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Research Article

Heterogeneity in trips to green natural spaces: A travel cost approach across UK sites

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ABSTRACT

The Covid-19 pandemic and related lockdowns saw a subsequent sharp rise in demand for outdoor recreation. This has resulted in congestion and particular stress on managing authorities of green natural spaces. This study examines drivers for outdoor recreation, across UK sites, for a representative sample of the English population during lockdowns and the easing of restrictions. Using a travel cost approach, this study focuses on addressing demand heterogeneity through a finite mixture model and cost sensitivity and finds that the characteristics of green and natural spaces English respondents visit are not always affecting trip frequency. Additionally, social inequalities and deprivation do not influence or had an inverse effect on demand for visits to UK green and natural spaces. When accounting for heterogeneity, a large variability in the frequency of visits is observed, with frequent visitors being less sensitive to changes in travel cost. Finally, we find that UK residents are less responsive to changes in travel cost that could be caused by increases in petrol prices, or in changes in their income. Future management decisions for green natural spaces need to account for the differences between casual and frequent outdoor recreationists.

Management implications

- Frequent visitors of green and natural spaces in the UK are not sensitive to changes such as increases in petrol prices, or in changes in their income.
- Living in socially deprived areas increases demand for visits to green and natural spaces in the UK.
- Failing to account for heterogeneity in green and natural space' visitor profiles can overestimate the value of economic welfare assigned to outdoor spaces.
- Future management decisions for green natural spaces need to account for the fact that most outdoor recreationists interact only causally with nature.
- With mounting pressures on the UK's green and natural spaces and most visitors being casual, infrequent ones, educational and informational campaigns and introducing entry restrictions to certain areas might be required.

1. Introduction

Increases in frequency of visits to national parks and green spaces during and after the Covid-19 pandemic around the world has been widely documented (Pröbstl-Haider et al., 2023). Evidence from case studies refer to visits to US national parks during Covid-19 that increased but has been found to be contingent on travel distance (Alba et al., 2022; Lu et al., 2023) while in the visits to United Kingdom (UK) green spaces increased steadily from 2020 as restrictions relaxed (Burnett et al., 2022) and during the pandemic on trails close to urban areas in Ireland (Power et al., 2023). Similarly, visits in green spaces and protected areas in Norway increased during Covid-19 and remained at high levels since (Venter et al., 2021), in Australia an 11% increase in visits linked to increased productivity was documented during Covid-19 (Buckley & Chauvenet, 2022) while in Japan an increase in visits to green spaces (apart from urban parks) was also documented (Kim et al., 2023).

The increase in visits has prompted a research shift in understanding its impacts (Ferguson et al., 2023) and drivers (Humagain and Singleton, 2021). For example, in US national parks, a 20% increase in visits was observed which, coupled with reductions in national park staff numbers, led to issues with facilities cleanliness and accessibility (The Guardian, 2022). Similar effects were reported in UK national parks and Areas of Outstanding National Beauty (AONBs) and the subsequent rise in interest in outdoor recreation with congestion and disorderly behaviour reported (Mackenzie & Goodnow, 2021; The Sunday Times, 2021).

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Focusing explicitly on visits to green and natural spaces (GNS) (including beaches and coastlines) that might include natural parks and protected areas (but not necessarily) is less common in academic studies. The quality of GNS is expected to play a role in the future demand for visits for such spaces, especially as increased interest for the outdoors appears to be a mainstay (Burnett et al., 2022) and increasing visitation rates being a goal of the UK Government (UK Government, 2016).

The quality of GNS is not expected to be the only determinant of demand, with the cost of travel also being a key driver for outdoor demand. 93% of visitors to UK national parks access them through cars (UK National Parks, 2020), a common finding when it comes to accessing outdoor green spaces (Tardieu and Tuffery, 2019; Cetin et al., 2021) making changes in gas prices very important in understanding outdoor recreation demand. Overall, disentangling trip visits and the drivers behind them can reveal a more complicated picture, for example, Landry et al. (2021) found that demand for outdoor recreation was negatively affected by Covid-19, explained by the household' ability to manage and withstand risk, as well as reductions in the country's annual consumer surplus per outdoor recreation participant. Similarly, Lu et al., (2023) report that socially disadvantaged groups were less likely to visit outdoor spaces in the US. Determining drivers behind demand for GNS across the UK is therefore required and, currently, mostly unexamined.

