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ARTICLE

Hazardous human–wildlife encounters, risk attitudes, and the value of shark nets for coastal recreation

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Abstract

Shark incidents are rare and graphic events, and their consequences can influence the behavior of beach users, including bathers, to a great extent. These incidents can be thought of as a fearsome risk that may lead decision makers to overreact or respond with inaction. This paper examines the reaction of recreational beach users, including bathers, to changes in the risk of shark incidents. In addition to valuing recreational visits to Durban Beach, South Africa, we study the reaction of beach visitors to a hypothetical scenario in which protective shark nets, deployed in coastal waters to protect bathers, are to be removed. To examine potential heterogeneity of the treatment effect in a travel cost-contingent behavior model, we develop a semiparametric multivariate Poisson lognormal (MPLN) model to jointly analyze observed and stated visit counts. Results show that removing protective shark nets at Durban beach would decrease recreational visits by more than 20%. Applying the semiparametric MPLN model we further find that both the value of a recreational visit and the predicted change in visitation rates vary as a function of whether recreationists usually enter the water, whether they have heard of previous shark incidents, and their general risk attitude.

KEYWORDS

beach recreation, contingent behavior, natural hazards, risk attitudes, shark incidents, travel cost

JEL CLASSIFICATION

Q26, Q51, Q56

1 | INTRODUCTION

Coastal recreation such as beach visits and bathing activities is an important source of tourism revenue and human wellbeing (Ghermandi & Nunes, 2013; MacKerron & Mourato, 2013). Using beaches for recreation, including physical and social activities, is highly valued, and different consequences of recreational beach use, such as economic development (Ghermandi & Nunes, 2013) and individual health benefits (Elliott et al., 2018), have been examined. However, beaches and coastal waters are a type of natural environment that also entail risks in the form of environmental hazards, such as rip currents, lightning, high winds, pollution, or encounters with potentially dangerous marine fauna. The latter category includes jellyfish or sea urchin stings and encounters with marine megafauna like sharks. Oftentimes, the institutions in charge of popular beaches and adjacent coastal waters provide protective services to reduce the chances of shark incidents and thereby protect bathers. In the case of sharks, such protection includes the use of shark spotters or shark-safety gears, such as large mesh-size gillnets or baited drumlines, deployed to minimize the likelihood of human–shark encounters (Dudley, 1997; Engelbrecht et al., 2017; Gibbs et al., 2020; Tate et al., 2021).

Shark incidents[1] are very rare but graphic events, more easily envisioned than actually witnessed. An average of approximately 75–100 shark incidents world wide are reported annually, of which only 1.3%–6% are fatal, whereas the rest are nonfatal ranging from minor lacerations to severe injuries (Midway et al., 2019). Yet, thanks to global research interest, documentary and fictional films and media coverage, these events are easy to understand and envisage by beach users. It has also been shown that shark-related media coverage often stresses the risk of these animals to people (Muter et al., 2013; Sabatier & Huveneers, 2018). Consequently, human–shark interactions evoke strong emotional reactions, such as fear, panic, and horror as often sensationalized in fictional films and media reporting. As such, the risk of being involved in a shark incident when recreating at a beach or other coastline (either actively in the water or passively as a bystander on land) constitutes what Sunstein and Zeckhauser (2011) term a *fearsome risk*. This type of risk may lead individuals to either overreact or push them toward inaction due to probability neglect, a cognitive bias by which individuals fail to adequately assess the low probability of the actual hazard occurring. The result of such probability neglect is a change of behavior either too drastic or insufficient in relation to the expected damage caused by the hazard. Translated to the case of recreational use of the coastal environment, this would mean that in the presence of a sudden increase in the probability of a fearsome hazard, such as a shark incident, individuals can be expected to either overly curtail or leave unchanged the number of recreational visits they make to that location.

The present paper examines the reaction of recreational users of the coastal environment to changes in the risk of shark incidents. We apply the travel cost-contingent behavior (TC-CB) method to study the impact of a change in the protection against shark incidents in coastal waters on recreational visits to a beach in Durban, South Africa. Specifically, we study the reaction of visit behavior to a hypothetical scenario in which protective shark nets, deployed in coastal waters to protect beach recreationists, are to be removed. Protective nets in coastal waters are a potentially lethal form of shark hazard mitigation strategy, the aim of which is localized fishing of potentially dangerous sharks in the vicinity of bathing areas (Gibbs et al., 2020). For the case of Durban (and other beaches off the coastline of KwaZulu-Natal Province), a shark control program involving net deployment has been in place since 1952 after a series of fatal shark incidents in the late 1940s and early 1950s. No fatal shark incidents have been recorded in KwaZulu-Natal since that time. However, this long-running program has been criticized in South Africa as having negative ecological consequences.[2] The use of gillnets as protective gear in the nearshore environment may lead to an increase

[1]We refer to any kind of human–shark encounter as shark incident. This includes what may commonly be referred to as "shark attack." However, because the term "attack" suggests intent to harm on the part of the animal, which may not always be warranted, we prefer the more neutral term "incident."

[2]There is also criticism of similar, long-running shark net programs in Australia (Gibbs et al., 2020) and Brazil (Hazin et al., 2013).

in shark mortality but also the incidental catch (and resulting death) of nontargeted marine species, such as dolphins, turtles, and rays (Dudley & Cliff, 1993, 2010; Reid et al., 2011; Hazin et al., 2013).

So in a situation where (ecological and economic) costs of shark control measures, and the deployment of protective nets in particular, are emphasized in the public debate, the natural consequence is to wonder about the extent of the benefits of this protection program. The present study therefore sought to assess (one aspect of) the social benefit of the presence of shark nets in coastal waters around the city of Durban: the contribution that shark nets make to the recreational value of beaches.

The TC-CB method has been used to assess the value of recreational nature visits and predict changes in visitation rates (and the associated recreational value) resulting from changes in site conditions (Parsons, 2017). A big and growing literature has sought to assess the value of, for instance, recreational visits to beaches (Bell & Leeworthy, 1990; Pascoe, 2019; Zhang et al., 2015) and other coastal locations (Czajkowski et al., 2015) as well as other activities, such as recreational diving (Du Preez et al., 2012; Zimmerhackel et al., 2018), whale and marine species watching (Farr et al., 2014; Loomis et al., 2000), or shark diving in marine waters (Pasos-Acuña et al., 2020). Whereas such applications of the travel cost method value recreation at the site under current conditions, the contingent behavior method is employed to assess changes in recreational values of outdoor locations when conditions at the site in question change. Looking specifically at beaches, researchers have studied the effect on recreational demand from changes in, for instance, beach width (Parsons et al., 2013), water quality (Bertram et al., 2020; Hanley et al., 2003), the occurrence of shark sightings (Zemah Shamir et al., 2019), the construction of a coastal path (Hynes & Greene, 2013), or an offshore windfarm (Parsons et al., 2020; Voltaire & Koutchade, 2020). The present study contributes to this literature on beach recreation valuation by exploring the impact of natural hazards, namely the risk of shark incidents, controlled by protective submerged nets, at Durban beachfront. The majority of valuation studies emphasize the benefit-generating characteristics of outdoor environments and recreational activities (including wildlife watching or other types of interaction) at these sites without acknowledging the risk to site users from possible hazardous wildlife encounters in certain locations. There is only a limited literature assessing recreational values of outdoor environments in the face of on-site environmental hazards examining effect of fire risk (Hesseln et al., 2003; Nobel et al., 2020; Starbuck et al., 2006), health emergencies (Landry et al., 2021), and oil spills (Egan et al., 2022; English et al., 2018; Lopes & Whitehead, 2023) and harmful algal blooms (Boudreaux et al., 2023). We are not aware of any study considering hazards from human–wildlife interactions.

Although the policy context of removing shark nets is provided by the concerns about shark and other marine wildlife mortality, the focus of this study is the response of the individual beach users to changes in on-site risk. From a behavioral perspective, reactions to changes in the risk of a shark incident may be moderated by certain factors that have a bearing on the occurrence of probability neglect (Sunstein & Zeckhauser, 2011). Therefore, the analysis examines the role of recreational activity (whether visitors enter the water), information on previous shark incidents and general risk attitudes using a semiparametric econometric framework to fit count data models used for TC-CB data collected on site. Semiparametric models allow for the estimation of smooth functions of parameter estimates (Fan et al., 1995; Racine, 2007; Racine & Li, 2004). In conjunction with the type of count data modeling used in TC-CB studies, these models make possible the exploration of systematic heterogeneity of visit predictions (including changes in visitation rates) and recreational values. The only study we are aware of and that employs this approach is Liu and Egan (2019), who adopt the use of a semiparametric approach to TC-CB data in an application to value visits to a lake in Ohio. These authors estimate smooth coefficient functions in a multivariate Poisson lognormal (MPLN) model (Egan & Herriges, 2006). Their model produces respondent-specific estimates of, for instance, the travel cost parameter as a function of a set of sociodemographic variables. It is possible to then plot variations in the value of a lake visit as a function of any of these sociodemographic variables without having to assume a functional form *ex ante*. Beyond that, the use of semiparametric estimation in environmental valuation is still quite limited, despite the approach's appeal in exploring observed heterogeneity of estimates. Dekker et al. (2014) use semiparametric estimation of the multinomial logit model in a study of preference formation in the context of the management of flood risks. Similar applications in the field of travel time valuation include Fosgerau (2007) and Koster and Koster (2015).

Specifically in the present study, we use the semiparametric MPLN model to obtain distributions of estimates in a count data model as functions of the three variables of interest (whether respondents enter the water, whether they have heard of previous shark incidents, and their risk attitude). This demonstrates how nonlinear effects and multi-part interaction effects of certain variables on recreational values and predictions of changes in visit counts can be detected in the data. As such, the present study differs from the approach in Liu and Egan (2019) in that we include a set of standard (i.e., sociodemographic) demand shifters directly in the count data equation and model these as a function of three variables specific to the behavioral research question of this study. Results show that removing protective shark nets at Durban beach would decrease recreational visits by more than 20% on average. Applying the semiparametric MPLN model to explore systematic variation of this average treatment effect, we further find limited variation of both the value of a recreational visit and the predicted reaction in visitation rates as a function of whether recreationists usually enter the water, whether they have heard of previous incidents, and of their general risk attitude.

