0.728)\ **$	$-0.130\ (0.504)$
Low_Far scenario	Reference	Reference
Local_tourist		$0.784\ (0.428)\ *$
Paid_accom		$0.353\ (0.373)$
Imp_swimming	$0.020\ (0.198)$	$0.134\ (0.223)$
Imp_nautical activity	$0.243\ (0.186)$	$-0.142\ (0.178)$
Familiarity	$-0.036\ (0.151)$	$-0.001\ (0.004)$
Male	$0.902\ (0.353)\ **$	$0.379\ (0.319)$
Age	$0.029\ (0.013)\ **$	$0.006\ (0.014)$
Household size	$0.340\ (0.130)\ ***$	$-0.055\ (0.165)$
Household income	$-3.02e-04$ $(1.59e-04)\ *$	$1.97e-06$ $(2.08e-05)$
Log likelihood	-114.293	-129.424
Wald χ^2	37.73	16.93
Pseudo R^2	18.15%	06.64%
Observations	272	354

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Results of the logistic regression models explaining the decision whether to change beach trip behavior

	Residents	**Tourists**
Constant	$1.946\ (0.925)\ **$	$0.006\ (0.898)$
Barceloneta	$-1.854\ (0.601)\ ***$	$-1.542\ (0.556)\ ***$
Bogatell	$-0.933\ (0.486)\ *$	$-2.144\ (0.766)\ **$
Sabanell	$-0.969\ (0.612)$	$-1.518\ (0.389)\ ***$
Blanes	$-1.930\ (0.723)\ ***$	$-0.722\ (0.481)$
Gran de Palamos	$-0.072\ (0.522)$	$-1.016\ (0.391)\ ***$
Fosca	$-0.196\ (0.543$	$-0.366\ (0.385)$
Golfet & Castell	Reference	Reference
High_Far scenario	$0.520\ (0.403)$	$0.294\ (0.357)$
High_Near scenario	$1.464\ (0.417)\ ***$	$0.928\ (0.339)\ ***$
Low_Near scenario	$0.691\ (0.472)$	$-0.070\ (0.358)$
Low_Far scenario	Reference	Reference
Local_tourist		$-0.502\ (0.297)\ *$
Paid_accom		$0.629\ (0.273)\ **$
Imp_swimming	$-0.151\ (0.156)$	$0.111\ (0.148)$
Imp_nautical activity	$0.010\ (0.166)$	$0.108\ (0.133)$
Familiarity	$-0.213\ (0.131)\ *$	$0.001\ (0.003)$
Male	$-0.201\ (0.306)$	$-0.358\ (0.251)$
Age	$-0.025\ (0.012)\ **$	$-0.013\ (0.010)$
Household size	$-0.246\ (0.130)\ *$	$-0.019\ (0.106)$
Household income	$1.13e-04$ $(6.71\mathrm{e}-05)\ *$	$8.61e-06$ $(1.64\mathrm{e}-05)$
Log likelihood	-136.558	-200.776
Wald χ^2	44.25	48.08
Pseudo R^2	19.54%	13.10%
Observations	272	354

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Predicted probabilities

	Decision whether to accept the OWF project			Decision whether to change trip behavior due to the OWF project	
	Residents	**Tourists**		**Residents**	**Tourists**
High_Far scenario	23.11 [14.30 – 31.93]	11.75% [06.49 – 17.02]		25.83 [16.60 – 35.07]	32.97% [23.90 – 42.05]
High_Near scenario	05.81 [01.25 – 10.36]	10.99 [05.63 – 16.35]		47.24 [35.52 – 58.96]	48.12 [38.81 – 57.42]
Low_Near scenario	05.44 [01.26 – 09.61]	10.38 [04.72 – 16.05]		29.24 [16.03 – 42.44]	25.47 [17.24 – 33.69]
Low_Far scenario	23.11 [14.38 – 31.85]	11.66 [05.72 – 17.60]		17.15 [09.96 – 24.34]	26.82 [18.70 – 34.94]

Note: [.]: 90% CIs by delta method

Table 6. RPNB_1: Results of the Random parameters negative binomial model

	Residents			**Tourists**	
	Mean coefficient	**Standard deviation**		**Mean coefficient**	**Standard deviation**
Constant	$0.264\ (0.226)$	N/A		$0.422\ (0.244)\ *$	N/A
TC	$-0.055\ \ (0.008)\ ***$	$0.001\ (0.007)$		$-0.016\ \ (0.002)\ ***$	$0.008\ (0.001)\ ***$
Barceloneta	$1.792\ (0.128)\ ***$	N/A		$1.285\ (0.149)\ ***$	N/A
Bogatell	$1.698\ (0.126)\ ***$	N/A		$1.058\ (0.172)\ ***$	N/A
Sabanell	$1.875\ (0.154)\ ***$	N/A		$1.257\ (0.098)\ ***$	N/A
Blanes	$2.357\ (0.150)\ ***$	N/A		$1.192\ (0.129)\ ***$	N/A
Gran de Palamos	$2.016\ (0.144)\ ***$	N/A		$1.240\ (0.102)\ ***$	N/A
Fosca	$0.678\ (0.135)\ ***$	N/A		$1.160\ (0.105)\ ***$	N/A
Golfet & Castell	Reference	N/A		Reference	N/A
RP	$-0.382\ (0.130)\ ***$	N/A		$-0.608\ (0.100)\ ***$	N/A
MRP	Reference	Reference		Reference	
OWF	$-0.414\ (0.158)\ ***$	$0.004\ (0.068)$		$-0.463\ (0.131)\ ***$	$0.004\ (0.060)$
Local_tourist				$0.263\ (0.083)\ ***$	$0.634\ (0.040)\ ***$
Paid_accom				$-0.641\ (0.071)\ ***$	$0.412\ (0.052)\ ***$
Swimming	$0.216\ (0.035)\ ***$	$0.135\ (0.010)\ ***$		$-0.007\ (0.037)$	$0.201\ (0.009)\ ***$
Nautical activities	$0.081\ (0.036)\ **$	$0.086\ (0.024)\ ***$		$0.029\ (0.036)$	$0.008\ (0.019)$
Men	$-0.251\ (0.069)\ ***$	$0.180\ (0.050)\ ***$		$0.080\ (0.064)$	$0.338\ (0.044)\ ***$
Age	$0.016\ (0.003)\ ***$	$0.017\ (0.001)\ ***$		$0.033\ (0.003)\ ***$	$0.005\ (0.001)***$
Household size	$0.025\ (0.029)$	$0.084\ (0.012)\ ***$		$-0.074\ (0.028)\ **$	$0.204\ (0.011)\ ***$
Household income	$-0.274e-04$ $(0.124e-04)\ **$	$0.803e-06$ $(0.907e-05)$		$-0.651\ e-05$ $(0.412e-05)$	$0.246e-05$ $(0.341e-05)$
α	$1.239\ (0.063)\ ***$	N/A		$1.459\ (0.076)\ ***$	N/A
Log likelihood	-3213.226			-3249.606	
McFadden Pseudo R^2	96.04%			94.33%	

Akaike Information Criterion (AIC)	6476.5		6557.2
Observations	816		993

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. RPNB_2: Results of the Random parameters negative binomial model results