Trips to outdoor natural spaces such as GNS are expected to be determined by an array of characteristics such as socio-demographic and site characteristics (Börger et al., 2021; Englin & Mendelsohn, 1991). What is sometimes overlooked in studies examining travel demand and behaviour is the existence of heterogeneity in the sample (Smith et al., 2016). This study aims at addressing heterogeneity through two ways: first, by estimating a traditional travel cost model including both travel and opportunity costs through the value of time (VTT) and second, by using a finite mixture model that segments respondents based on their preferences, following (Smith et al., 2016). Consumer surpluses, an economic indicator of welfare, are estimated for the English public through continuous and finite models to account for trip heterogeneity, using data from a rolling, England-wide survey administered by Natural England and responses spanning over April 2020 and September 2022. Finally, this paper examines the sensitivity of demand of outdoor recreation through visits to GNS when changes in income and travel expenditures are considered. Results should shed light on the demand and associated costs for English residents for GNS and the impact of the perceived quality of GNS on recreation demand for GNS for different segments of visitors, as well as how visitation rates impact welfare and, finally, inform management scenarios for GNS in the UK.

2. Literature review

Although the travel cost method has found primary use in valuing the non-market value of specific ecosystems or sites, it has also seen a considerable application in nation-wide studies for GNS such as forests (Bartczak et al., 2008; Borzykowski et al., 2017; Ezebilo, 2016), national parks (e.g., Mayer & Woltering, 2018; Shoji et al., 2023), protected areas (e.g., Sinclair et al., 2022), urban parks (Jaung & Carrasco, 2020) or generic outdoor recreation spaces (e.g., Bergstrom & Cordell, 1991; Landry et al., 2021). This study contributes to this literature by measuring demand for outdoor recreation in GNS in the UK, from a country-wide representative English sample, during the Covid-19 pandemic all the way through the easing and lifting of UK-wide restrictions to travel and meet outdoors.

Habitat quality and site characteristics are commonly examined in the travel cost literature, with mixed results. Tardieu and Dufferin (2019) find negative correlations between habitat quality and demand for recreational spaces that have high habitat quality. Englin and Mendelsohn (1991) included several site characteristics of forests as well as interaction terms between them to determine welfare changes from the presence of individual characteristics. Such characteristics can also be included in travel cost models from the point of visitors' perceptions (Juutinen et al., 2022). Nevertheless, including site characteristics is not preferred in some studies due to endogeneity between site choice and site characteristics. In other words, visitors would eventually reach equilibrium between site characteristics (such as congestion or aesthetic beauty) and number of visitors or visits (Timmins & Murdock, 2007). In our analysis we assume that issues such as congestion are similar *across* GNS, a reasonable assumption given the coarse data available for UK GNS.

With respect to the incorporation of VTT in the demand function, this has been a matter of debate in the travel cost literature. Conceptually, opportunity costs such as the VTT can influence demand regardless of mode of transport, although it is expected that they would vary between transport modes (Department of Department for Transport, 2015). By default, opportunity cost might be negligible if trips are frequent, distances travelled are short and the duration of the recreational activity is short (Hynes et al., 2022). Including VTT in the demand function can therefore lead to overestimate travel demand for those living close to the recreational sites, a decision that could be driven by their inherent high demand for recreation (Tardieu and Dufferin, 2019). In this study we use varying estimates for VTT provided by the UK's Department of Transport and focus on visitors to UK GNS using motorised transport. We comment on the impact of using such VTT estimates in the discussion section of the paper, as past studies have found that different values of VTT result in considerable differences in welfare estimates (Palmquist et al., 2010; Fezzi et al., 2014).

Finite mixture models have seen considerable use in non-market valuation in association with discrete choice modelling to estimate shadow prices for environmental goods and services (Mariel et al., 2021). Travel cost models with a latent class/finite mixture component are much less common when it comes to measuring travel demand for recreational purposes. Early studies combining the two approaches include Scarpa et al., (2007) that measure demand for recreation in Italy using socio-economic variables to construct the finite mixture and Baerenklau (2010) that examine endogeneity in spatial preferences through a finite mixture model on a zonal travel cost model using key sociodemographic characteristics as class determinants. Haab et al. (2012) examined preference heterogeneity for recreational fishing in the US by using trip, catch and volume characteristics as determinants of the finite mixture models. Hynes and Greene (2013) also use key socio-demographics and recreational preferences as determinants of the finite mixture to estimate demand for two beach areas in the west of Ireland. Finally, Smith et al., (2016) use climate conditions, place awareness and risk perceptions as drivers of latent preference heterogeneity to estimate demand for winter outdoor recreation through a trave cost model in Lake Superior in the US. In this study we use a mixture of site characteristics, sociodemographic characteristics and regional social data as determinants of the finite mixture model. The next section describes the type of data used and the continuous and finite mixture models used in conjunction with a travel cost method to estimate demand for recreation in GNS in the UK.