The remainder of the paper is structured as follows. Section 2 reviews the literature on shark protection and human reactions of environmental hazards. Section 3 introduces the methods and data before Section 4 presents the results. Section 5 provides some discussion and concludes.

2 | SHARKS, SHARK INCIDENCES, AND REACTIONS TO ENVIRONMENTAL HAZARDS

Human–shark interactions are naturally low-probability, high-consequences incidents. Although the likelihood of such in situ interactions is very low, their consequences do not only include fatalities or heavy injuries but also economic impacts such as reductions of tourism revenues (Midway et al., 2019). Such economic effects may even be more devastating in developing countries and tourist destination islands such as the Bahamas, Seychelles, Reunion, and South Africa (Chapman & McPhee, 2016). In South Africa, Durban beachfront became a focal point for shark attacks between 1942 and 1951 when a series of 21 shark incidents (7 fatal) sparked public fear and threatened economic collapse in tourism revenue (Dudley et al., 2010). Subsequently, in 1952 the city authorities officially decided to adopt a system that by then had proved effective in Australia since 1937 to safeguard bathers through deployment of the large mesh-size gillnets and drumlines (Dudley, 1997; Reid et al., 2011). The latter have baited hooks attached to a line vertically suspended from a floating device (formerly a drum). At the time of study, approximately 5.2 km of sandy beaches in Durban were protected with 17 nets, and no serious shark incident had been reported at this beach since 1964, attesting to the success of this shark-control program in curtailing human–shark incidents (Cliff, 1991; Dudley et al., 2010).

Although shark nets (and drumlines when deployed) do not provide full protection against shark encounters, they still minimize the likelihood of human–shark interaction in the water (Cliff & Dudley, 2011; Dudley et al., 2010). Nevertheless, this type of environmental risk is also influenced by other contextual factors. The likelihood of a human–shark encounter is naturally higher in the presence of large crowds of bathers, for instance during festive seasons when there are hundreds of bathers in the water at any given time. Furthermore, ongoing global climate change,[3] increasing

[3]Chapman and MacPhee (2016) review the literature on factors contributing to the occurrence of shark incidents. They state that climate variability affects a number of determinants of the presence of sharks, such as ocean circulation patterns, turbidity, and availability and distribution of nutrients and prey.

human population and the type of water-based recreational activities could possibly exacerbate future risks of human–shark incidents (Bradshaw et al., 2021; McPhee, 2014). Therefore, the likelihood or repetition of similar historical shark incidents coupled with subsequent economic impact on beach tourism at Durban and adjacent popular swimming beaches cannot be completely ruled out despite the effectiveness of shark nets. Yet so far, although the incidence of human–shark encounters has been rising globally, the number of incidents in South Africa buck this trend (Chapman & McPhee, 2016).

When shark incidents do happen, provoked or unprovoked, they typically receive strong media attention and specific coverage. For instance, Reid and Medvecky (2021) find for the case of New Zealand that media reporting about sharks uses more emotive terms than descriptive terms. Neff (2015) studies how narratives supported by fictional films (in particular the 1975 film *Jaws*) shape policies of shark management in Australia. One aspect is the emphasis on the purported intention of sharks to kill. All this points toward the idea that, against the backdrop of the social construct of "shark attacks," information on shark incidents leads individuals to overreact to the chances of such an event. This conforms to the availability heuristic (Tversky & Kahneman, 1973) that may lead to probability neglect, a decision bias explaining stark changes in thought and behavior, which are not justified by the small to modest changes in statistical risk that cause them (Sunstein & Zeckhauser, 2011). For the case of beach visits, a drastic reduction in site visits could potentially reduce welfare derived from recreation more than the increase in welfare due to safety by keeping away from the beach. Such beach visitors would "give up too much to avoid the risk" (Sunstein & Zeckhauser, 2011, p. 436). If public information on previous shark incidents invokes this type of decision bias, a very pronounced reaction in terms of reductions of beach visits can be expected. However, actual shark incidents may not always have negative effects on the public perception of shark populations. Neff and Yang (2013) find that self-reported pride in local shark populations among visitors to a beach in Cape Town, South Africa, did not change after an actual shark incident at that location. Consequently, we do not form any specific expectation of how the knowledge of a previous shark incidence, as an indicator of the cognitive availability of such information, will affect the change in beach visits resulting from the change in the risk of a shark encounter.

In terms of responding to an increase in the likelihood of a shark incident, the individual's attitude toward accepting and taking risks may play a role for any behavioral reaction. Risk attitudes have traditionally been used to classify decision makers as risk loving, risk neutral or risk averse. With respect to the specific application in this study, the expectation is that reductions in visit frequency following a removal of protective shark nets are less pronounced for less risk averse beach users. In other words, we expect that beach recreationists who are (extremely) risk averse will adjust their beach visits the most, whereas risk-loving individuals may not alter their beach use (very much) when shark nets are removed. Empirically, risk attitudes have been assessed by means of incentivized lotteries (Holt & Laury, 2002), whereas other researchers have employed self-stated survey items. The latter have been shown to capture interindividual differences in risk attitudes and thereby be a behaviorally valid way to assess individual risk attitudes (Dohmen et al., 2011). Building on this research, the present study employs a self-stated measure of the willingness to take risks incorporated in a TC-CB questionnaire.

Finally, beach visitors outside of the water are naturally not directly at risk of encounters with sharks, so the protective function of shark nets plays a role merely for those who go into the water. Yet even respondents who do not enter the water may be affected by the higher chances of a shark incident because witnessing such an event as a bystander may be quite gruesome. However, this impact may be smaller than the one on swimmers and people who usually enter the water. We therefore expect that, ceteris paribus, respondents who usually enter the water reduce their visits more when shark nets are removed than those who frequent the beach but stay on land.

The effect (and interplay) of these three aspects, the availability of information on previous shark incidents, individual risk attitude, and beach use on the valuation and predicted changes of beach visits will be assessed in a semiparametric MPLN model. The model as well as the variables to operationalize these three aspects are introduced in Sections 3.2 and 3.3.

3 | METHODS AND DATA

3.1 | Contingent behavior scenario

The individual travel cost method collects data on the number of recreational visits of users of an environmental resource and their respective travel costs. It is then possible to estimate a demand curve for recreational visits and infer the value of such a visit (Ward & Beal, 2000). The contingent behavior method augments the simple travel cost analysis by showing respondents one (or more) scenarios of changing conditions at the site and asking them how often they would visit the site under these circumstances (Englin & Cameron, 1996). This allows for predictions of changes in site visitation and consequently the effects on the value of recreational visits.

The scenario to assess contingent behavior in the present study involved a removal of the protective shark nets positioned in the coastal waters. These nets and their function were introduced toward the end of the first part of the questionnaire (Figure 1). The scenario specified that approximately 40 sharks are caught in these nets per year. However, no further information was given to respondents as to what happens to these animals. Nor did the scenario allude to concerns about the potentially detrimental impact of nets on shark populations because the aim of the survey was to elicit the reaction of beach visits only to an increase in the probability of a shark incident separately from any ecological concerns. The scenario exposition was followed by a few questions as to whether respondents had heard of the presence of the nets or any historical shark incidents, and how they would rate the importance of the nets. Subsequently, they were asked: "Now suppose it was decided to remove the shark nets and leave the beaches unprotected, how would this affect the number of visits you make to the beach in the next 3 months?" Follow-up questions asked exactly how many visits respondents would take under these circumstances. Using these responses, two visit counts per respondents are recorded; one concerning the previous 3 months with the nets present and a second for the subsequent 3 months without the protective nets in place.

Durban has the longest history of netting than any other beach along the KwaZulu-Natal coastline. The net installations at Durban beaches first started in 1952 after a series of 21 shark attacks (seven fatal) between 1943 and 1951, and this had a devastating impact on beach tourism in the city. The shark nets are deployed approximately 400 m offshore, and each net is approximately 300 m long and 6 m deep. To date, Durban is the most netted beach with 17 nets of approximately 5.2 km length from the uShaka Marine World to the end of Umgeni River mouth. On average, these nets catch about 40 sharks per year, including all three species of most dangerous sharks: great white, tiger, and Zambezi.

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FIGURE 1 Introduction of shark nets in the questionnaire.

3.2 | A semiparametric MPLN model

In the following we introduce the multivariate Poisson lognormal (MPLN) model (Egan & Herriges, 2006). Respondents to our survey report beach visit counts in the past 3 months and state how often they would visit the beach in the subsequent 3 months if protective shark nets were to be removed. To accommodate seasonal effects, sampling took place at different times throughout the year.[4] Past TC-CB studies have employed fixed (Englin & Cameron, 1996) and random effects Poisson and negative binomial models (Bertram et al., 2020) to accommodate the quasipanel structure of these data. However, these single-equation models do not allow for a correction of on-site sampling, whereby the past visit count is subject to zero truncation and endogenous stratification, but the future (hypothetical) counts may well include zero. These can only be incorporated in multivariate models, which operate with correlated equations, such as the MPLN model or the seemingly unrelated negative binomial (SUNB) model (Egan & Herriges, 2006), which hark back to the correction for univariate count data models in Shaw (1988).[5,6]

We consider respondent i who reports on J visits to a recreational site, $\boldsymbol{y}_i = \left[y_{i1}, y_{i2}, \ldots, y_{iJ}\right]$. $j = 1, 2, \ldots, J$ indicates the scenario, with $j = 1$ typically denoting the observed number of (past) visits and $j = 2, \ldots, J$ indicating (future) contingent behavior visits. Because the number of visits to a site is a non-negative integer, an appropriate distribution, such as the Poisson distribution is applied whereby the probability of respondent i to report y_{ij} visits in scenario j is

$$\Pr\left(Y = y_{ij} | \lambda_{ij}\right) = \frac{e^{-\lambda_{ij}} \lambda_{ij}^{y_{ij}}}{y_{ij}!}, \quad j = 1, 2, \ldots, J \tag{1}$$