	Residents			Tourists	
	Mean coefficient	**Standard deviation**		**Mean coefficient**	**Standard deviation**
Constant	0.216 (0.205)	N/A		0.218 (0.234)	N/A
TC	-0.053 (0.008) $***$	0.001 (0.007)		-0.011 (0.002) $***$	0.008 (0.001) $***$
Barceloneta	1.773 (0.122) $***$	N/A		1.353 (0.150) $***$	N/A
Bogatell	1.681 (0.123) $***$	N/A		1.142 (0.169) $***$	N/A
Sabanell	1.879 (0.148) $***$	N/A		1.257 (0.097) $***$	N/A
Blanes	2.396 (0.143) $***$	N/A		1.206 (0.128) $***$	N/A
Gran de Palamos	2.043 (0.137) $***$	N/A		1.291 (0.101) $***$	N/A
Fosca	0.710 (0.134) $***$	N/A		1.100 (0.105) $***$	N/A
Golfet & Castell	Reference	N/A		Reference	Reference
RP	-0.318 (0.088) $***$	N/A		-0.552 (0.085) $***$	N/A
MRP	Reference	Reference		Reference	
High_Far scenario	-0.271 (0.157) $*$	0.001 (0.126)		-0.509 (0.142) $***$	0.069 (0.111)
High_Near scenario	-1.280 (0.149) $***$	1.791 (0.199) $***$		-0.676 (0.138) $***$	0.343 (0.115) $***$
Low_Near scenario	-0.526 (0.206) $**$	0.006 (0.182)		-0.228 (0.178)	0.016 (0.153)
Low_Far scenario	Reference	Reference		Reference	Reference
Local_tourist				0.401 (0.082) $**$	0.706 (0.041) $***$
Paid_accom				-0.651 (0.071) $***$	0.497 (0.053) $***$
Swimming	0.202 (0.034) $***$	0.129 (0.010) $***$		0.005 (0.037)	0.208 (0.009) $***$
Nautical activities	0.073 (0.036) $**$	0.186 (0.024) $***$		0.003 (0.036)	0.152 (0.020) $***$
Men	-0.217 (0.066) $***$	0.224 (0.048) $***$		0.102 (0.065)	0.463 (0.044) $***$
Age	0.016 (0.002) $***$	0.016 (0.001) $***$		0.032 (0.003) $***$	0.007 (0.001)$***$
Household size	0.027 (0.028)	0.084 (0.011) $***$		-0.057 (0.028) $**$	0.105 (0.010) $***$
Household income	$-0.225e-04$ (0.113$e-04$) $**$	0.376$e-05$ (0.842$e-05$)		$-0.490e-05$ (0.398$e-05$)	0.489$e-05$ (0.337$e-05$)

α	$1.392\ (0.063)\ ***$	N/A		$1.463\ (0.071)\ ***$	N/A
Log likelihood	-3209.682			-3252.359	
McFadden Pseudo R^2	96.04%			94.32%	
Akaike Information Criterion (AIC)	6477.4			6570.7	
Observations	816			993	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Distributions of parameters for explanatory variables specified as random parameters

	Residents	**Tourists**		**Residents**	**Tourists**
Variables	RPNBM_1	RPNBM_1		RPNBM_2	RPNBM_2
TC	NS	97.1% − | 02.9% +			91.6% − | 08.4% +
OWF	NS				
High_Far scenario				NS	NS
High_Near scenario				76.1% − | 23.9% +	97.6% − | 02.4% +
Low_Near scenario				NS	NS
Low_Far scenario				Reference	Reference
Local_tourist		34.1% − | 65.9% +			28.4% − | 71.6% +
Paid_accom		93.9% − | 06.1 % +			90.5% − | 09.5 % +
Swimming	05.5% − | 94.5% +	NS		05.8% − | 94.2% +	NS
Nautical activities	17.4% − | 82.6 % +	NS		34.8% − | 65.2 % +	NS
Men	91.8% − | 8.2% +	NS		83.4% − | 15.6% +	NS
Age	17.6% − | 82.4% +	0.0% − | 100.0% +		16.6% − | 83.4% +	0.0% − | 100.0% +
Household size	NS	64.1% − | 35.9% +		NS	70.5% − | 29.5% +
Household income	NS	NS		NS	NS

NS: Standard deviation is not significant

Table 9. Results of the Multivariate Poisson Lognormal model adjusted for on-site sampling

	Residents			**Tourists**	
	MPLN_1	**MPLN_2**		**MPLN_1**	**MPLN_2**
Constant	0.411 (0.118) ***	0.599 (0.121) ***		−0.052 (0.134)	−0.388 (0.138) ***
TC	−0.111 (0.007) ***	−0.087 (0.006) ***		−0.012 (0.003) ***	−0.013 (0.002) ***
Barceloneta	1.384 (0.069) ***	1.870 (0.080) ***		1.156 (0.103) ***	1.448 (0.087) ***
Bogatell	1.112 (0.062) ***	1.300 (0.065) ***		0.651 (0.084) ***	0.840 (0.080) ***
Sabanell	1.564 (0.069) ***	0.673 (0.060) ***		1.078 (0.053) ***	2.143 (0.059) ***
Blanes	1.890 (0.067) ***	1.620 (0.058) ***		−0.083 (0.062) ***	0.301 (0.051) ***
Gran de Palamos	1.707 (0.067) ***	1.260 (0.059) ***		1.140 (0.059) ***	1.370 (0.049) ***
Fosca	0.111 (0.066) ***	0.049 (0.069) ***		1.310 (0.059) ***	1.656 (0.058) ***
Golfet & Castell	Reference	Reference		Reference	*Reference*
RP	−0.675 (0.063) ***	−0.675 (0.079) ***		−0.395 (0.105) ***	−0.382 (0.066) ***
MRP	Reference	Reference		Reference	Reference
OWF	−0.521 (0.071) ***			−0.459 (0.076) ***	
High_Far scenario		−0.215 (0.060) ***			−0.457 (0.061) ***
High_Near scenario		−0.731 (0.059) ***			−0.376 (0.068) ***
Low_Near scenario		−0.541 (0.081) ***			−0.471 (0.064) ***
Low_Far scenario		Reference			Reference
Local_tourist				0.160 (0.038) ***	0.065 (0.037) *
Paid_accom				−1.040 (0.035) ***	−0.942 (0.041) ***
Swimming	−0.023 (0.016)	−0.135 (0.019) ***		0.147 (0.020) ***	0.126 (0.020) ***
Nautical activities	0.179 (0.012) ***	0.062 (0.011) ***		−0.064 (0.018) ***	−0.072 (0.014) ***
Men	−0.289 (0.027) ***	−0.281 (0.026) ***		−0.355 (0.038) ***	0.338 (0.028) ***
Age	0.034 (0.001) ***	0.031 (0.001) ***		0.032 (0.001) ***	0.025 (0.001)***
Household size	−0.068 (0.009) ***	0.087 (0.009) ***		−0.029 (0.015) *	−0.051 (0.014) ***