3. Data and methods

The data used in this study are part of Natural England's new, rolling People and Nature Survey (PANS) for England,[1] an online survey sampling around 25,000 individuals, across England, on a monthly basis. Data analysed in this study span from April 2020 to September 2022 (effectively both years of the survey's new format, replacing the Monitor of Engagement with the Natural Environment (MENE) survey). Data collected record number, frequency of and activities carried out during recreational trips to GNS (such as natural parks, forests, rivers, lakes etc), their characteristics (cleanliness, accessibility, aesthetic beauty

[1] Data available at: https://www.gov.uk/government/collections/people-and-nature-survey-for-england.

etc.), environmentally-friendly attitudes and behaviours and, finally, aspects of wellbeing affected by visiting these spaces and the impact of Covid-19 had on visiting and appreciating these spaces. The satisfaction of visitors has long been considered as an indicator of quality of services provided by GNS (Geng et al., 2023; Rodger et al., 2015). The quality of data for research purposes has been confirmed by previous studies using earlier data cohorts (e.g., de Bell et al., 2020). Respondents were asked to indicate in a map their most recent green and natural space they visited, and the coordinates of the location were provided in the dataset.

The PANS dataset also provides weighted samples for gender, age groups, education and geographic location for each of the 9 English regions. Social characteristics of areas were captured through the official measure of relative deprivation in England, the Index of Multiple Deprivation (IMD) which assigns numbers from 1 to 10, with 1 referring to an area being in the most deprived 10% of Lower Super Output Area (LSOAs) in England. A score of IMD was assigned to each survey participant based on their address which was not made available to the public. The variable used (Index of Multiple Deprivation, IMD) is a combined, weighted index of deprivation for an area, taking into account factors such as income, education, health etc. The data described below refer to the data modules of interest to this study alone. Due to the modular structure of the PANS survey cross-analysing questions from certain questionnaire sections is not possible. Therefore, some sections appear as incomplete or missing responses, and after removing incomplete surveys (such as those that did not record trip time or trip expenditure by answering “Don’t know” or “Do not wish to disclose” in these questions) a useable sample of 8766 responses remained. The summary statistics for the visit variables are presented in Table 1 below.

The summary statistics in Table 1 show that, on average, a PANS participant visits a GNS around 5 times every two weeks that is mostly within 10 miles from their place of residence and spends £13 in out-of-pocket expenses in each trip. The frequency of trips increased in 2021 and 2022, probably in line with the relaxing of Covid-19 restrictions (data collection began in April 2020 so no definitive conclusions can be made regarding earlier restrictions and responses to the survey). Responses are equally distributed across the 10 deprivation deciles. Most GNS were perceived to be in good condition and welcoming to survey participants.

Table 1 reports summary statistics for travel costs which were defined as: a) value of travel time (VTT) and b) out-of-pocket expenditure. The combination of these two types of costs is expected to reflect to total travel cost for an English PANS participant to visit a GNS and is defined by the formula below:

$$tc = 2(mc * d + \mu * 5.12 * time) + exp, \quad (1)$$

where *mc* is the marginal cost per mile of travel using weekly UK petrol prices[2] for the week the latest trip reported in the survey, *d* is the mid-point of the one-way trip distance interval (five distance intervals were reported, ranging from 1 to 2 miles up to more than 50, as shown in the section ‘Trip characteristics’ in Table 1) reported by each respondent while *exp* refers to the out-of-pocket expenditure for the trip for each respondent. The variable μ denotes a mean value of a multiplier[2] used for different trip modes, recreational purposes and types of congestion and comfort of trip for each respondent (taking the value 0.885 for transport modes of car, van or motorbike and the value of 1.34 for public transport), according to the UK’s Department of Transport’s Value of Travel Time report (Department of Department for Transport, 2015, pp 13–14). The value 5.12 refers to the value of travel time in £/hour for “non-work” purposes provided the same report’s and $time_i$ refers to the one-way travel time to the trip’s destination. The average VTT in the sample is around £8.8 per GNS trip while the out-of-pocket expenditures (such as food and snacks, parking fees, admission fees etc) is £13.3, similar with other recent studies in Western contexts (e.g., Ji et al., 2022). As expected, areas in England were mostly recorded in the dataset as the latest trip of English respondents, compared to areas in Wales, Scotland or Northern Ireland.

Table 1
Summary statistics for the PANS sample for English visitors of green and natural spaces for the period between April 2020 and September 2022; *: Likert scale taking values from 1 (Strongly disagree) to 5 (Strongly agree), apart from “The place felt welcoming/safe” where the scale is reversed (1 indicates “Strongly agree” and 5 “Strongly disagree”).