The expected number of visits by respondent i in scenario j, λ_{ij}, can be parameterized as a function of respondent and site characteristics: $\lambda_{ij} = \exp\left(\phi_j + \boldsymbol{\beta}_j \boldsymbol{x}_{ij} + \varepsilon_{ij}\right)$. $\boldsymbol{x}_{ij}$ is a vector of respondent-specific variables, and $\boldsymbol{\beta}_j$ is a conforming parameter vector to be estimated alongside a set of scenario-specific constants, ϕ_j. Correlation between visit counts reported by the same individual is captured by means of a scenario-specific error term ε_{ij} following a multivariate normal distribution with mean zero, that is, $\varepsilon_{ij} \sim \mathrm{N}(0, \Sigma)$. With $J = 2$ equations in the present application, whereby $j = 1$ denotes the observed visit counts and $j = 2$ the contingent counts, the elements of the variance–covariance matrix Σ are given by

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}. \tag{2}$$

The joint probability of a series of J trip counts $\boldsymbol{y}_i$ is

$$\Pr\left(\boldsymbol{y}_i | \lambda_i\right) = \prod\nolimits_{j=1}^{J} \Pr\left(Y = y_{ij} | \lambda_{ij}\right) = \int\int \ldots \int \prod\nolimits_{j=1}^{J} \frac{e^{-\lambda_{ij}} \lambda_{ij}^{y_{ij}}}{y_{ij}!} \frac{\exp\left(-0.5 \boldsymbol{\varepsilon}'_i \Sigma^{-1} \boldsymbol{\varepsilon}_i\right)}{\sqrt{(2\pi)^J |\Sigma|}} d\varepsilon, \tag{3}$$

[4]On-site interviewing in Wave 1 took place in December 2018 and January 2019 to cover the midsummer festive season around Christmas and New Year. Wave 2 extended from August to November 2019, covering winter, spring and early summer.

[5]Among the few applications of the MPLN model in the recreation valuation literature are Awondo et al. (2011), Voltaire and Koutchade (2020), and Börger et al., (2021).

[6]Alternative approaches are the multivariate Poisson Gamma (Beaumais & Appéré, 2010) and the generalized negative binomial discrete factor model (Landry & Liu, 2009; Nobel et al., 2020).

where $\boldsymbol{\varepsilon}_i = [\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{iJ}]$. The estimation of ϕ_j and $\boldsymbol{\beta}_j$ is possible by means of simulated maximum likelihood because the J-dimensional integral in (3) does not have a closed-form solution. Throughout the analysis, modified Latin hypercube sampling with 1000 random draws per individual is used to simulate the likelihood.

Because travel cost surveys are typically conducted on site and therefore systematically exclude nonvisitors (referred to as zero truncation), whereas oversampling site users with an increasing number of visits (referred to as endogenous stratification or size-based sampling), past research has proposed solutions to correct for the ensuing bias. For the univariate case and the Poisson distribution, Shaw (1988) showed that both zero truncation and endogenous stratification resulting from on-site data collection can be corrected by specifying $\Pr\left(Y = y_{ij} | \lambda_{ij}\right) = \frac{e^{-\lambda_{ij}} \lambda_{ij}^{y_{ij}-1}}{\left(y_{ij}-1\right)!}$, so simply replacing y_{ij} by $y_{ij} - 1$. For the multivariate case, Egan and Herriges (2006) argue that the bias introduced by on-site sampling applies directly to the observed visit counts (i.e. $j = 1$) and only *incidentally* to all stated frequencies (i.e. for $j = 2, \ldots, J$). They propose weighting the joint probability of $\boldsymbol{y}_i$ of J observed and stated visit counts in (3) as follows to correct for both endogenous stratification *and* zero-truncation of observed visit counts.

$$\Pr\left(\boldsymbol{y}_i | \lambda_i\right) = \frac{\tilde{y}_{i1}}{E\left(y_{i1} | \boldsymbol{x}_i\right)} \int\int \cdots \int \prod_{j=1}^{J} \frac{e^{-\lambda_{ij}} \lambda_{ij}^{y_{ij}}}{y_{ij}!} \frac{\exp\left(-0.5 \boldsymbol{\varepsilon}'_i \Sigma^{-1} \boldsymbol{\varepsilon}_i\right)}{\sqrt{(2\pi)^J |\Sigma|}} d\varepsilon, \tag{4}$$

where $\tilde{y}_{i1}$ is the observed trip count as recorded on site, that is the zero-truncated form of the underlying y_{i1}, which includes $y_{i1} = 0$.

In the above model, it is assumed that, although this is generally possible, the effects of $\boldsymbol{x}_i$ on $\Pr\left(\boldsymbol{y}_i | \lambda_i\right)$ do not vary across scenarios, that is, $\boldsymbol{\beta}_j = \boldsymbol{\beta}\ \forall j = 1, \ldots, J$ (following e.g. Voltaire & Koutchade, 2020). This is justified because both observed past and stated future visit counts are assessed at the same time during the on-site survey. It is also unlikely that sociodemographic characteristics, such as age, gender, and income change during the reporting period. However, the models do estimate separate constants ϕ_j for each scenario.

Travel cost is one of the elements of $\boldsymbol{x}_{ij}$, so the cost coefficient β_c is one of the elements of $\boldsymbol{\beta}$. Due to the semilog specification of the expected trip count λ_{ij} the consumer surplus of an average visit is $-\beta_c^{-1}$. Confidence intervals can be computed by means of simulation (Krinsky & Robb, 1986).

To explore the potential effect of risk perceptions and other visit-related variables on beach visit valuation and predicted changes in visit counts following shark net removal we employ a semiparametric version of the MPLN model. In this specification, each element of the parameter vector $\boldsymbol{\beta}$ is a function of another set of respondent-specific variables $\boldsymbol{z}$ (which are different from those in $\boldsymbol{x}$) as in

$$\boldsymbol{\beta} = \boldsymbol{\beta}(\boldsymbol{z}). \tag{5}$$

This model allows the elements of $\boldsymbol{\beta}$ to vary around the respective estimates in the parametric model in (4) without having to specify the functional form of $\boldsymbol{\beta}(\cdot)$. This is achieved by estimating a set of local likelihood models in which respondents are weighted according to a multidimensional kernel density function. This specification of the model is in the spirit of the semiparametric MPLN model suggested by Liu and Egan (2019). The kernel density function, however, is specified more explicitly following Racine and Li (2004) and Fröhlich (2006), and in applications by Dekker et al. (2014) and Koster and Koster (2015). The degree of smoothing of the function $\boldsymbol{\beta}(\cdot)$ is controlled by a vector of bandwidth parameters $\boldsymbol{\delta}$ the elements of which enter the kernel density function $w_{\bar{i}}(\boldsymbol{z}; \boldsymbol{\delta})$ as follows

$$w_{\bar{i}}(\boldsymbol{z};\boldsymbol{\delta}) = \prod_{q=q_1}^{q_2} \delta_{\text{ind}}^{\left|Z_{\bar{i},q}-z_q\right|} \prod_{q=q_2+1}^{Q} \delta_{\text{dum}}^{1\left(Z_{\bar{i},q} \neq z_q\right)}. \tag{6}$$

$Z_{\bar{i},q}$ and z_q are the qth element of $\boldsymbol{Z}_{\bar{i}}$, a matrix of all possible combinations of values of the elements of $\boldsymbol{z}$, and the qth element of $\boldsymbol{z}$ itself, respectively. $1(\cdot)$ is the indicator function, which is equal to 1 if $Z_{q,\bar{i}} \neq z_q$ and 0 otherwise. The kernel weights in (6) reflect the multidimensional distance of an individual from a reference individual $\bar{i}$ according to Q characteristics (the elements of $\boldsymbol{z}$). $\boldsymbol{z}$ may contain q_2 indicator variables (i.e., continuous or discrete with natural ordering) and $Q-q_2$ dummy (i.e., binary) variables. Fröhlich (2006) suggests using potentially different bandwidth parameters for each category of indicator variables and to employ a cross-validation approach to identify the best set of parameters.[7] As a result, the present study employs $\delta_{\text{dum}} = 0.7$ for the dummy variables and $\delta_{\text{ind}} = 0.5$ for the indicator variable in $\boldsymbol{z}$.

The local log-likelihood function is weighted by a kernel density weight $w_{\bar{i}}(\boldsymbol{z};\boldsymbol{\delta})$

$$LL_{\bar{i}} = \sum_{i=1}^{N} w_{\bar{i}}(\boldsymbol{z};\boldsymbol{\delta}) \log\left(\Pr\left(\boldsymbol{y}_i | \lambda_i\right)\right). \tag{7}$$

The number of local models is equal to the number of elements in $\boldsymbol{Z}_{\bar{i}}$. This produces a set of estimates of $\boldsymbol{\phi}_j$ and $\boldsymbol{\beta}_j$ for each possible combination of values of the elements of $\boldsymbol{z}$. As elements of $\boldsymbol{z}$ we employ the three variables expected to affect the valuation of a beach visit and, importantly, the change in beach visits after a removal of protective shark nets as discussed in Section 2. Although these variables may exert these effects independently, it is likely that they exhibit important interaction effects. For this reason, they are used as indicator variables in the semiparametric MPLN model. The dummy variable *usually. enter* captures whether a respondent usually goes into the water when visiting the beach. This variable indicates the direct exposure to a potential human–shark encounter. The dummy variable *heard* indicates whether a respondent has ever heard of a shark incident at Durban beach. This variable serves as an indicator of whether details of a human–shark encounter may be present in a respondent's mind, whether there is a chance that there is a vivid picture of such an event. Finally, the self-stated risk attitude (*risk*) captures the extent to which respondents are willing to take risks in a general context (Dohmen et al., 2011).