Household income	$-2.56e-05$ (8.80$e-06$) ***	$-4.59e-05$ (1.10$e-05$) ***		$-9.63e-06$ (2.62$e-06$) ***	$-1.080e-05$ (3.400$e-06$) ***
$\sigma_{RP_{2011}}$	1.699 (0.392) ***	2.018 (0.483) ***		2.761 (0.711) ***	2.211 (0.516) ***
$\sigma_{MRS_{2012}}$	0.983 (0.228) ***	1.091 (0.261) ***		1.149 (0.270) ***	1.215 (0.266) ***
σ_{OWF}	1.796 (0.447) ***	1.337 (0.318) ***		1.517 (0.365) ***	1.587 (0.397) ***
$Cov\ (RP_{2011}, MRS_{2012})$	0.970 (0.058) ***	1.258 (0.071) ***		1.264 (0.146) ***	1.544 (0.090) ***
$Cov\ (RP_{2011}, Trips_{OWF})$	1.303 (0.071) ***	0.840 (0.071) ***		1.485 (0.150) ***	1.432 (0.094) ***
$Cov\ (MRS_{2012}, Trips_{OWF})$	1.134 (0.064) ***	0.759 (0.064) ***		1.247 (0.077) ***	1.213 (0.064) ***
Log likelihood	−3,307.507	−3,345.772		−3,431.033	−3,407.34
Observations	816	816		993	993

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. The estimates of consumer surplus per trip

Models		**Accounting for unobserved heterogeneity in trip preferences**		**Accounting for on-site sampling bias**
RPNB_1 and MPLN_1	Residents	€18.22		€9.01
	Tourists	€63.49		€80.23
RPNB_2 and MPLN_2	Residents	€18.81		€11.54
	Tourists	€89.76		€74.66

Table 11. Conditional expectations and welfare estimates

	Residents				**Tourists**		
	Predicted mean trip	CS per season	Change in CS relative to 2012		Predicted mean trip	CS per season	Change in CS relative to 2012
2012 summer season 90% CI	29.95 [27.74 – 32.15]	€563.35			19.56 [17.93 – 21.17]	€1,755.71	
OWF scenario	20.55 [19.29 – 21.82]	€386.55	−31.40%		12.21 [11.35 – 13.08]	1,095.97	−37.58%
High_Far scenario 90% CI	22.11 [20.77 – 23.44]	€415.89	−26.18%		11.08 [10.28 – 11.87]	€994.54	−43.35%
High_Near scenario 90% CI	10.62 [9.69 – 11.53]	€199.76	−64.54%		9.75 [9.05 – 10.45]	€875.16	−50.15%
Low_Near scenario 90%CI	17.13 [16.09 – 18.17]	€322.22	−42.80%		14.98 [13.91 – 16.04]	€1,344.60	−23.42%
Low_Far scenario 90% CI	29.00 [27.25 – 30.76]	€545.49	−03.17%		18.61 [17.28 – 19.92]	€1,670.43	−04.86%

Table 12. Welfare loss estimates caused by visual disamenities from 570 MW offshore wind power installations (in million Euros).

		Residents				**Tourists**		
		Distance to coastline				Distance to coastline		
Density		Near (3 km)	Moderate (10 km)	Far (20 km)		Near (3 km)	Moderate (10 km)	Far (20 km)
	High (8 wind farms)	102.8	150.0	77.1		338.2	760.2	540.8
	Low (2 wind farms)	17.0	37.5	2.3		39.5	190.1	14.7

Example – High (8 wind farms)_Near(3 km) for residents: $P = 1{,}413{,}575$; $CS_{baseline} = 563.35$; $\Delta CS_{OWF_i} = 0{,}6454$; $VI = 0.20$

Supplementary Material

Table A. The surveyed beaches

Municipality	Beach	Kind of Beach	Environment	Average width (m)	Length (m)	Beach Surface (m^2)	Coast line evolution[1] (m/year)	Microbiologic Quality	Phytoplankton Proliferation	Certification (Blue Flag)
BARCELONA	Barceloneta	semi-closed	urban	40	600	24000	4,9/-1,2	Excellent	Low	YES
BARCELONA	Bogatell	closed	urban	32	625	18676	-2,4	Excellent	Null	YES
BLANES	Sabanell	semi-closed	mixed	32	2380	75921	-1,1	Excellent	Low	YES
BLANES	Blanes	closed	urban	44	610	26170	0,02	Excellent	Null	YES
PALAMOS	Gran de Palamós	semi-closed	urban	55	990	48650	-0,21	Excellent	Medium	NO
PALAMOS	Fosca	closed	mixed	37	514	16461	-1,1	Excellent	High	YES
PALAMOS	Castell	closed	natural	63	339	22715	-1,03	Excellent	Medium	NO
PALAFRUGELL	Golfet	closed	natural	17	75	1277	ND	Excellent	Null	NO

Table B. Changes in beach trip behaviour and mean trips for residents under OWF conditions

	High – Far scenario	Low – Far scenario	High – Near scenario	Low – Near scenario	Pooled scenario
More trips	0.0%	0.0%	0.0%	0.0%	0.0%
No change	71.4%	78.9%	52.5%	63.4%	68.8%
Fewer trips	7.8%	3.2%	10.2%	7.3%	6.6
Stated percent decrease:					
20%	*////*	*////*	*1.7%*	*////*	*0.4%*
30%	*1.3%*	*1.1%*	*////*	*////*	*0.8%*
40%	*1.3%*	*///*	*1.7%*	*////*	*0.7%*
45%	*1.3%*	*2.1%*	*////*	*////*	*1.1%*
50%	*2.6%*	*////*	*3.4%*	*2.4%*	*1.8%*
60%	*////*	*////*	*1.7%*	*4.8%*	*1.2%*
65%	*1.3%*	*////*	*////*	*////*	*0.4%*
80%	*////*	*////*	*1.7%*	*////*	*0.4%*
No trips at all	20.8%	17.9%	37.3%	29.3%	24.6%
Mean (range) [standard deviation]	25.96 (0 – 120) [32.23]	29.41 (0 – 120) [34.33]	21.53 (0 – 120) [30.72]	15.93 (0 – 120) [25.99]	24.69 (0 – 120) [32.00]

Table C. Changes in beach trip behaviour and mean trips for tourists under OWF conditions

	High – Far scenario	Low – Far scenario	High – Near scenario	Low – Near scenario	Pooled scenario
More trips	0%	0%	0%	0%	0%
No change	69.2%	72.6%	57.3%	71.6%	67.4%
Fewer trips	2.2%	3.6%	4.5%	13.4%	5.4%
Stated percent decrease:					
25%	*////*	*////*	*////*	*1.5%*	*0.3%*
30%	*////*	*////*	*1.1%*	*////*	*0.3%*
40%	*////*	*////*	*////*	*3.0%*	*0.6%*
50%	*2.2%*	*2.4%*	*2.2%*	*7.5%*	*3.3%*
65%	*////*	*////*	*////*	*1.5%*	*0.3%*
70%	*////*	*1.2%*	*////*	*////*	*0.3%*
75%	*////*	*////*	*1.1%*	*///*	*0.3%*
No trips at all	28.6%	23.8%	38.2%	14.9%	27.2%
Mean (range) [standard deviation]	15.13 (0 – 120) [25.02]	14.40 (0 – 120] [23.92]	13.34 (0 – 93) [22.81]	19.07 (0 – 120) [25.15]	15.26 (0 – 120) [24.17]