	Mean	Std. Dev.	Min	Max
Socio-economic characteristics				
Participant is female	0.496	0.500	0	1
Age	46.173	15.391	20	65
No educational qualifications	0.039	0.193	0	1
High-school education (GCSE level)	0.628	0.483	0	1
University education and higher	0.333	0.471	0	1
IMD decile 1	0.089	0.296	0	1
IMD decile 2	0.104	0.305	0	1
IMD decile 3	0.109	0.311	0	1
IMD decile 4	0.097	0.296	0	1
IMD decile 5	0.100	0.300	0	1
IMD decile 6	0.102	0.303	0	1
IMD decile 7	0.106	0.307	0	1
IMD decile 8	0.102	0.303	0	1
IMD decile 9	0.095	0.294	0	1
IMD decile 10	0.097	0.296	0	1
Number of Children	0.533	0.925	0	6
Total annual household income before tax (in 2020 £)	33,951	13,326	14,999	50,000
Trip Characteristics				
Miles [less than 1]	0.390	0.488	0	1
Miles [1–2 miles]	0.263	0.441	0	1
Miles [3–10 miles]	0.240	0.427	0	1
Miles [11–50 miles]	0.078	0.268	0	1
Miles [more than 50]	0.028	0.166	0	1
Number of visits to GNS in the last 14 days	5.408	5.454	1	100
Days between last visit and interview	5.270	4.224	0	14
Mode of transport used petrol	0.376	0.484	0	1
Value of Travel Time (VTT, in 2020 £)	8.819	6.708	2.266	34.392
Out-of-pocket expenditure (in £)	13.301	41.965	0	500
Year of survey: 2020	0.130	0.336	0	1
Year of survey: 2021	0.493	0.500	0	1
Year of survey: 2022	0.377	0.485	0	1
Perceived site characteristics*				
There were adequate facilities (e.g., car parks, playgrounds, benches etc)	3.998	0.924	1	5
The place was accessible and well maintained (including good paths)	4.014	0.901	1	5
There was lots of litter/dog mess/ graffiti	4.201	0.824	1	5
The place felt welcoming/safe	2.816	1.425	1	5
It was a good place to get fresh air/peace and tranquillity	4.175	0.825	1	5
There was a variety of plants and wildlife	4.345	0.737	1	5
Observations	8766			

3.1. Empirical demand model and entrance fees

We assume a single recreation demand model (Phaneuf & Smith, 2005) through a Random Utility Maximisation (RUM) model (Hanemann, 1978). We use a Poisson-distributed trip count model, common in the literature (Englin et al., 1998; Siderelis et al., 2000), to examine the effects that perceived GNS site characteristics and hypothetical introduction of entrance fees have on the expected trip frequency (demand) for respondent *i* as:

$$E(trip_i) = \exp\left(a + \beta_i tc_i + \gamma I_i + \delta_i X_i\right), \quad (2)$$

[2] Source of UK gas prices used in the dataset: https://www.racfoundation.org/data/uk-pump-prices-over-time.

where a refers to perceived GRS characteristics stated by respondent i, β_j refers to the travel cost coefficient for each trip of respondent i for each total trip cost tc_i, γ is the fixed income coefficient of gross annual household income I_ι and X_i refers to individual (such as gender and age) and residential-area characteristics (such as the indices of multiple deprivation the area the respondent lives in) for respondent i. As the mean of the dependent variable (number of visits/trips) and its variance are over dispersed (see Table 1 and the minimum and maximum values) the negative binomial model is preferred from the Poisson model,[3] the two most common models used in travel cost studies (Deely et al., 2022). By the nature of the data collection there were no respondents reporting zero visits to GNS over the last 14 days so accounting for excess zeros in the data was not needed. Additionally, no issues of endogenous stratification (as data are collected by a random sample and not on-site). Following a Poisson distribution for $trip_i$ the log-likelihood for respondent i by expected number of trips φ_i is as:

$$\varphi_i = \exp\left(a + \beta_i tc_i + \gamma I_\iota + \delta_i X_i\right), \tag{3}$$

with the cumulative log-likelihood for respondent i, during month t being:

$$LL_{it} = \sum \left(trip_i * \left(a + \beta_i tc_i + \gamma I_\iota + \delta_i X_i\right) \text{-} \varphi_i\right), t = 1, \ldots 12 \tag{4}$$

Through Eq. (4) the log-likelihood of the PANS respondents can be estimated for a full year for demand for visits to green and natural spaces in the UK, through quasi-maximum likelihood.