3.3 | Data collection and variable specification

The data were collected in an in-person survey on the beachfront in Durban,[8] South Africa in two waves, between December 2018 and January 2019, and August and November 2019 to capture seasonal variation in beach use. Visitors to the beach were approached randomly and interviewed by a group of trained enumerators from the KwaZulu-Natal Sharks Board. Two types of respondents were encountered: (1) respondents who visit the beach on a one-day trip; (2) respondents who go to the beach as part of a multiday holiday. A sample of $n = 400$ responses was collected. For the present analysis, only 1-day visitors are retained in the dataset ($n = 220$). Removing further cases for

[7]The cross-validation mechanism applied here follows Sipotpongstorn et al. (2021). For a specific set of bandwith parameters, all local models are estimated, each based on all but the respondents in the respective cell (cf. Figure 2), that is, except the respondents who match the reference respondent of the respective local model. We then use the estimated parameters to compute the sum of the individual log-likelihood contributions of only those respondents in the respective cell, and sum this over all local models. This is an indicator of how well the parameters estimated based on the (weighted) information of respondents *outside* of that cell explain the data of respondents *in* that cell. This procedure is repeated for different sets of bandwidth parameters and the set that produces the best log-likelihood is selected.

[8]This included the following stretches of beach: uShaka, Addington, South Beach, Wedge Beach, North Beach, Bay Beach, and Battery Beach.

TABLE 1 Sample characteristics.

Variable	Description	Mean	Std. dev.	Min.	Max.
travel. cost	Round-trip cost in USD incl. time cost	9.39	24.61	0.01	148.39
second. wave	Survey wave (1 - Jul-Nov19, 0 - Dec18-Jan19)	0.49	0.50	0.00	1.00
male	Respondent gender (1 - male, 0 - female)	0.56	0.50	0.00	1.00
age	Age in years/10	3.57	1.34	1.80	8.30
black. african	Respondent ethnicity (1 - black African, 0 - other)	0.63	0.48	0.00	1.00
ln.hh.income	log of household income in ZAR	1.60	1.31	0.00	3.69
info. substitute	Respondent provided information on substitute site (1 - Yes, 0 - No)	0.42	0.50	0.00	1.00
usually. enter	Respondent usually enters the water (1 - Yes, 0 - No)	0.68	0.47	0.00	1.00
heard	Respondent has heard of a shark incident in the past (1 - Yes, 0 - No)	0.24	0.43	0.00	1.00
risk	Risk attitude, assessed on a scale from 0 to 10	4.64	3.50	0.00	10.00

Note: $n = 176$. Upper section of the table shows elements of $\boldsymbol{x}$, the lower section shows elements of $\boldsymbol{z}$. Travel costs are converted using an exchange rate of ZAR14.43/USD.

which travel distance could not be calculated or which had other missing values for visit frequency resulted in a dataset of $n = 176$ respondents for analysis.

For 1-day trip respondents the distance between their stated home address and the beach and vehicle-specific travel time was extracted from Google Maps. Travel cost was calculated contingent on travel mode. For private and hired vehicles travel, a per-km running cost of ZAR 1.767 (USD 0.12) for a mid-value car was used and divided by the reported number of passengers in the vehicle. This figure from the South African Revenue Service (RSA, 2018) includes fuel and maintenance costs. For trips undertaken by public transport, publicly available return fares from the respective locations were used. The opportunity cost of travel was calculated as 1/3 of the individual-specific hourly income (assuming 2200 annual work hours) multiplied with the round-trip travel time specific to the travel mode (motorized or walking). Average round-trip travel cost was at USD 9.39 (ZAR 135.50), yet there is substantial variation (Table 1).[9]

Notably among the sample characteristics, 68% of respondents state they usually enter the water in some form when visiting the beach (*usually. enter*). Respondents were also asked about details of the next best alternative beach to visit. As this set of variables (name of the beach and distance from home) had numerous missing values, a dummy variable was created indicating if a respondent provided any information on a substitute beach or not (*info.substitute*). This variable is used as an indicator for whether a substitute site was available from the perspective of the respondent. For 42% of respondents this was the case.

Risk attitude (*risk*) was assessed on an 11-point scale as the respondent's willingness to take risks in a general context: "How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks.'" The response scale ranged from 0 = not at all to 10 = very. This follows state of the art assessment of risk attitudes (Dohmen et al., 2011). These authors also show that such stated risk questions are behaviorally valid

[9]Because the beach under study is directly adjacent to Durban city center, travel cost for some respondents was as low as USD 0.01. These are individuals who only live a few meters away from the site and access it on foot.

TABLE 2 Descriptive statistics of visit counts.

Metric	N	Mean	Std. dev.	95% Conf. int.
Visits (observed)	176	10.02	17.78	[7.65–12.95]
Visits (stated)	176	8.59	17.52	[6.10–11.45]
Share (No change)	176	0.39	0.49	[0.32–0.47]
Share (Change)	176	0.61	0.49	[0.53–0.68]

Note: Confidence intervals are simulated by taking 1000 draws with replacement from the empirical trip frequency distribution and reporting the 2.5th and 97.5th percentiles of these draws.

TABLE 3 Baseline multivariate Poisson lognormal (MPLN) model.

	MPLN model	
Metric	**Coeff.**	**s.e.**
constant	0.610***	(0.187)
const_CB	−0.445***	(0.096)
travel.cost	−0.237***	(0.050)
second.wave	−0.120	(0.077)
age	−0.167***	(0.037)
male	1.276***	(0.092)
black.african	−0.607***	(0.125)
ln.hh.income	0.239***	(0.036)
info.substitute	−0.100	(0.093)
Log-likelihood	−1003	
Observations	176	

Note: *** indicate the 1% level of significance, respectively. Likelihood simulated with 1000 random draws using modified Latin hypercube sampling.

in that they predict risk-taking behavior in incentivized experiments. Further, an ordinary least squares regression model shows (Table A.1 in Data S1) that male respondents report higher willingness to take risks, whereas this willingness decreases with age conforming to pervious findings (Dohmen et al., 2011). In sum, the self-stated risk variable appears to be a valid indicator of risk-taking behavior and can therefore be used to explain variations of welfare estimates and (changes in) trip counts.

Looking at descriptive statistics of visit counts (Table 2), respondents made on average 10.02 visits to the beach over the previous 3 months (13.17 in the first survey wave, 6.80 in the second wave). For the scenario of removing the shark nets, they report an anticipated mean visit frequency over the subsequent 3 months of 8.59 visits (11.08 in the first wave, 6.05 in the second wave). The share of respondents who state a different count of anticipated visits as a consequence of the scenario is 61%.

4 | RESULTS

4.1 | The recreational values of beach visits and shark nets

Model 1 in Table 3 is the baseline MPLN count data model. The coefficients of most variables in the trip frequency equation are significant. As expected, the effect of travel cost (*travel.cost*) on expected

TABLE 4 Predictions of visit frequencies and changes between the OB and CB scenarios (over 3 months).

Variable	Mean	95% CI
Predicted visit count/3 months (OB)	3.73	[3.28–4.28]
Predicted visit count/3 months (CB)	2.93	[2.55–3.46]
Change (CB prediction–OB prediction)	−0.80	[−1.15 - −0.45]
Percentage change (CB prediction–OB prediction)	−21.51	[−29.73 - −12.38]

Note: Confidence intervals are obtained by simulating the likelihood model 1000 times using the estimates and the variance–covariance matrix.
Abbreviations: CB, contingent behavior; OB, observed behavior.

visits is negative and significant. Male respondents (*male*) make more visits, so do younger respondents as indicated by the negative coefficient of *age*. Black Africans make fewer visits than other ethnic groups (*black.african*), whereas respondents with higher household income (*ln.hh.income*) visit the beach more often. The fact that respondents were able to provide information on a substitute beach (name or distance from home or both) has a negative effect on visit counts (*info.substitute*), albeit not significant. Based on the travel cost parameter, the average value of a recreational visit to Durban beachfront can be calculated as USD 29.26 [95% confidence interval: 20.80–49.91], equivalent to ZAR 422.24 [300.17–718.83].

The estimates in Table 3 can further be used to predict visit counts and changes thereof between the observed and contingent behavior scenarios (Table 4).[10] Past visits are predicted at 3.73 whereas only 2.93 visits on average are predicted in case the protective shark nets are removed. This is a change of 0.80 visits over the period of 3 months, which is equivalent to a 21.51% reduction relative to the past visit count. Note that the predictions of observed and stated visit counts are well below the average visit counts recorded in the survey (Table 2). This reflects the fact that the MPLN model accommodates the effects of on-site sampling, namely zero truncation of past visit counts and endogenous stratification, such that these estimates and predicted visit frequencies reflect those of the underlying population of interest. We estimate an annual welfare loss for the individual beach user resulting from net removal equivalent to USD 93.63 [14.66–236.16] (ZAR 1351 [212–3408]). This figure is the product of [$0.80 \times 4 =$] 3.20 lost visits per year and the average value of a visit (USD 29.26).

4.2 | The role of usage patterns, information on past shark incidents, and risk attitudes

To test whether *usually. enter, heard*, and *risk* affect predictions of stated and observed site visits, one could simply include them in $\boldsymbol{x_i}$ and rerun the model in Table 3. However, to examine whether these variables influence the predicted change in visits in the contingent scenario and the value a visitor derives from a trip to the beach, interaction terms with the contingent behavior dummy (*const_CB*) and the travel cost variable would be necessary. The inclusion and interpretation of a total of six interaction terms in the model would be practically challenging, a point also noted by Koster and Koster (2015). Furthermore, the power of the estimation would be low because the interactions

[10]These predictions are based on the Poisson distribution given in Eq. (1). The necessary λ_{ij} to predict the probability of visit frequency Y of respondent i in scenario j (with $j=1$ being past visits and $j=2$ referring to the net removal scenario) is given by the estimated parameters $\widehat{\phi}_j$ and $\widehat{\boldsymbol{\beta}}_j$, as well as the covariates $\boldsymbol{x}_{ij}$ and the error term ε_{ij} according to $\lambda_{ij} = \exp\left(\widehat{\phi}_j + \widehat{\boldsymbol{\beta}}_j \boldsymbol{x}_{ij} + \varepsilon_{ij}\right)$. Probabilities for $Y \in \{0, 1, \ldots, 150\}$ are evaluated and multiplied by their respective visit count. For ε_{ij}, we take 1000 random draws using modified Latin hypercube sampling to generate as many realizations of Σ according to eq. (2). This procedure yields 1000 predicted trip counts per scenario j per individual, which can be averaged across random draws and individuals, and changes in mean visit frequencies can be calculated. In the simulation, to derive confidence intervals of predicted visit counts (or consumer surplus estimates), we take 1000 draws from a multivariate normal distribution described by the parameter vector $\widehat{\boldsymbol{\beta}}$ (of the baseline model or any one of the local models in the semi-parametric approach) and the corresponding variance–covariance matrix to simulate the respective likelihood model. We then perform the above prediction (or extract the consumer surplus estimate) for each simulated model and report the 2.5th and 97.5th percentiles of the resulting empirical distribution.