Table D. Results of the random-effects negative binomial (RENB) model

	RENB_1			RENB_2	
	Residents	**Tourists**		**Residents**	**Tourists**
	Coefficients (std. dev)	Coefficients (std. dev)		Coefficients (std. dev)	Coefficients (std. dev)
Constant	−1.000 (0.300) ***	−0.224 (0.378)		−1.142 (0.298) ***	−0.288 (0.379)
TC	−0.022 (0.009) ***	−0.002 (0.001)		−0.021 (0.010) **	−0.001 (0.001)
Barceloneta	1.099 (0.168) ***	0.598 (0.225) ***		1.101 (0.168) ***	0.648 (0.226) ***
Bogatell	0.753 (0.178) ***	0.659 (0.275) ***		0.810 (0.178) ***	0.671 (0.277) **
Sabanell	1.024 (0.209) ***	0.485 (0.154) ***		1.174 (0.208) ***	0.516 (0.155) ***
Blanes	1.568 (0.202) ***	0.607 (0.195) ***		1.700 (0.201) ***	0.655 (0.197) ***
Gran de Palamos	0.698 (0.198) ***	0.900 (0.158) ***		0.693 (0.197) ***	0.942 (0.158) ***
Fosca	0.164 (0.192)	0.569 (0.166) ***		0.169 (0.192)	0.511 (0.166) ***
Golfet & Castell	Reference	Reference		Reference	Reference
RP	−0.561 (0.068) ***	−0.682 (0.067) ***		−0.498 (0.065) ***	−0.638 (0.065) ***
MRP	Reference	Reference		Reference	Reference
OWF	−0.482 (0.066) **	−0.482 (0.061) ***			
High_Far scenario				−0.322 (0.106) ***	−0.591 (0.108) ***
High_Near scenario				−1.010 (0.154) ***	−0.663 (0.120) ***
Low_Near scenario				−0.415 (0.161) ***	−0.234 (0.110)
Low_Far scenario				Reference	Reference
Local_tourist		0.316 (0.128) **			0.298 (0.129) **
Paid_accom		−0.573 (0.115) ***			−0.585 (0.115) ***
Swimming	0.060 (0.052)	−0.032 (0.061)		0.041 (0.052)	−0.044 (0.061)
Nautical activities	0.005 (0.048)	0.007 (0.055)		0.011 (0.049)	0.022 (0.056)

Men	$-0.025\ (0.095)$	$0.353\ (0.103)^{***}$		$0.025\ (0.095)$	$0.354\ (0.103)\ ***$
Age	$0.013\ (0.004)\ ***$	$0.014\ (0.004)\ ***$		$0.015\ (0.004)\ ***$	$0.014\ (0.004)\ ***$
Household size	$0.038\ (0.038)$	$-0.073\ (0.044)\ *$		$0.046\ (0.038)$	$-0.068\ (0.044)$
Household income	$-2.48e-05$ $(1.48e-05)\ *$	$2.87e-07$ $(5.49e-06)$		$-2.58e-05$ $(1.48e-05)\ *$	$-2.92e-07$ $(5.48e-06)$
Parameter, r	$1.619\ (0.201)$	$1.192\ (0.108)$		$1.632\ (0.202)$	$1.193\ (0.108)$
Parameter, s	$15.842\ (3.387)$	$4.638\ (0.713)\ ***$		$15.552\ (3.289)$	$4.599\ (0.698)$
Log likelihood	-3197.807	-3228.482		-3190.669	-3227.130
Wald χ^2	$295.16\ ***$	337.37		$299.18\ ***$	334.67
CS per visitor per trip	€45.13	N/A		€48.75	N/A
Observations	816	993		816	993

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E. RPNB_1: Results of the Random parameters negative binomial model for beach users in both 2011 and 2012 summer season

	Residents			**Tourists**	
	Mean coefficient	**Standard deviation**		**Mean coefficient**	**Standard deviation**
Constant	$0.708\ (0.198)\ ***$	N/A		$1.838\ (0.263)\ ***$	N/A
TC	$-0.071\ \ (0.008)\ ***$	$0.001\ (0.007)$		$-0.091\ \ (0.006)\ ***$	$0.066\ (0.005)\ ***$
Barceloneta	$1.229\ (0.119)\ ***$	N/A		$1.585\ (0.205)\ ***$	N/A
Bogatell	$1.030\ (0.124)\ ***$	N/A		$0.328\ (0.196)\ *$	N/A
Sabanell	$1.304\ (0.138)\ ***$	N/A		$0.954\ (0.103)\ ***$	N/A
Blanes	$1.753\ (0.131)\ ***$	N/A		$0.462\ (0.122)\ ***$	N/A
Gran de Palamos	$1.365\ (0.130)\ ***$	N/A		$0.635\ (0.101)\ ***$	N/A
Fosca	$0.800\ (0.143)\ ***$	N/A		$0.676\ (0.107)\ ***$	N/A
Golfet & Castell	Reference	N/A		Reference	N/A
RP	$-0.037\ (0.111)$	N/A		$-0.064\ (0.125)$	N/A
MRP	Reference	Reference		Reference	Reference
OWF	$-0.350\ (0.137)\ **$	$0.011\ (0.054)$		$-0.349\ (0.145)\ **$	$0.013\ (0.055)$
Local_tourist				$0.157\ (0.089)\ *$	$0.093\ (0.036)\ ***$
Paid_accom				$-0.286\ (0.077)\ ***$	$0.190\ (0.062)\ ***$
Swimming	$0.272\ (0.032)\ ***$	$0.009\ (0.009)$		$0.095\ (0.039)\ **$	$0.130\ (0.009)\ ***$
Nautical activities	$-0.051\ (0.032)$	$0.388\ (0.026)\ ***$		$0.027\ (0.037)$	$0.031\ (0.020)$
Men	$-0.372\ (0.061)\ ***$	$0.420\ (0.044)\ ***$		$0.015\ (0.065)$	$0.313\ (0.043)\ ***$
Age	$0.015\ (0.002)\ ***$	$0.014\ (0.001)\ ***$		$0.013\ (0.002)\ ***$	$0.008\ (0.001)\ ***$
Household size	$0.053\ (0.026)\ **$	$0.061\ (0.010)\ ***$		$-0.002\ (0.031)$	$0.049\ (0.010)\ ***$
Household income	$0.657e-05$ $(0.163e-04)$	$0.233e-05$ $(0.980e-05)$		$-0.167e-04$ $(0.339e-05)\ ***$	$0.102e-05$ $(0.285e-05)$
α	$2.229\ (0.135)\ ***$	N/A		$2.244\ (0.143)\ ***$	N/A
Log likelihood	-2556.608			-2287.717	

McFadden Pseudo R^2	96.50%		95.46%
Akaike Information Criterion (AIC)	5163.2		4633.4
Observations	603		570

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table F. RPNB_2: Results of the random parameters negative binomial model for beach users in both 2011 and 2012 summer season