It is expected that there are distinct differences in the expected demand for trips to GNS, with different underlying densities in the sample. This study accounts for such differences with the use of a Finite Mixture Model (FMM) (Deb & Trivedi, 1997) for the observed categorical variable (number of trips to GNS). The FMM is then fitted with a negative binomial regression for each class, following Cameron and Trivedi (2022). FMMs allow researchers to account for unobserved heterogeneity and identify groupings of responses and therefore have seen wide use in the past 20 years (Long & Freese, 2001). Recently, they have seen limited application in the field of explaining travel demand using count data (e.g., Hynes & Greene, 2013; Smith et al., 2016). Given their probabilistic nature, FMMs combine at least two density functions for the observed variable (in this case, the number of trips undertaken in the last two weeks to GNS in the UK) which functions are assumed to be derived from d unique classes $c_1, c_2, \ldots, c_d$ in proportions $p_1, p_2, \ldots, p_d$. The density of a $d-$ class mixture model can be written as:

$$f(trip_i) = \sum_{i=1}^{d} p_i c_i (trip_i | x^{'} \beta_i) \tag{5}$$

where p_i is the probability of the i th class $0 \le p_i \le 1$ and $\sum p_i = 1$ and c_i is the conditional probability function of the value of $trip_i$ for the i th class model. The probability for a respondent to belong in the j th class is depicted as:

$$p_j = \frac{exp(\mu_i)}{\sum_{j=1}^{d} exp(\mu_i)}, \tag{6}$$

where μ_i is the (linear) predicted value for the j th class and can be estimated with a multinomial logistic regression. The probability function of the negative binomial model, following Smith et al. (2016) to estimate demand for travel in GNS can be depicted as:

$$P(f_i) = \frac{\Gamma(trips_i + \xi_i)}{\Gamma(\xi_i)\Gamma(trips_i + 1)} \left(\frac{\xi_i}{(\xi_i + \ trips_i)} \right)^{\xi_i} \left(\frac{\lambda_i}{(\lambda_i + \ \xi_i)} \right)^{trips_i}, \tag{7}$$

where $\lambda_i = \exp\left(x^{'}\beta_i\right)$ and follows a gamma random distribution and $\xi_i = \left(\frac{1}{\varepsilon}\right)\lambda_i^j$ is the precision parameter and ε is the overdispersion parameter for the Poisson distribution and j is a constant. If $\xi_i = 0$ then the negative binomial model and the Poisson model have the same distributions (Cameron & Trivedi, 1986). For a detailed description of the continuous negative binomial and the finite mixture negative binomial models use within a travel cost framework see Smith et al. (2016).

The average Consumer Surplus, per survey respondent (the total value of welfare a respondent enjoys by visiting a GNS, depicted in monetary terms), per trip, can be estimated as:

$$CS = -\frac{1}{\beta_{travelcost}} \tag{8}$$

4. Results

Results of both the negative (continuous) binomial and the finite mixture negative binomial model are presented in Table 1 below. GNS visits were truncated at three daily visits to deal with exceptionally large number of trips, similar to Blaine et al. (2015) and Heberling and Templeton (2009). Three daily visits were considered to be the maximum number of trips to GNS a survey respondent could undertake, taking into account that 0.67% of England's population lives inside National Parks (Office of National Statistics, 2021). This also ensures that no bias in the resulting estimates can be introduced by having opportunity costs in the demand function; a concern for studies examining recreational visits from local communities in local sites (e.g., Börger et al., 2021; Hynes et al., 2022). Responses that indicated that the purpose of the trip was to visit an allotment or community garden, or an urban green space were removed as they are considered to be either side trips or not contain substantial elements of travel cost. This resulted in 2498 useable responses. Given that some respondents did not describe the characteristics of the sites they visited resulted in 2102 useable responses which were used in the continuous and finite mixture models presented.

In the second column, a simple negative binomial regression model with only the travel cost and the income variable was estimated. The third column depicts the estimates from the negative binomial regression model while the fourth and fifth columns depict the results from a two-segment (class) finite mixture negative binomial regression model, estimated following Eq. (7). To allow for comparisons across continuous and discrete models some socio-demographic variables presented in Table 1 were not used. This is due to the fact that, despite their ability to account for heterogeneity of responses, FMMs perform better when few covariates are used (Hilbe, 2011). Therefore, only key sociodemographic characteristics such as gender, age and education were used. To avoid endogeneity issues, trip characteristics such as mode of transportation and out-of-pocket expenses were not used to construct the FMM. The FMM negative binomial regression was estimated using the expectation-maximisation (EM) algorithm with five random draws taken when computing the starting values.