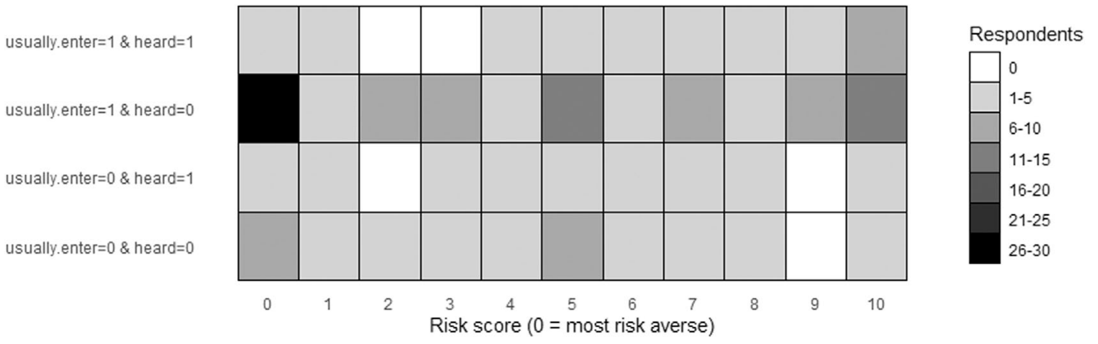

FIGURE 2 Number of respondents in each of the 44 subgroups.

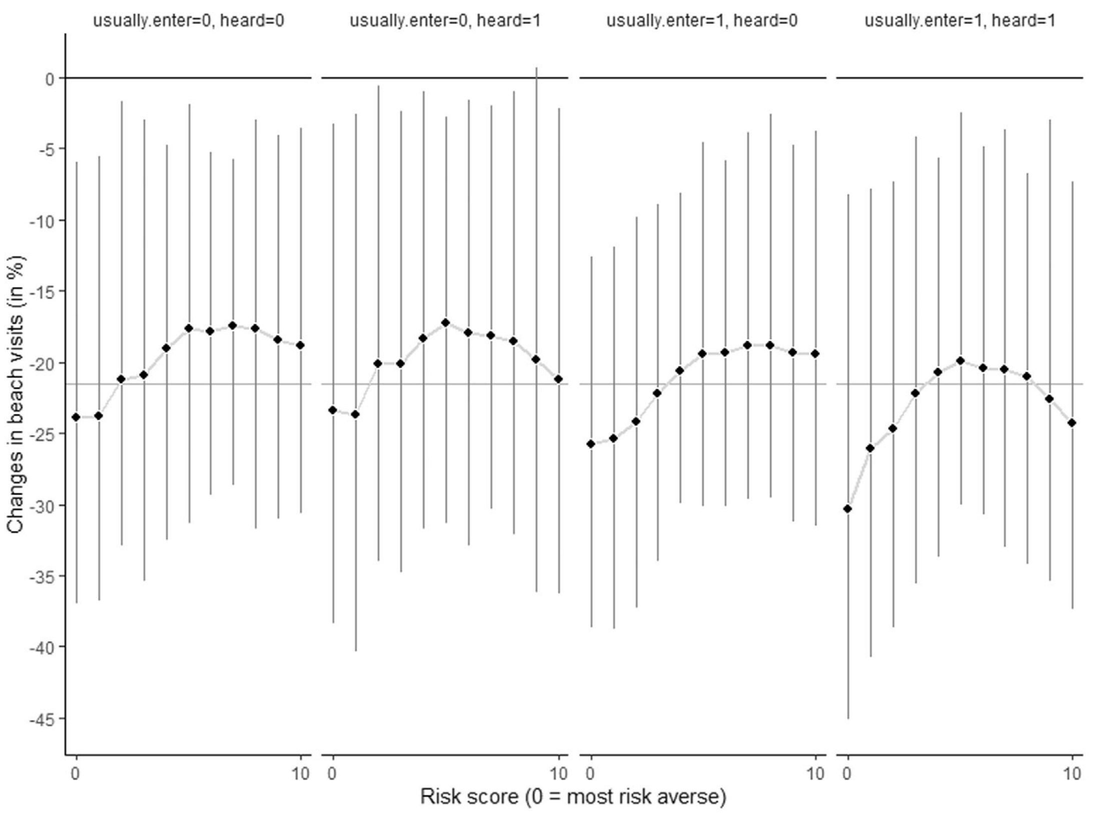

FIGURE 3 Predictions of relative changes in visit counts for a period of 3 months. Each point represents the predicted change in visits based on one of the 44 local models. Gray horizontal lines indicate the sample mean of −21.51%. Vertical lines indicate 95% confidence intervals.

would split the (already small) sample into even smaller subgroups of respondents. Also, nonlinear effects of any of these variables could not be detected even with such an interaction model. To avoid these complications, we ran a semiparametric MPLN model using *usually.enter*, *heard*, and *risk* as indicator variables in $\boldsymbol{Z}_{\bar{i}}$. Given the number of possible combinations of the value of these variables ($2 \cdot 2 \cdot 11 = 44$), there are 44 local models (Figure 2). For each of these, the predicted change in visits

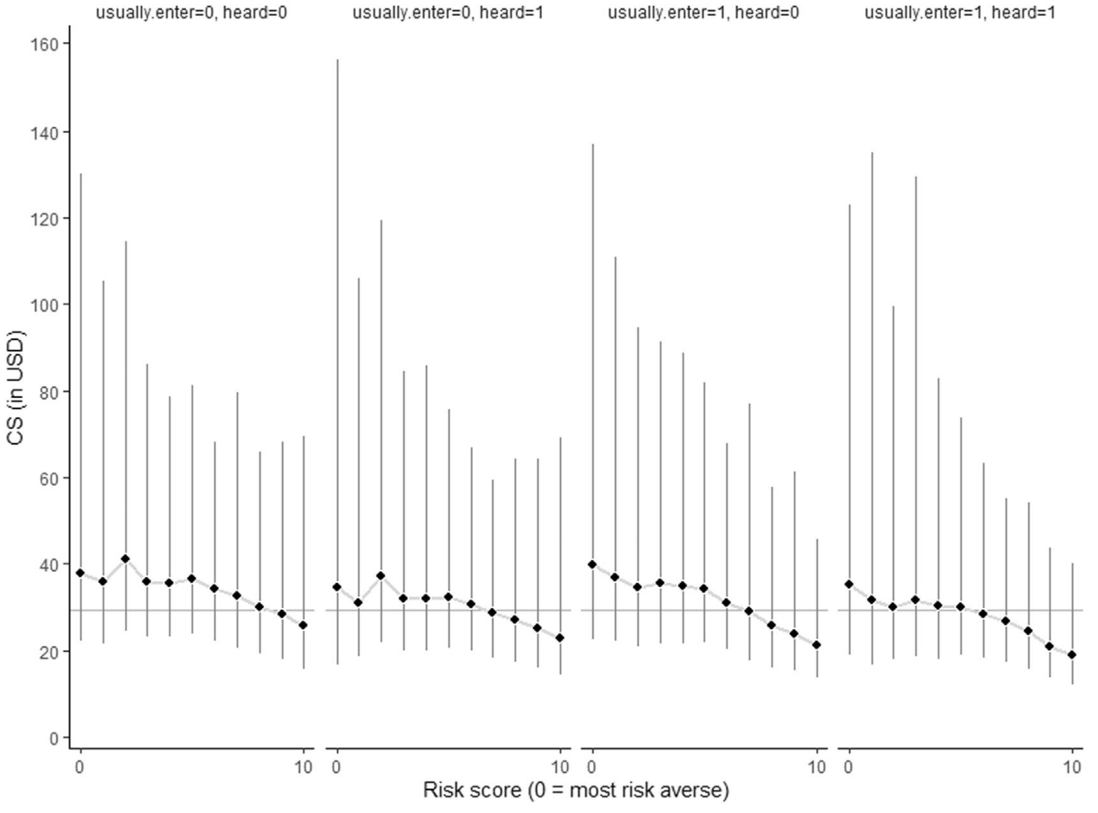

FIGURE 4 Value (consumer surplus–CS) of a recreational beach visit. Each point represents the value visit of a beach visit estimated in one of the 44 local models. Gray horizontal lines indicate sample mean value of USD 29.26. Vertical lines indicate 95% confidence intervals.

following the removal of the shark nets (Figure 3) and the estimated value of a beach visit (Figure 4) can be computed. Note that each of the 44 local models is estimated using the full sample ($n = 176$) such that estimates like those in Table 3 can be extracted. The difference to the baseline model is that in the local models respondents are weighted according to the kernel weights depending how "similar" they are to the reference respondent of each model. For instance, in the first local model, respondents who do not enter the water (*usually.enter* = 0), had not heard about past incidents (*heard* = 0), and state 0 on the risk scale are the reference and obtain a kernel weight of 1. Other respondents receive a weight >0 and <1 in the estimation depending how dissimilar they are to this reference on those three dimensions.

Before looking at the results, it is interesting to study the distribution of respondents across these 44 subgroups (Figure 2). Although most subgroups have between 1 and 5 respondents, only five subgroups are empty, whereas one has more than 20 respondents ($n = 26$). The figure also illustrates clearly that the sample contains respondents with each possible risk score; even extremely risk-averse (score of 0) and risk-loving individuals (score of 10) are represented in the sample. This insight is important when it comes to the interpretation of the variations in visit count changes and valuations across subgroups.