	Residents			**Tourists**	
	Mean coefficient	**Standard deviation**		**Mean coefficient**	**Standard deviation**
Constant	0.859 (0169) ***	N/A		1.617 (0.207) ***	N/A
TC	−0.072 (0.008) ***	0.003 (0.007)		−0.081 (0.005) ***	0.062 (0.004) ***
Barceloneta	1.151 (0.108) ***	N/A		1.393 (0.168) ***	N/A
Bogatell	0.946 (0.114) ***	N/A		0.441 (0.162) ***	N/A
Sabanell	1.241 (0.127) ***	N/A		0.825 (0.086) ***	N/A
Blanes	1.685 (0.119) ***	N/A		0.410 (0.101) ***	N/A
Gran de Palamos	1.341 (0.117) ***	N/A		0.530 (0.084) ***	N/A
Fosca	0.779 (0.130) ***	N/A		0.541 (0.089) ***	N/A
Golfet & Castell	Reference	N/A		Reference	N/A
RP	−0.017 (0.067)	N/A		−0.056 (0.066)	N/A
MRP	Reference	Reference		Reference	
High_Far scenario	−0.192 (0.118)	0.027 (0.094)		−0.892 (0.102) ***	1.423 (0.118) ***
High_Near scenario	−1.888 (0.165) ***	2.371 (0.223) ***		−0.982 (0.117) ***	1.601 (0.148) ***
Low_Near scenario	−0.317 (0.159) **	0.028 (0.142)		−0.218 (0.120) *	0.003 (0.096)
Low_Far scenario	Reference	Reference		Reference	Reference
Local_tourist				0.155 (0.076) **	0.388 (0.030) ***
Paid_accom				−0.394 (0.064) ***	0.274 (0.053) ***
Swimming	0.248 (0.029) ***	0.043 (0.008) ***		0.127 (0.032) ***	0.096 (0.007) ***
Nautical activities	−0.120 (0.028) ***	0.367 (0.023) ***		0.041 (0.031)	0.118 (0.017) ***
Men	−0.315 (0.054) ***	0.207 (0.039) ***		0.007 (0.053)	0.075 (0.035) **
Age	0.014 (0.002) ***	0.016 (0.001) ***		0.013 (0.002) ***	0.009 (0.001) ***
Household size	0.040 (0.023) *	0.053 (0.010) ***		0.037 (0.025)	0.082 (0.008) ***
Household income	$0.110e-04$	$0.637e-05$		$-0.220e-05$	$0.708e-05$

	$(0.151e-04)$	$(0.903e-05)$		$(0.323e-05)$ ***	$(0.265e-05)$ ***
α	$3.037\ (0.139)$ ***	N/A		$3.714\ (0.208)$ ***	N/A
Log likelihood	-2526.076			-2272.762	
McFadden Pseudo R^2	96.553%			95.49%	
Akaike Information Criterion (AIC)	5110.2			4611.5	
Observations	603			570	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G. Results of the Multivariate Poisson Lognormal model unadjusted for on-site sampling

	Residents			**Tourists**	
	MPLN_1	**MPLN_2**		**MPLN_1**	**MPLN_2**
	Coefficients (std. dev)	Coefficients (std. dev)		Coefficients (std. dev)	Coefficients (std. dev)
Constant	0.965 (0.110) ***	1.037 (0.111) ***		1,852 (0,122) ***	1.960 (0.125) ***
TC	−0.073 (0.005) ***	−0.090 (0.006) ***		−0,008 (0,001) ***	−0.002 (0.002)
Barceloneta	0.931 (0.059) ***	0.766 (0.067) ***		2,347 (0,105) ***	1.131 (0.096) ***
Bogatell	1.509 (0.066) ***	1.399 (0.0715) ***		1,818 (0,096) ***	0.993 (0.098) ***
Sabanell	1.581 (0.073) ***	1.013 (0.071) ***		0,526 (0,051) ***	1.887 (0.065) ***
Blanes	1.073 (0.058) ***	1.896 (0.073) ***		0,470 (0,052) ***	0.554 (0.059) ***
Gran de Palamos	1.182 (0.059) ***	1.201 (0.074) ***		2,068 (0,061) ***	1.074 (0.047) ***
Fosca	−0.631 (0.068) ***	0.323 (0.077) ***		3,106 (0,081) ***	0.974 (0.057) ***
Golfet & Castell	Reference	Reference		Reference	*Reference*
RP	−0.832 (0.070) ***	−0.965 (0.055) ***		−0,791 (0,045) ***	−0.969 (0.059) ***
MRP	Reference	Reference		Reference	Reference
OWF	−0.749 (0.058) ***			−0,530 (0,040) ***	
High_Far scenario		−0.899 (0.089) ***			−0.932 (0.070) ***
High_Near scenario		−0.937 (0.073) ***			−1.245 (0.097) ***
Low_Near scenario		−0.899 (0.075) ***			−0.155 (0.068) **
Low_Far scenario		Reference			Reference
Local_tourist				0,373 (0,038) ***	0.054 (0.053)
Paid_accom				−1,347 (0,042) ***	−1.426 (0.047) ***
Swimming	0.100 (0.015) ***	0.060 (0.016) ***		−0,019 (0,020)	0.144 (0.025) ***
Nautical activities	0.060 (0.011) ***	0.126 (0.018) ***		0,223 (0,016) ***	−0.398 (0.018) ***
Men	−0.175 (0.022) ***	−0.148 (0.031) ***		−1,538 (0,051) ***	−0.082 (0.030) ***
Age	0.022 (0.001) ***	0.025 (0.001) ***		0,032 (0,001) ***	0.010 (0.001)***
Household size	0.009 (0.011)	0.012 (0.009)		−0,152 (0,017) ***	−0.098 (0.015) ***

Household income	$-3.82e-06$ ($9.40e-06$)	$-2.36e-05$ ($1.02e-05$) ***		$-2{,}32e-05$ ($7{,}76e-06$) ***	$-1.68e-05$ ($4.01e-06$) ***
$\sigma_{RP_{2011}}$	1.978 (0.505) ***	1.823 (0.422) ***		2,407 (0,515) ***	2.032 (0.481) ***
$\sigma_{MRS_{2012}}$	0.989 (0.226) ***	1.055 (0.247) ***		1,775 (0,382) ***	1.392 (0.327) ***
σ_{OWF}	1.617 (0.412) ***	1.838 (0.554) ***		1,986 (0,401) ***	1.698 (0.412) ***
$Cov\ (RP_{2011}, MRS_{2012})$	1.169 (0.065) ***	1.198 (0.069) ***		3,590 (0,157) ***	2.227 (0.122) ***
$Cov\ (RP_{2011}, Trips_{OWF})$	1.458 (0.076) ***	1.505 (0.064) ***		3,258 (0,153) ***	1.772 (0.113) ***
$Cov\ (MRS_{2012}, Trips_{OWF})$	0.948 (0.052) ***	1.132 (0.055) ***		2,965 (0,135) ***	1.800 (0.098) ***
Log likelihood	−3,217.282769	−3,215.955		−3,382.056	−3,283.062
Observations	816	816		993	993

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table H. Coastline impacted by visual disamenities from 570 MW offshore wind power installations (% of the Catalonian coastline in brackets).