The log-likelihood (LL) test for the negative binomial regressions (*lnalpha*) at the bottom of the table confirms that the data are not Poisson. The FMM regression splits the sample into two segments, with their means being statistically significantly different (see bottom of Table 2). The first segment consisting of 81% of respondents of the total sample who visit GNS less often (on average 3 times in the last two weeks) while the second segment of the population is much smaller (around 19% of the sample) and visits GNS much more often (11 times, on average, in the last 14 days). The log likelihood shows that the FMM negative binomial regression fits slightly better to the data than the continuous (standard) negative binomial model, similar to other studies

[3] This was confirmed by estimating a Poisson model for Eq (0.4) and comparing the residual deviance with the degrees of freedom. The goodness-of-fit X^2 test was highly significant (p $<$ 0.001), indicating some overdispersion of data. As a rule of thumb, the ratio of the deviance and the degrees of freedom should be around 1 and in the case of the Poisson regression it was around 3, also indicating overdispersion.

Table 2
Negative binomial Poisson regression estimates for continuous and finite mixture models using the PANS sample, ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Number of visits in the past 14 days	Simple model	Pooled model	FMM model Segment 1	FMM model Segment 2
travel_cost	−0.001** (0.001)	−0.001*** (0.001)	0.001 (0.001)	−0.001** (0.001)
Sociodemographic characteristics				
Income	0.001*** (0.001)	0.001** (0.001)	0.001*** (0.001)	0.001*** (0.001)
Participant is female	–	−0.010 (0.038)	−0.029 (0.034)	−0.026 (0.039)
Age	–	0.006*** (0.001)	0.005*** (0.001)	0.006*** (0.001)
No educational qualifications	–	0.129 (0.100)	0.840*** (0.088)	−1.881*** (0.169)
High-school education (GCSE level)	–	−0.10 (0.041)	−0.097** (0.038)	−0.126*** (0.044)
Perceived site characteristics				
There were adequate facilities (e.g., car parks, playgrounds, benches etc)	–	−0.064 (0.046)	0.001 (0.42)	−0.043 (0.045)
The place was accessible and well maintained (including good paths)	–	−0.010 (0.057)	0.016 (0.053)	0.033 (0.056)
There was lots of litter/dog mess/graffiti	–	−0.030 (0.043)	0.001 (0.038)	−0.139*** (0.046)
The place felt welcoming/ safe	–	−0.055 (0.039)	−0.025 (0.035)	−0.039 (0.040)
It was a good place to get fresh air/peace and tranquillity	–	−0.091** (0.040)	−0.104*** (0.035)	0.035 (0.043)
There was a variety of plants and wildlife	–	0.196*** (0.046)	0.162*** (0.043)	0.074 (0.052)
Deprivation characteristics				
IMD decile 2	–	0.002 (0.087)	0.008 (0.074)	0.073 (0.090)
IMD decile 3	–	−0.149* (0.084)	−0.081 (0.073)	−0.335*** (0.099)
IMD decile 4	–	−0.055 (0.084)	−0.092 (0.076)	−0.239*** (0.092)
IMD decile 5	–	−0.038 (0.086)	0.005 (0.074)	−0.201** (0.100)
IMD decile 6	–	0.086 (0.085)	0.035 (0.073)	−0.202** (0.092)
IMD decile 7	–	0.087 (0.084)	−0.029 (0.074)	−0.228*** (0.087)
IMD decile 8	–	−0.052 (0.085)	−0.012 (0.074)	−0.308*** (0.096)
IMD decile 9	–	0.063 (0.087)	0.082 (0.078)	−0.092 (0.095)
IMD decile 10	–	0.061 (0.089)	0.087 (0.076)	−0.293*** (0.097)
Constant	1.395*** (0.048)	1.094*** (0.127)	0.667*** (0.114)	2.317*** (0.154)
Lnalpha	−0.753 (0.040)	−0.802 (0.044)	−1.403 (0.070)	
Alpha	0.471 (0.019)	0.448 (0.020)	–	–
Prob > X^2	0.003	<0.001	<0.001	<0.001
Log likelihood	−6316.1272	−4956.9686	−4878.8037	
LL test	***	***	***	***
Pseudo R^2	0.02	0.01	0.02	0.03
Marginal means for number of GNS visits per 14 days	–	–	3.01*** (0.05)	11.70*** (0.24)
Marginal class probabilities	–	–	0.807 (0.011)	0.193 (0.025)
Observations	2498	2100	2102	

(e.g., Grogger & Carson, 1991; Smith et al., 2016). The distribution of the number of visits across the two groups is presented in Fig. 1 below and it shows that the overdispersion of data is due to a smaller number of participants who visit GNS much more often than the majority of the respondents who visit GNS slightly less frequently.