Figures 3 and 4 summarize the results of the 44 local models. Systematic variations across the 44 subgroups can be detected for the reaction to the removal of shark nets as indicated by the predicted relative change in beach visits (Figure 3). We report relative changes because the predictions of the absolute numbers of visits is not constant across risk categories and variations of the variable *usually.enter* and *heard*. In fact, there is generally a positive association between risk attitude on observed and stated visits as indicated in the predictions of visits in the 44 subgroups (Figures A.1 and A.2 in Data S1). Regardless of whether they enter the water or are aware of previous shark accidents, more risk-loving recreationists make more visits to the beach. Among those who enter the water and have heard of previous shark incidents, for instance, this positive relationship is particularly pronounced, with stated trips predicted for those with a risk score of 10 standing out at 4.38 but only being 3.22 for those with a risk score of 0. Consequently, one needs to look at relative instead of absolute changes in beach visits.

Looking at the percentage changes of beach visits resulting from the removal of the nets (Figure 3), we see variation around the sample mean in all four subgroups. For those who do not usually enter the water (the two left-most plots in Figure 3), most local models predict below-average reductions in visits. For those who do go into the water (the two right-most plots in Figure 3), a number of local models at the risk-averse end of the scale predict well above-average reductions in visit frequencies. This shows that routinely going into the water or not is the more decisive of the two binary variables when predicting changes to site visits. Figure 3 also displays 95% confidence intervals that are well clear of zero in the subgroups with *usually.enter* = 1 but much closer to (and in one case including) zero if respondents keep out of the water. It is also in this latter group that predictions exhibit the largest degree of uncertainty.

Among the group who enter the water but are unaware of past shark incidents, we see a positive association throughout between risk attitude and recreational behavior. As these recreationists become more willing to take risks, the percentage reduction in beach visits declines. Extremely risk-averse beach users in this category would reduce their visits by 25.81%, whereas very risk-loving recreationists would only show a reduction of 19.42%. In the subgroup who usually go into the water and are aware of previous incidents (right-hand side of Figure 3), this positive association is only visible among risk-averse recreationists. For very risk-loving individuals, the relationship is reversed, which may simply be a result of the high number of predicted visits of this group (cf. Table A.1 Data S1).

In the remaining two subgroups, the profile exhibits a flatter inverse u-shape, that is, the difference in relative changes is smaller between very risk-averse and very risk-loving beach users. We can conclude that no relationship between risk attitude and behavior reaction to shark net removal exists for such beach-goers. In these two subgroups, very risk-averse individuals react less strongly than equally risk-averse beach visitors who routinely enter the water.

Systematic variations between subgroups can also be explored for the value of a recreational visit to Durban beachfront. Although the average value of a beach visit was estimated at USD 29.26, this mean value varies between 19.06 and 41.08 across the different subgroups of respondents described by combinations of *usually.enter, heard*, and *risk*. A number of patterns emerge (Figure 4). Overall, there is a downward trend of the value of a beach visit with increasing willingness to take risks for all four subgroups. Unlike for the case of predicted changes in visit frequency, this pattern of consumer surplus does not differ across subgroups. The level of precision of these estimates, however, does vary with the risk score. The slightly higher value estimates of risk-averse individuals come with much larger confidence intervals compared to the smaller estimates of the more risk-loving beach users. This level of precision among risk-loving individuals is also higher when they usually enter the water compared to those not doing that. This indicates a relationship between travel cost and visit counts, which is much closer for the former group, hence consumer surplus can be estimated more precisely.

5 | DISCUSSION AND CONCLUSIONS

This paper provides valuations of recreational visits to Durban beachfront, South Africa, as well as predictions of changes in the number of such visits for a hypothetical scenario in which protective shark nets in the coastal waters would be removed. At the sample average level, results show that age, gender, ethnic group, and household income affect visit counts, whereas the effect of an indicator of the availability of a substitute beach destination is insignificant. Although a clear income effect, indicating that higher income households frequent the beach more often, is not always found in the international travel cost literature, it appears to be consistent in studies conducted in South Africa (Du Preez et al., 2012; Du Preez & Lee, 2016; Nahman & Rigby, 2008).

On average, a recreational visit to Durban beach has a value to 1-day visitors of USD 29.26 (ZAR 422.22). Such visits would decrease by 21.51% if the authority in charge of the protective shark nets were to remove these devices from the coastal waters. This constitutes a substantial loss in recreational visits and the associated welfare effects, and may thereby justify the current nature of the sharks control program. We further speculate that the estimated decrease of recreational value in the absence of shark nets could even be more pronounced if the count data had also been collected from multiday beach recreationists. In addition, the reported welfare estimates need to be interpreted as lower bounds with respect to all users of the beach. The latter also includes multiday visitors, yet despite recent advances in modeling holiday visits as multidestination trips (Parsons et al., 2021) these were not included in the analysis. On the other hand, the count data model used in this study is not capable of explicitly modeling substitution effects between sites. It may therefore be possible that respondents would not simply reduce their beach days under the net-removal scenario but plan on visiting another beach where nets are kept.

Specific information on the reliance of *local* tourist operators on beach recreation is hard to come by, but it is possible to collate some ballpark figures to gauge the economic impact of a 21.51% reduction in beach visits. KwaZulu-Natal Province attracted around 6.2 m domestic visitors in 2019 (Tourism KZN 2020), whereby approximately half of these visitors are reported to interact with the coastal environment in some way (Tourism KZN 2016). Considering an average spend per domestic visitor in 2018 of USD 76 (ZAR 1105) (Tourism KZN 2016) gives a total spend of USD 257.3 m (ZAR 3.7b) of all domestic beach-related visits. Although it is not possible to extrapolate estimates of reduced beach visits to Durban beaches to the province as a whole, the above figures still demonstrate the potential loss of revenue from domestic tourists alone with every percentage reductions in beach visitors. Given that protective nets are installed along many of KwaZulu-Natal's beaches, a removal of these and a failure to use alternative nonlethal bather protection techniques (McPhee et al., 2021) highlight the potential scale of impact on the tourism industry in the province.

Another caveat applies with respect to the estimated welfare change from a removal of the shark nets. Results of the semiparametric model indicate that risk-averse respondents who usually enter the water will reduce beach visits more when nets are removed (Figure 3). It may, however, be the case that (some of) these respondents would still come to the beach the same number of times but now avoid going into the water. This means that the actual loss in recreational value for these respondents is bigger than indicated by the reduced predicted visit frequency because the effect of merely losing the chance to bath goes unnoticed by the model (which only examines beach visits). However, the questionnaire did not assess this type of behavior change, so we are not able to indicate its extent. If such behavior exists, the estimated 21% reduction in beach visits would underestimate the real welfare loss from forgone recreation because some of the visits still taking place will be on land only instead of engaging in some form of water-based activity.

The exploration of variations in changes of visit counts according to the 44 subgroups by means of the semiparametric model sheds some light on the influence of natural hazards on recreational visits to nature. The analysis confirms that reductions in recreational visits as a reaction to the increase of a hazard, such as a shark incident, are most pronounced for highly risk-averse beach goers. However, this finding comes with some qualifications, as we only find this clear effect for those who usually go into the water.

Nevertheless, this confirms the expectation that swimmers and individuals who enter the sea would adjust their beach visits more. Looking at predictions of percentage changes in visits, the two subgroups who enter the water show the most pronounced reductions for risk-averse individuals.

For risk-loving recreationists, one of the two groups (those who have not heard of previous shark incidents) reduces their predicted visits less strongly.

However, the analysis remains ambiguous when it comes to the influence of information on past shark incidents, a variable that we have interpreted as an indicator of the availability of graphical information of such events. For this variable, the expectation of a potential effect on anticipated changes in beach use given the deliberations around probability neglect as a result of a fearsome risk in Sunstein and Zeckhauser (2011) could not be detected in the data. The inability to confirm an effect into either direction supports the idea that probability neglect may either lead to action bias (Patt & Zeckhauser, 2000) or overly inaction, yet no effect appears to prevail. A potential reason for this null result is that another moderating effect is not controlled for, such as the type of information respondents have about previous incidents. If these are, in fact, rather positive in the sense that they emphasize the minor consequences, or low probability, of an incident in a nonsensational way, this would not bring into focus the large adverse consequence of the event happening and therefore not trigger probability neglect. Of course, another potential reason for the failure to find an effect is that the indicator variable for the cognitive availability of a shark incident as an adverse risk used in this study does not validly capture this effect. Although the current dataset does not allow for a further test of the validity of this indicator, future research on the influence of risk perception on demand for nature recreation needs to develop an indicator that conforms more closely with theory.

As a note of caution, it should be remarked that none of the differences between visit count predictions (Figures 3, A.1 and A.2 in Data S1) and recreational values (Figure 4) are significantly different between subgroups because simulated confidence intervals overlap. This may well be due to the small sample size collected in the beach survey (and consequently in the individual local models). However, the semiparametric models still indicate patterns and trends of variation in the consumer surplus estimates and visit count predictions.

In the wider policy context, results from this study may have value to inform the trade off between increased bather protection through nets (and drumlines) and mitigation of ecological impacts of these devices in the form of shark mortatility and bycatch of other species (Gibbs et al., 2020). Whereas this study presented a clear binary choice between presence and removal of protective shark nets, different intermediate combinations of measures have been proposed (e.g. McPhee et al., 2021; Tate et al., 2021). If such alternative strategies are perceived by recreationists as sufficiently safe and simultaneously alleviate the ecological toll shark nets are taking, this may soften the trade off between safety (and thus recreational value) and ecological damage. To the extent this trade- off cannot be fully dissolved, however, estimates of the reaction of beach visits and resultant welfare losses are important to guide policy choices.