Density of turbines			Distance from wind farms to coastline				
			3 km	5 km	10 km	15 km	20 km
	70 MW	8 wind farms	115.8 (20%)	193.1 (33%)	349.1 (60%)	299.7 (52%)	212.3 (37%)
	337.9 MW	2 wind farms	29.0 (5%)	48.3 (8%)	87.3 (15%)	74.9 (13%)	53.1 (9%)

Source: Voltaire et al. (2017)

Statistical program: The R code developed to estimate the MPLN adjusted for on-site sampling bias

```
log_like_MPLN <- function(param, mydata, on_site=TRUE){
    # Data log-likelihood function assuming independent between trips
    #
    nn.ind <- length(mydata)
    Like_i <- function(data, param, on_site){

      density.y <- function(y, t){
        exp(-lambda[t])*(lambda[t]^y)/factorial(y)
      }
      log.density.y <- function(y, t){
        - lambda[t] + y*log(lambda[t]) - log(factorial(y))
      }
      ##
      y          <- as.matrix(data$y)
      X          <- as.matrix(data$X)
      n.T        <- nrow(y)
      n.X        <- ncol(X)
      ######################################################
      val        <- t(X%*%param)
      lambda     <- exp(val)
      dy         <- log.density.y(y,1:n.T)
      dy         <- sum(dy)

      if(on_site){
        Like.obs      <- log(y[2]) - val[2] + dy
      }else{
        Like.obs      <- dy
      }

      return(Like.obs)
    }

    log_like <- 0
    for (i in 1:nn.ind) {
```

```
        log_like <- log_like +  Like_i( mydata[[i]], param, on_site)
      }
      return(-log_like)
    }
    ###
    Like_i_M_MPLN <- function(rand, data, param, on_site){
      # Likelikood function of Mixed Poison Lognormal for each individual i
      y            <- as.matrix(data$y)
      X            <- as.matrix(data$X)
      n.T          <- nrow(y)
      n.X          <- ncol(X)
      rdraw        <- nrow(rand)
      ##################################################
      parameter_a      <- param[1:n.X]
      parameter_b      <- matrix(0,nrow = 3,ncol = 3)
      #matrix duplication
      parameter_b[1,1] <- exp(param[n.X+1])
      parameter_b[2,1] <- param[n.X+2]
      parameter_b[3,1] <- param[n.X+3]
      parameter_b[2,2] <- exp(param[n.X+4])
      parameter_b[3,2] <- param[n.X+5]
      parameter_b[3,3] <- exp(param[n.X+6])
      parameter_bb     <- tcrossprod(parameter_b)
      val_temp1        <- t(X%*%parameter_a)
      val_temp2        <- val_temp1[2] + 0.5*parameter_bb[2,2]
      val_temp3        <- matrix(rep(c(val_temp1),rdraw),byrow = TRUE, ncol=3 )  +
tcrossprod(rand,parameter_b)

      sdensity   <- sapply(1:rdraw, function(r){
        lambda       <- as.matrix(exp(val_temp3[r,]))
        dy           <- exp(sum(-lambda + y*log(lambda)-log(factorial(y))))/rdraw
        return(dy)
      })
      density.i <- sum(sdensity)
      Like.obs  <- ifelse(on_site,(y[2]/exp(val_temp2))*density.i,density.i)
      return(Like.obs)
    }
```

```
#
boot_fx <- function(i,mydata, mysim,param, on_site){
    # Allow defining individual loglikelihood using by function parLapply of package parallel
    log_like <- log(Like_i_M_MPLN(mysim[[i]], mydata[[i]], param, on_site))
    return(log_like)
}

#
log_like_M_MPLN <- function(param, mydata, mysim, on_site,
numscore,pseudo_draw,rdraw){
    # This function compute the minus data log_likelihood
    # Data is by parallelise using the  package paralell
    nn.ind    <- length(mydata)
    cl        <- makeCluster(numscore)     # set the number of processor cores
    setDefaultCluster(cl=cl) # set 'cl' as default cluster
    clusterExport(cl, varlist=c("Like_i_M_MPLN"))
    plog_like <- parLapply(cl,1:nn.ind,boot_fx,mydata, mysim, param, on_site)
    stopCluster(cl)
    log_like <- Reduce("+", plog_like)
    return(-log_like)
}
#
estim <- function(mydata , y , model, rdraw=100,pseudo_draw=FALSE,on_site=TRUE,
numscore=1){
    #Allow treatment of data, estimation of the model and tratment of results

    ######################################Scale the data using function
scale##################################
    hh                  <- levels(factor(mydata$id))
    nn.ind                <- length(hh)
    nn.obs                <- length(mydata$id)
    mydata$const              <- 1
    cols                <- model[-1]
    sd_cols               <- c(1,apply(mydata[cols], 2, function(x) sqrt(sum(x^2)/(nn.obs-1))))
    mean_cols               <- c(1,apply(mydata[cols],2,mean))
    mydata[cols]            <- scale(x=mydata[cols], center = FALSE, scale = TRUE)
```

```
#######################################Make data as a
list##################################################
mydata_list=NULL
for (i in 1:nn.ind) {
  yit        <- as.matrix(mydata[mydata[,"id"]==hh[i],y])
  xit        <- as.matrix(mydata[mydata[,"id"]==hh[i],model])
  mydata_list[[i]]=list(y=yit,
                        X=xit)
}
########################Simulation using Halton draws or pseudo random
draws################################
stride <- 1000
mysim_list     <- lapply(1:nn.ind, function(i){
  if(pseudo_draw){
    val      <- mvrnorm(n=rdraw, mu=rep(0,3), Sigma=diag(1,3))
  }else{
    x        <- rhalton(rdraw, 3 ,singleseed = i*stride)
    x        <- qnorm(x)
    val      <- x
  }
})
#####################################Definition of initial values of parameters
########################################
parm        <- rep(0,ncol(mydata_list[[1]]$X))
names(parm)   <- model
est_ind      <- optim(   par      = parm,
                         fn       = log_like_MPLN, gr = NULL,
                         mydata   = mydata_list,
                         on_site  = on_site,
                         method   = c("BFGS"),
                         hessian = T)
par_ind      <- est_ind$par
theta       <- c(theta_11=0,theta_12=0, theta_13=0, theta_22=0 , theta_23=0 ,
theta_33=0 )
init_param    <- c(par_ind,theta)
#######################################Minimization of minus data log-
likelihood using optim ########
```

```
est          <- optim(    par      = init_param,
                          fn       = log_like_M_MPLN, gr = NULL,
                          pseudo_draw    = FALSE,
                          rdraw=rdraw,
                          mydata   = mydata_list,
                          mysim    = mysim_list,
                          on_site  = on_site,
                          numscore = numscore,
                          method   = c("BFGS"),
                          hessian = T)
#################################### Treatment of
result##########################################
vcov_est                <- solve(est$hessian)
se                      <- sqrt(diag(vcov_est))
######################Ajustment of parameter by accounting for data
scale############################
se[1:length(model)]       <- se[1:length(model)]/sd_cols
parms                     <- est$par
parms[1:length(model)]    <- parms[1:length(model)]/sd_cols
t                         <- parms/se
pval                      <- 2*(1-pt(abs(t),nrow(data)- length(model) - 6+1))