Due to missing data the simple model contains more observations than the continuous and the FMM negative binomial regressions (see bottom of Table 2). The sign of the travel cost (*travel_cost*) is statistically significant in the pooled model and in the FMM Segment 2. Apart from Segment 1, the coefficient of travel cost is negative which corresponds with RUM in the sense that as expenditure grows trip demand decreases (Deely et al., 2022; Smith et al., 2016; Ji et al., 2022). A positive sign for travel cost such as in Segment 1 might indicate that extra costs such as capital equipment are required for longer trips that could include activities such as fishing and diving (Grogger & Carson, 1991) but the non-significance of the coefficient does not allow for further interpretation. With respect to income, it is statistically significant and positive in all models, consistent with RUM theory that as income increases visits to GNS are more desirable. Age is statistically significant in all models and segments with the positive sign aligning with past studies (e.g., Hynes & Greene, 2013). In the negative binomial regression models, for an added visit to a GNS, the difference in the log of expected count for GNS visits if a site was considered to be peaceful is expected to reduce by 0.104 log points (for Segment 1), indicating that those visiting GNS less often tend not to value this characteristic. Similarly, for an added visit to a GNS, the difference in the log of expected count for GNS visits if a site was considered to be rich in plants and wildlife is expected to increase by 0.162 log points (for Segment 1), indicating that those visiting GNS less often tend to value this characteristic. Whether a respondent is a female and education levels are not statistically significant determinants of GNS demand, across models.

With respect to the social deprivation characteristics of the areas where visitors of GNS reside, for frequent visitors of GNS (i.e., those in Segment 2) living in areas of high or low deprivation decreases demand for trips to GNS. This indicates that living in socially deprived areas does not affect the small proportion of the population that visits GNS often, perhaps being indicative of their resolve to access such sites. Interestingly, given the multinomial nature of the analysis, the base level is the lowest deprivation decile of households which means that those who are living in the most deprived areas in the UK (i.e., IMD decile 1) are also more likely to visit GNS (i.e., being in Segment 2). Those who visit GNS less often (i.e., those in Segment 1 which are the majority of the sample), living in less deprived areas does not statistically affect the number of trips to GNS. Given that the IMD are a composite indicator that includes aspects such as income and education deprivation indicators, it is possible that some of the presented results are confounded with other variables such as income used in the analysis.

We ran regressions using only travel cost estimates (without the opportunity cost component of VTT) for all three model specifications. The travel cost coefficients in these models were widely inconsistent and, apart from the simple model, had a positive sign. While different values of VTT can cause differences in welfare estimates (see the next paragraphs on this topic), excluding opportunity cost for longer trips deteriorates the explanatory power of the analysis. Our analysis, using

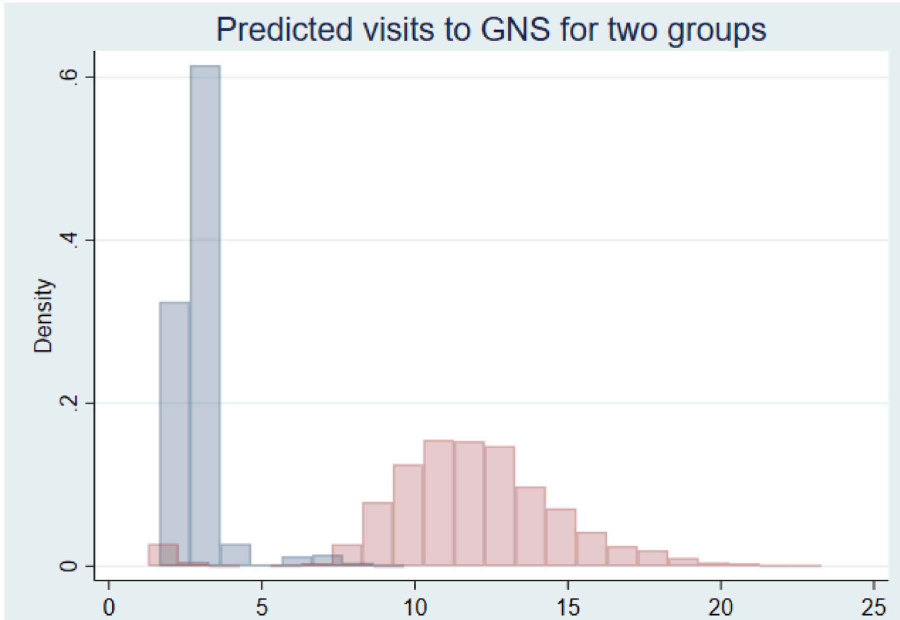

Fig. 1. Predicted visits for the two segments of respondents to the PANS survey, estimated through a finite mixture model fitted through a negative binomial regression.

official VTT estimates for the UK, should offer policy-relevant insights on the validity of the VTT estimates for recreation purposes only. Similarly low R-squared numbers are also reported in Englin and Mendelsohn (1991). Given the number of covariates used in the negative binomial FMM regression it is not surprising that some variables are not statistically significant.