On a methodological level, this paper showcases the use of a semiparametric count data model in recreation demand analysis. It thereby combines the state of the art modeling of a panel of count data (i.e., accommodating incidental truncation of zero trips and endogenous stratification) with a semiparametric approach based on local likelihood estimation. Although the use of local maximum likelihood models has been used in other fields in non-market valuation, such as transport mode choice and travel time valuation (Fosgerau, 2007; Koster & Koster, 2015), and stated preference environmental valuation (Dekker et al., 2014), we know of only Liu and Egan (2019) who apply this type of model in a travel cost context. Yet although the latter explore the effect of standard sociodemographic variables on recreational values, the present application goes beyond this by studying systematic variations in the recreational use of a coastal location in the face of an increased environmental hazard. It is by means of the flexibility of this semiparametric modeling approach that differences in treatment effects can be explored and depicted, even with a comparably small sample. Such heterogeneous treatment effects could potentially also be studied using random parameters and latent class specifications of count data models (Hynes & Greene, 2013, 2016). There may also be a possibility to study these through rather complex use of interaction effects in parametric count data models. However, the strength of the approach put forward in this paper is that no functional form of the indicator variables and/or the potential interaction among them needs to be specified *ex ante*.

The detection of a risk effect on changes in beach visits in only one out of four possible subgroups in this study would have been substantially more cumbersome (and may potentially have gone unnoticed) with conventional, that is, parametric count data models. To do that, at least a four-way interaction term consisting of the dummy indicating stated visits (*const_CB*), *usually.enter*, *heard*, and *risk* would have had to be included in the MPLN model, which would pose a considerable interpretation challenge.

A point for further methodological research is the selection of the bandwidth parameters. The present analysis follows Fröhlich (2006) in using separate bandwidth parameters for sets of indicator and dummy variables. The set of best parameters is then identified by means of a cross-valuation procedure (Fröhlich, 2006; Sipotpongstorn et al., 2021). Although this procedure is more transparent than an approach that simply selects bandwidth parameters to maximize interpretability of results (a procedure Koster and Koster (2015) call "eye-balling"), yet further improved selection mechanisms are conceivable. Dekker et al. (2014), for instance, use a grid search algorithm in conjunction with an indicator of model fit (the corrected Akaike information criterion) to determine appropriate values for the bandwidth parameters. As the use of semiparametric count data models in TC-CB application becomes more mainstream, we would expect to see more studies to explore the effect of different bandwidth parameters on the stability and interpretability of results. We leave this aspect for future research.

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REFERENCES

Awondo, Sebastain N., Kevin J. Egan, and Dwyer. Daryi F. 2011. "Increasing Beach Recreation Benefits by Using Wetlands to Reduce Contamination." *Marine Resource Economics* 26(1): 1–15.

Beaumais, Olivier, and Gildas Appéré. 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(12): 2315–22.

Bell, Frederick W., and Vernon R. Leeworthy. 1990. "Recreational Demand by Tourists for Saltwater Beach Days." *Journal of Environmental Economics and Management* 18(3): 189–205.

Bertram, Christine, Heini Ahtiainen, Jürgen Meyerhoff, Kristine Pakalniete, Eija Pouta, and Katrin Rehdanz. 2020. "Contingent Behavior and Asymmetric Preferences for Baltic Sea Coastal Recreation." *Environmental and Resource Economics* 75(1): 49–78.

Börger, Tobias, Danny Campbell, Mathew P. White, Lewis R. Elliott, Lora E. Fleming, Joanne K. Garrett, Caroline Hattam, Stephen Hynes, Tuija Lankia, and Tim Taylor. 2021. "The Value of Blue-space Recreation and Perceived Water Quality Across Europe: A Contingent Behavior Study." *Science of the Total Environment* 771: 145597.

Boudreaux, Greg, Frank Lupi, Brent Sohngen, and Alan Xu. 2023. "Measuring Beachgoer Preferences for Avoiding Harmful Algal Blooms and Bacterial Warnings." *Ecological Economics* 204(Part A): 107653.

Bradshaw, Corey J. A., Phoebe Meagher, Madeline J. Thiele, Robert G. Harcourt, and Charlie Huveneers. 2021. "Predicting Potential Future Reduction in Shark Bites on People." *Royal Society Open Science* 8: 201197.

Chapman, Blake K., and Daryl McPhee. 2016. "Global Shark Attack Hotspots: Identifying Underlying Factors Behind Increased Unprovoked Shark Bite Incidence." *Ocean & Coastal Management* 133: 72–84.

Cliff, Geremy. 1991. "Shark Attacks on the South African Coast between 1960 and 1990." *South African Journal of Science* 87: 513–8.

Cliff, Geremy, and Sheldon F. J. Dudley. 2011. "Reducing the Environmental Impact of Shark Control Programs: A Case Study from KwaZulu-Natal, South Africa." *Marine and Freshwater Research* 62: 700–9.

Czajkowski, Mikolaj, Heini Ahtiainen, Janne Artell, Wiktor Budziński, Berit Hasler, Linus Hasselström, Jürgen Meyerhoff, et al. 2015. "Valuing the Commons: An International Study on the Recreational Benefits of the Baltic Sea." *Journal of Environmental Management* 156: 209–17.

Dekker, Thijs, Paul Koster, and Roy Brouwer. 2014. "Changing with the Tide: Semiparametric Estimation of Preference Dynamics." *Land Economics* 90(4): 717–45.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner. 2011. "Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences." *Journal of the European Economic Association* 9(3): 522–50.

Du Preez, Mario, Matt Dicken, and Stephen G. Hosking. 2012. "The Value of Tiger Shark Diving within the Aliwal Shoal Marine Protected Area: A Travel Cost Analysis." *South African Journal of Economics* 80(3): 387–99.

Du Preez, Mario, and Deborah Ellen Lee. 2016. "The Economic Value of the Trans Baviaans Mountain Biking Event in the Baviaanskloof Mega-Reserve, Eastern Cape, South Africa: A Travel Cost Analysis Using Count Data Models." *Journal of Outdoor Recreation and Tourism* 15: 47–54.

Dudley, Sheldon F. J., and Geremy Cliff. 1993. "Some Effects of Shark Nets in the Natal Nearshore Environment." *Environmental Biology of Fishes* 36: 243–55.

Dudley, Sheldon F. J. 1997. "A Comparison of the Shark Control Programs of New South Wales and Queensland (Australia) and KwaZulu-Natal (South Africa)." *Ocean and Coast Management* 34: 1–27.

Dudley, Sheldon, F. J., and Geremy Cliff. 2010. "Shark Control: Methods, Efficacy, and Ecological Impact." In *Sharks and Their Relatives II–Biodiversity, Adaptive Physiology, and Conservation*, edited by Jeffrey C. Carrier, John A. Musick, and Michael R. Heithaus, 583–608. Boca Raton: CRC Press.

Engelbrecht, Tamlyn, Alison Kock, S. Sarah Waries, and M. Justin O'Riain. 2017. "Shark Spotters: Successfully Reducing Spatial Overlap Between White Sharks (Carcharodon Carcharias) and Recreational Water Users in False Bay, South Africa." *PLoS One* 12(9): e0185335.

Egan, Alexandra L., John Rolfe, Sue Cassells, and B. Louise Chilvers. 2022. "Potential Changes in the Recreational Use Value for Coastal Bay of Plenty, New Zealand Due to Oil Spills: A Combined Approach of the Travel Cost and Contingent Behaviour Methods." *Ocean & Coastal Management* 228: 106306.

Egan, Kevin, and Joseph Herriges. 2006. "Multivariate Count Data Regression Models with Individual Panel Data from an On-site Sample." *Journal of Environmental Economics and Management* 52(2): 567–81.

Elliott, Lewis R., Mathew P. White, James Grellier, Sian E. Rees, Ruth D. Waters, and Lora E. Fleming. 2018. "Recreational Visits to Marine and Coastal Environments in England: Where, What, Who, Why, and When?" *Marine Policy* 97: 305–14.

Englin, Jeffrey, and Trudy Ann Cameron. 1996. "Augmenting Travel Cost Models with Contingent Behavior Data." *Environmental and Resource Economics* 7(2): 133–47.

English, Eric, Roger H. von Haefen, Joseph Herriges, Christopher Leggett, Frank Lupi, Kenneth McConnell, Michael Welsh, Adam Domanski, and Norman Meade. 2018. "Estimating the Value of Lost Recreation Days from the Deepwater Horizon Oil Spill." *Journal of Environmental Economics and Management* 91: 26–45.

Fan, Jianqing, Nancy E. Heckman, and M. P. Wand. 1995. "Local Polynomial Kernel Regression for Generalized Linear Models and Quasi-Likelihood Functions." *Journal of the American Statistical Association* 90(429): 141–50.

Farr, Marina, Natalie Stoeckl, and Rabiul Alam Beg. 2014. "The Non-consumptive (Tourism) 'Value' of Marine Species in the Northern Section of the Great Barrier Reef." *Marine Policy* 43: 89–103.

Fosgerau, Mogens. 2007. "Using Nonparametrics to Specify a Model to Measure the Value of Travel Time." *Transportation Research Part A: Policy and Practice* 41(9): 842–56.

Fröhlich, Markus. 2006. "Non-parametric Regression for Binary Dependent Variables." *Econometrics Journal* 9(3): 511–40.

Ghermandi, Andrea, and Paulo A. Nunes. 2013. "A Global Map of Coastal Recreation Values: Results from a Spatially Explicit Meta-analysis." *Ecological Economics* 86: 1–15.

Gibbs, Leah, Lachlan Fetterplace, Mattthew Rees, and Quentin Hanich. 2020. "Effects and Effectiveness of Lethal Shark Hazard Management: The Shark Meshing (Bather Protection) Program, NSW, Australia." *People and Nature* 2(1): 189–203.

Hanley, Nick, David Bell, and Begonia Alvarez-Farizo. 2003. "Valuing the Benefits of Coastal Water Quality Improvements Using Contingent and Real Behavior." *Environmental and Resource Economics* 24(3): 273–85.

Hazin, Fábio, H. V., André S. Afonso, Pedro C. De Castilho, Luciana C. Ferreira, and Bruno C. L. M. Rocha. 2013. "Regional Movements of the Tiger Shark, Galeocerdo Cuvier, off Northeastern Brazil: Inferences Regarding Shark Attack Hazard." *Anais da Academia Brasileira de Ciências* 85: 1053–62.

Hesseln, Hayley, John B. Loomis, Armando Gonzalez-Caban, and Susan Alexander. 2003. "Wildfire Effects on Hiking and Biking Demand in New Mexico: A Travel Cost Study." *Journal of Environmental Management* 69: 359–68.