results                   <- cbind(parms,se,t,pval)
colnames(results)         <- c("coef","se","t","pvalue")
rownames(results)         <- c(model,names(theta))
Likelihood                <- -est$value
AIC                       <- -2*Likelihood + 2*(length(model)+6)
# print(results,digits=3)
res_log_cholesky_parametrization <- results
############ Matrix omega ####################
omega             <- matrix(0,3,3)
omega[1,1]        <- exp(est$par[length(model)+1])
omega[2,1]        <- est$par[length(model)+2]
omega[3,1]        <- est$par[length(model)+3]
omega[2,2]        <- exp(est$par[length(model)+4])
omega[3,2]        <- est$par[length(model)+5]
omega[3,3]        <- exp(est$par[length(model)+6])
omega             <- tcrossprod(omega)
```

```
colnames(omega)    <- c("O2011", "O2012", "OC")
rownames(omega)    <- c("O2011", "O2012", "OC")
vech_omega         <- vech(omega)
############ Method of delta to compute the standard error of sigma
##################
vcov_theta         <-
vcov_est[(length(model)+1):(length(model)+6),(length(model)+1):(length(model)+6)]
f_a <- function(x){
   a <- exp(2*x[1])
}
f_b <- function(x) x[2]*exp(x[1])
f_c <- function(x) x[3]*exp(x[1])
f_d <- function(x) x[2]^2 + exp(2*x[4])
f_e <- function(x) x[2]*x[3] + x[5]*exp(x[4])
f_f <- function(x) x[3]^2 + x[5]^2 + exp(2*x[6])

d_a <- grad(f_a,x=est$par[(length(model)+1):(length(model)+6)])
d_b <- grad(f_b,x=est$par[(length(model)+1):(length(model)+6)])
d_c <- grad(f_c,x=est$par[(length(model)+1):(length(model)+6)])
d_d <- grad(f_d,x=est$par[(length(model)+1):(length(model)+6)])
d_e <- grad(f_e,x=est$par[(length(model)+1):(length(model)+6)])
d_f <- grad(f_f,x=est$par[(length(model)+1):(length(model)+6)])

se_omega <- function(d,v){
   ecart <- sqrt(t(d)%*%v%*%d)
   return(ecart)
}
ecart_omega    <- rep(0,6)
ecart_omega[1] <- se_omega(d_a,vcov_theta)
ecart_omega[2] <- se_omega(d_b,vcov_theta)
ecart_omega[3] <- se_omega(d_c,vcov_theta)
ecart_omega[4] <- se_omega(d_d,vcov_theta)
ecart_omega[5] <- se_omega(d_e,vcov_theta)
ecart_omega[6] <- se_omega(d_f,vcov_theta)
#####################################
parms[(length(model)+1):
        (length(model)+6)]  <- vech_omega
```

```
    se[(length(model)+1):
          (length(model)+6)]     <- ecart_omega
    t                      <- parms/se
    pval                     <- 2*(1-pt(abs(t),nrow(data)- length(model)- 6 +1))
    results                  <- cbind(parms,se,t,pval)
    colnames(results)        <- c("coef","se","t","pvalue")
    rownames(results)        <- c(model,
"omega_11","omega_21","omega_31","omega_22","omega_32","omega_33")
    ################################ Population Trips
################################
    lambda         <- 0
    for (i in 1:nn.ind) {
       X          <- as.matrix(mydata_list[[i]]$X)
       lambda      <- lambda + exp(X%*%as.matrix(est$par[1:length(model)]))/nn.ind
    }
    mean_trip_pop             <- lambda*exp(0.5*diag(omega))
    mean_trip_on_site          <- c(mean_trip_pop[1],1,mean_trip_pop[3])+
mean_trip_pop[2]*c(exp(omega[2,1])-1,exp(omega[2,2]),exp(omega[2,3])-1)
    colnames(lambda)           <- "Pop_Mean_Trips"
    rownames(lambda)           <- c("OB2011","OB2012", "CB")
    colnames(mean_trip_pop)    <- "Pop_Mean_Trips"
    rownames(mean_trip_pop)    <- c("OB2011","OB2012", "CB")

    return(list(res_log_cholesky_parametrization  =  res_log_cholesky_parametrization,
            res_omega                      =  results,
            loglikelihood                  =  Likelihood,
            lambda                         =  lambda,
            mean_trip_pop                  =   mean_trip_pop,
            mean_trip_on_site              =  mean_trip_on_site,
            AIC                            =  AIC))
  }
```

```
# Coded by Art B. Owen, Stanford University.
# April 2017
#
rhalton <- function(n,d,n0=0,d0=0,singleseed,seedvector){
  #
  # Randomly scrambled Halton sequence of n points in d dimensions.
  #
  # If you already have n0 old points, set n0 to get the next n points.
  # If you already have d0 old components, set d0 to get the next d inputs.
  # Get points n0 + 0:(n-1) in dimensions d0 + (1:d)
  #
  # seedvector = optional vector of d0+d random seeds, one per dimension
  # singleseed = optional scalar seed (has lower precedence than seedvector)
  # Handle input dimension correctness and corner cases
  if( min(n0,d0) < 0 )
    stop(paste("Starting indices (n0, d0) cannot be < 0, input had (",n0,",",d0,")"))
  if( min(n,d) < 0 )
    stop(paste("Cannot have negative n or d"))
  if( n==0 || d==0 ) # Odd corner cases: user wants n x 0 or 0 x d matrix.
    return(matrix(nrow=n,ncol=d))
  D <- nthprime(0,getlength=TRUE)
  if( d0+d > D )
    stop(paste("Implemented only for d <=",D))
  # Seed rules
  if( !missing(singleseed) && length(singleseed) != 1 )
    stop("singleseed, if supplied, must be scalar")
  if( !missing(seedvector) && length(seedvector) < d0+d )
    stop("seedvector, if supplied, must be have length at least d0+d")
  if( missing(seedvector) && !missing(singleseed) )
    seedvector <- singleseed + 1:(d0+d) - 1
  # Generate and return the points
  ans <- matrix(0,n,d)
  for( j in 1:d ){
    dimj <- d0+j
    if( !missing(seedvector) )set.seed(seedvector[dimj])
    ans[,j] <- randradinv( n0 + 0:(n-1), nthprime(dimj) ) # zero indexed rows
  }
```

```
    ans
}
randradinv <- function(ind,b=2){
    # Randomized radical inverse functions for indices in ind and for base b.
    # The calling routine should set the random seed if reproducibility is desired.
    if(any(ind!=round(ind)))
        stop("Indices have to be integral.")
    if(any(ind<0))
        stop("Indices cannot be negative.")
    if(!(is.vector(b) && length(b)==1 && b==floor(b) && b>1))
        stop("b must be a single integer >= 2")
    b2r <- 1/b
    ans <- ind*0
    res <- ind
    while( 1-b2r < 1 ){ # Assumes floating point comparisons, fixed precision.
        dig <- res %% b
        perm <- sample(b)-1
        pdig <- perm[1+dig]
        ans <- ans + pdig * b2r
        b2r <- b2r/b
        res <- (res - dig)/b
    }
    ans
}
nthprime <- function(n,getlength=FALSE){
    # Get the n'th prime, using a hard coded list (or get the length of that list).
    # First fifty-eight prime numbers from OEIS A000040, April 2017
    primes <- c( 2, 3, 5, 7, 11, 13, 17, 19, 23, 29,
                 31, 37, 41, 43, 47, 53, 59, 61, 67, 71,
                 73, 79, 83, 89, 97, 101, 103, 107, 109, 113,
                 127, 131, 137, 139, 149, 151, 157, 163, 167, 173,
                 179, 181, 191, 193, 197, 199, 211, 223, 227, 229,
                 233, 239, 241, 251, 257, 263, 269, 271)
    # First 1000 prime numbers from primes.utm.edu/lists/small/1000.txt, April 2017
    primes <- c(
        2, 3, 5, 7, 11, 13, 17, 19, 23, 29
        , 31, 37, 41, 43, 47, 53, 59, 61, 67, 71
```

, 73, 79, 83, 89, 97, 101, 103, 107, 109, 113
, 127, 131, 137, 139, 149, 151, 157, 163, 167, 173
, 179, 181, 191, 193, 197, 199, 211, 223, 227, 229
, 233, 239, 241, 251, 257, 263, 269, 271, 277, 281
, 283, 293, 307, 311, 313, 317, 331, 337, 347, 349
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, 419, 421, 431, 433, 439, 443, 449, 457, 461, 463
, 467, 479, 487, 491, 499, 503, 509, 521, 523, 541
, 547, 557, 563, 569, 571, 577, 587, 593, 599, 601
, 607, 613, 617, 619, 631, 641, 643, 647, 653, 659
, 661, 673, 677, 683, 691, 701, 709, 719, 727, 733
, 739, 743, 751, 757, 761, 769, 773, 787, 797, 809
, 811, 821, 823, 827, 829, 839, 853, 857, 859, 863
, 877, 881, 883, 887, 907, 911, 919, 929, 937, 941
, 947, 953, 967, 971, 977, 983, 991, 997, 1009, 1013
, 1019, 1021, 1031, 1033, 1039, 1049, 1051, 1061, 1063, 1069
, 1087, 1091, 1093, 1097, 1103, 1109, 1117, 1123, 1129, 1151
, 1153, 1163, 1171, 1181, 1187, 1193, 1201, 1213, 1217, 1223
, 1229, 1231, 1237, 1249, 1259, 1277, 1279, 1283, 1289, 1291
, 1297, 1301, 1303, 1307, 1319, 1321, 1327, 1361, 1367, 1373
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, 1453, 1459, 1471, 1481, 1483, 1487, 1489, 1493, 1499, 1511
, 1523, 1531, 1543, 1549, 1553, 1559, 1567, 1571, 1579, 1583
, 1597, 1601, 1607, 1609, 1613, 1619, 1621, 1627, 1637, 1657
, 1663, 1667, 1669, 1693, 1697, 1699, 1709, 1721, 1723, 1733
, 1741, 1747, 1753, 1759, 1777, 1783, 1787, 1789, 1801, 1811
, 1823, 1831, 1847, 1861, 1867, 1871, 1873, 1877, 1879, 1889
, 1901, 1907, 1913, 1931, 1933, 1949, 1951, 1973, 1979, 1987
, 1993, 1997, 1999, 2003, 2011, 2017, 2027, 2029, 2039, 2053
, 2063, 2069, 2081, 2083, 2087, 2089, 2099, 2111, 2113, 2129
, 2131, 2137, 2141, 2143, 2153, 2161, 2179, 2203, 2207, 2213
, 2221, 2237, 2239, 2243, 2251, 2267, 2269, 2273, 2281, 2287
, 2293, 2297, 2309, 2311, 2333, 2339, 2341, 2347, 2351, 2357
, 2371, 2377, 2381, 2383, 2389, 2393, 2399, 2411, 2417, 2423
, 2437, 2441, 2447, 2459, 2467, 2473, 2477, 2503, 2521, 2531
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, 2621, 2633, 2647, 2657, 2659, 2663, 2671, 2677, 2683, 2687

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, 3433, 3449, 3457, 3461, 3463, 3467, 3469, 3491, 3499, 3511
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, 4073, 4079, 4091, 4093, 4099, 4111, 4127, 4129, 4133, 4139
, 4153, 4157, 4159, 4177, 4201, 4211, 4217, 4219, 4229, 4231
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, 5099, 5101, 5107, 5113, 5119, 5147, 5153, 5167, 5171, 5179
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```
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      , 5861, 5867, 5869, 5879, 5881, 5897, 5903, 5923, 5927, 5939
      , 5953, 5981, 5987, 6007, 6011, 6029, 6037, 6043, 6047, 6053
      , 6067, 6073, 6079, 6089, 6091, 6101, 6113, 6121, 6131, 6133
      , 6143, 6151, 6163, 6173, 6197, 6199, 6203, 6211, 6217, 6221
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      , 6311, 6317, 6323, 6329, 6337, 6343, 6353, 6359, 6361, 6367
      , 6373, 6379, 6389, 6397, 6421, 6427, 6449, 6451, 6469, 6473
      , 6481, 6491, 6521, 6529, 6547, 6551, 6553, 6563, 6569, 6571
      , 6577, 6581, 6599, 6607, 6619, 6637, 6653, 6659, 6661, 6673
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      , 7649, 7669, 7673, 7681, 7687, 7691, 7699, 7703, 7717, 7723
      , 7727, 7741, 7753, 7757, 7759, 7789, 7793, 7817, 7823, 7829
      , 7841, 7853, 7867, 7873, 7877, 7879, 7883, 7901, 7907, 7919
   )
   p <- length(primes)
   if( getlength )
      return(p)
   if( any(n<1) )
      stop(paste(sep="","The n'th prime is only available for n >= 1, not n = ",min(n)))
   if( any(n>p) )
      stop(paste(sep="","The present list of primes has length ",p,
               ". It does not include the n'th one for n = ",max(n),"."))
   return(primes[n])
}
```

```
setwd("C:/Users/REE/Documents/Project/Multivariate_Poisson_Log_Normal_model/Paper_revision/on_site")
	source("fun_MPLN.R")
	library(OpenMx)
	library(parallel)
	library(stats)
	library(MASS)
	library(readxl)
	library(numDeriv)
	model_const		<- c("const")

	model_1_resident		<- c("const","t_cost",
"barceloneta","bogatell","sabanell","blanes","g_palamos","de_la_fosca",
				"RP", "OWF",
				"imp_swim","imp_nautical","men","age", "nb_size","h_income")
	model_2_resident		<- c("const","t_cost",
"barceloneta","bogatell","sabanell","blanes","g_palamos","de_la_fosca",
				"RP",
				"HF_B", "HN_B" , "LN_B" ,
				"imp_swim","imp_nautical","men","age", "nb_size","h_income")
	model_1_tourist		<- c("const","t_cost",
"barceloneta","bogatell","sabanell","blanes","g_palamos","de_la_fosca",
				"RP", "OWF",
				"local_tourist", "paid_accom",
				"imp_swim","imp_nautical","men","age", "nb_size","h_income")
	model_2_tourist		<- c("const","t_cost",
"barceloneta","bogatell","sabanell","blanes","g_palamos","de_la_fosca",
```

```
                    "RP",
                    "HF_B", "HN_B" , "LN_B" ,
                    "local_tourist", "paid_accom",
                    "imp_swim","imp_nautical","men","age", "nb_size","h_income")
y                   <- c("trips")

# Upload and treatment of data
#data               <- read_excel("ResidentsOwf.xlsx")
data                <- read_excel("TouristsOwf.xlsx")
mydata              <- data[order(data$id,data$time),]
res                 <- estim(mydata=mydata, y=y, model = model_1_tourist, rdraw =
1000, on_site=TRUE, pseudo_draw=FALSE, numscore=3)
```