Holt, Charles A., and Susan K. Laury. 2002. "Risk Aversion and Incentive Effects." *American Economic Review* 92(5): 1644–55.

Hynes, Stephen, and William Greene. 2013. "A Panel Travel Cost Model Accounting for Endogenous Stratification and Truncation: A Latent Class Approach." *Land Economics* 89(1): 177–92.

Hynes, Stephen, and William Greene. 2016. "Preference Heterogeneity in Contingent Behavior Travel Cost Models with On-site Samples: A Random Parameter vs. a Latent Class Approach." *Journal of Agricultural Economics* 67(2): 348–67.

Koster, Paul R., and Hans R. Koster. 2015. "Commuters' Preferences for Fast and Reliable Travel: A Semiparametric Estimation Approach." *Transportation Research Part B: Methodological* 81: 289–301.

Krinsky, Itzhak, and A. Leslie Robb. 1986. "On Approximating the Statistical Properties of Elasticities." *Review of Economics and Statistics* 68(4): 715–9.

Landry, Craig E., and Haiyong Liu. 2009. "A Semiparametric Estimator for Revealed and Stated Preference Data—An Application to Recreational Beach Visitation." *Journal of Environmental Economics and Management* 57(2): 205–18.

Landry, Craig E., John Bergstrom, John Salazar, and Dylan Turner. 2021. "How Has the COVID-19 Pandemic Affected Outdoor Recreation in the U.S.? A Revealed Preference Approach." *Applied Economic Perspectives and Policy* 43(1): 443–57.

Liu, Weiwei, and Kevin J. Egan. 2019. "A Semiparametric Smooth Coefficient Estimator for Recreation Demand." *Environmental and Resource Economics* 74(3): 1163–87.

Loomis, John, Shizuka Yorizane, and Douglas Larson. 2000. "Testing Significance of Multi-destination and Multi-purpose Trip Effects in a Travel Cost Method Demand Model for Whale Watching Trips." *Agricultural and Resource Economics Review* 29(2): 183–91.

Lopes, Ana F., and John C. Whitehead. 2023. "Estimating the Ex-ante Recreational Loss of an Oil Spill Using Revealed and Stated Preference Data." *Land Economics* 99: 102022–84R.

MacKerron, George, and Susana Mourato. 2013. "Happiness is Greater in Natural Environments." *Global Environmental Change* 23(5): 992–1000.

McPhee, Daryl P. 2014. "Unprovoked Shark Bites: Are They Becoming More Prevalent?" *Coastal Management* 42: 478–92.

McPhee, Daryl P., Craig Blount, Marcus P. Lincoln Smith, and Victor M. Peddemors. 2021. "A Comparison of Alternative Systems to Catch and Kill for Mitigating Unprovoked Shark Bite on Bathers or Surfers at Ocean Beaches." *Ocean & Coastal Management* 201: 105492.

Midway, Stephen R., Tyler Wagner, and George H. Burgess. 2019. "Trends in Global Shark Attacks." *PLoS One* 14(2): e0211049.

Muter, Bret A., Meredith L. Gore, Katie S. Gledhill, Christopher Lamont, and Charlie Huveneers. 2013. "Australian and U.S. News Media Portrayal of Sharks and Their Conservation." *Conservation Biology* 27(1): 187–96.

Nahman, Anton, and Dan Rigby. 2008. "Valuing Blue Flag Status and Estuarine Water Quality in Margate, South Africa." *South African Journal of Economics* 76(4): 721–37.

Neff, Christopher. 2015. "The Jaws Effect: How Movie Narratives Are Used to Influence Policy Responses to Shark Bites in Western Australia." *Journal of Political Science Australian* 50(1): 114–27.

Neff, Christopher L., and Jean Y. H. Yang. 2013. "Shark Bites and Public Attitudes: Policy Implications from the First Before and After Shark Bite Survey." *Marine Policy* 38: 545–7.

Nobel, Anne, Sebastien Lizin, Nele Witters, Francois Rineau, and Robert Malina. 2020. "The Impact of Wildfires on the Recreational Value of Heathland: A Discrete Factor Approach with Adjustment for On-site Sampling." *Journal of Environmental Economics and Management* 101: 102317.

Parsons, George R., Zhe Chen, Michael K. Hidrue, Naomi Standing, and Jonathan Lilley. 2013. "Valuing Beach Width for Recreational Use: Combining Revealed and Stated Preference Data." *Marine Resource Economics* 28(3): 221–41.

Parsons, George R. 2017. "Travel Cost Models." In *A Primer on Nonmarket Valuation*, edited by Patricia A. Champ, Kevin J. Boyle, and Thomas C. Brown, 187–233. Springer Netherlands: Dordrecht.

Parsons, George, Jeremy Firestone, Lingxiao Yan, and Jenna Toussaint. 2020. "The Effect of Offshore Wind Power Projects on Recreational Beach Use on the East Coast of the United States: Evidence from Contingent-behavior Data." *Energy Policy* 144: 111659.

Parsons, George, Christopher G. Leggett, Joseph Herriges, Kevin J. Boyle, Nancy Bockstael, and Zhe Chen. 2021. "A Site-portfolio Model for Multiple-destination Recreation Trips: Valuing Trips to National Parks in the Southwestern USA." *Journal of the Association of Environmental and Resource Economists* 8(1): 1–25.

Pascoe, Sean. 2019. "Recreational Beach Use Values with Multiple Activities." *Ecological Economics* 160: 137–44.

Pasos-Acuña, Carmen, Marco Antonio Almendarez-Hernández, Edgar Mauricio Hoyos-Padilla, Maria Carmen Blázquez, and James Thomas Ketchum. 2020. "Economic Valuation of Diving with Bull Sharks in Natural Conditions: A Recent Activity in Cabo Pulmo National Park, Gulf of California, Mexico." In *Socio-Ecological Studies in Natural Protected Areas*, edited by Alfredo Ortega-Rubio, 485–509. Cham: Springer.

Patt, Anthony, and Richard Zeckhauser. 2000. "Action Bias and Environmental Decisions." *Journal of Risk and Uncertainty* 21(1): 45–72.

Racine, Jeff, and Qi Li. 2004. "Nonparametric Estimation of Regression Functions With Both Categorical and Continuous Data." *Journal of Econometrics* 119(1): 99–130.

Racine, Jeff S. 2007. "Nonparametric Econometrics: A Primer." *Foundations and Trends in Econometrics* 3(1): 1–88.

Reid, D. D., W. D. Robbins, and V. M. Peddemors. 2011. "Decadal Trends in Shark Catches and Effort From the New South Wales, Australia, Shark Meshing Program 1950–2010." *Marine & Freshwater Research* 62: 676–93.

Reid, Oscar Schouten, and Fabien Medvecky. 2021. "Sharks and New Zealand News Media." *Marine Policy* 134: 104751.

Sabatier, Etienne, and Charlie Huveneers. 2018. "Changes in Media Portrayal of Human–wildlife Conflict During Successive Fatal Shark Bites." *Conservation and Society* 16(3): 338–50.

RSA. 2018. Rate per Kilometre Fixed under Section 8(1)(b)(ii) and (iii) of Income Tax Act, 1962 *Republic of South Africa, Government Gazette* 633, No. 41473.

Shaw, Daigee. 1988. "On-site Samples' Regression." *Journal of Econometrics* 37(2): 211–23.

Sipotpongstorn, Nithi, Param Silvapulle, Jiti Gao, and Jean-Pierre Fenech. 2021. "Local Logit Regression for Loan Recovery Rate." *Journal of Banking and Finance* 126: 106093.

Starbuck, C. Meghan, Robert P. Berrens, and Michael McKee. 2006. "Simulating Changes in Forest Recreation Demand and Associated Economic Impacts due to Fire and Fuels Management Activities." *Forest Policy and Economics* 8(1): 52–66.

Sunstein, Cass R., and Richard Zeckhauser. 2011. "Overreaction to Fearsome Risks." *Environmental and Resource Economics* 48(3): 435–49.

Tate, Rick D., Brendan P. Kelaher, Craig P. Brand, Brian R. Cullis, Christopher R. Gallen, Stephen D. A. Smith, and Paul A. Butcher. 2021. "The Effectiveness of Shark-Management-Alert-in-Real-Time (SMART) Drumlines as a Tool for Catching White Sharks, Carcharodon Carcharias, off Coastal New South Wales, Australia." *Fisheries Management and Ecology* 28: 496–506.

Tourism KZN. 2016. *Annual Report 2015/2016*. Durban: KwaZulu-Natal Tourism Authority.

Tourism KZN. 2020. *Breaking New Ground. Annual Report 2019/2020*. Durban: KwaZulu-Natal Tourism Authority.

Tversky, Amos, and Daniel Kahneman. 1973. "Availability: A Heuristic for Judging Frequency and Probability." *Cognitive Psychology* 5(2): 207–32.

Voltaire, Louinord, and Obafemi Philippe Koutchade. 2020. "Public Acceptance of and Heterogeneity in Behavioral Beach Trip Responses to Offshore Wind Farm Development in Catalonia (Spain)." *Resource and Energy Economics* 60: 101152.

Ward, Frank A., and Diana Beal. 2000. *Valuing Nature with Travel Cost Models. A Manual*. Cheltenham: Edward Elgar.

Zemah Shamir, Z., S. Zemah Shamir, D. Tchernov, A. Scheinin, and N. Becker. 2019. "Shark Aggregation and Tourism: Opportunities and Challenges of an Emerging Phenomenon." *International Journal of Sustainable Development & World Ecology* 26(5): 406–14.

Zhang, Fan, Xiao Hua Wang, Paulo A. L. D. Nunes, and Chunbo Ma. 2015. "The Recreational Value of Gold Coast Beaches, Australia: An Application of the Travel Cost Method." *Ecosystem Services* 11: 106–14.

Zimmerhackel, Johanna S., Abbie A. Rogers, Mark G. Meekan, Khadeeja Ali, David J. Pannell, and Marit E. Kragt. 2018. "How Shark Conservation in the Maldives Affects Demand for Dive Tourism." *Tourism Management* 69: 263–71.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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