Next comes the welfare analysis, using the (continuous) negative binomial regression (pooled model) and the FMM negative binomial regression estimated in Table 2. Results are presented in Table 2 below and show the Consumer Surplus (CS) for each added visit to a GNS for PANS respondents. Sensitivity to travel cost and income are also presented through travel cost and income elasticities, for each model, reported in Table 3.

The average CS per person, per trip for each model was estimated through Eq. (8) and are reported in Table 3 exclude Segment 1 respondents as the travel cost coefficient is positive which conflicts with random utility theory. The range of CS is between £65.3 and £167 per person, per trip, for the FMM Segment 2 and pooled negative binomial regression model, respectively. This shows that preference heterogeneity exists between visitors of GNS in the UK and failure to account for it can result in considerable overestimation of the true CS, also evident by the larger CS estimated for the pooled model where the travel cost coefficient in Table 2 has the correct size but is not significant.

Results of the welfare analysis show that a 1% increase in travel costs would decrease the number of visits to GNS by 3.2% for the simple model while it would bring similar increases in GNS visits in the pooled and FMM model Segment 2 (1.8% and 0.1%, respectively). This indicates that the frequent GNS visitors of Segment 2 are determined to visit GNS despite the costs incurred. Changes in income would result in bigger differences in trips to GNS, with a 1% increase in annual gross household income resulting in increases between 15.1% (pooled model) and 10.2% (Segment 2 participants in the FMM model). The inelastic nature of the travel cost elasticity is expected in studies including site characteristics as demand determinants (e.g., Englin & Mendelsohn, 1991).

Table 3
Consumer Surplus, estimated with the Delta Method with cost and income mean elasticities **, *** denote statistical significance at the 5% and 1% levels, respectively.

	CS per trip	[Delta method 95% Confidence Interval		Travel cost elasticity	Income elasticity
Simple model	£ 167.24**	13.44	321.04	−0.032	0.138
Pooled model	£284.91	−233.659	803.471	−0.018	0.151
FMM model Segment 2	£ 65.34***	34.461	96.227	−0.001	0.102

5. Discussion and conclusions

This paper focuses on determining the factors driving demand for trips to outdoor green natural spaces such as those found in national parks in the UK, of the English population. Using responses across waves of the English-wide PANS survey over the period of 31 months between April 2020 and September 2022, findings indicate frequent visits to GNS (almost one every three days, on average) and find the state of GNS to be good in terms of cleanliness, biodiversity and accessibility (see summary statistics in Table 1). An in-depth analysis though indicates that large differences exist amongst the English public, both in frequencies of trips to green and natural spaces and the measures of welfare they enjoy by those visits.

With respect to the travel cost model, using both travel cost time and opportunity cost (VTT) in the demand function was deemed necessary as we focused on visitors using motorised transport modes. Nevertheless, excluding those who travelled with other modes (on foot, bicycles etc) and those who lived close to the site can create a misrepresentation of the true travel cost as these people might be driven by a high recreational demand to choose to live so close to GNS (Tardieu and Dufferin, 2019). Variations in the value of VTT, if included, are also likely to create large variations in CS (Fezzi et al., 2014), which can explain the divergence in the CS estimates in Table 3.

Demand for trips to GNS is driven by socio-demographic characteristics such as age and education and travel costs, a common finding in the literature (e.g., Juutinen et al., 2022; Tienhaara et al., 2021). The characteristics of green and natural spaces English respondents visit are not always affecting trip frequency; only if GNS are perceived as peaceful and offering sightings of flora and fauna have an effect on trip demand (see the middle section of Table 2). This finding is in line with Tardieu and Tuffery (2019) that find that site characteristics play the most important role when it comes to choosing a GNS for recreation. Englin and Mendelsohn (1991) find that individual characteristics are mostly correlated between them and therefore differences in the signs of site attributes can be observed in the demand function. In travel cost studies using visitors' perceptions as indicators of site quality, Börger et al. (2021), Juutinen et al. (2022) and Zeng et al. (2023) report such variables as having a positive influence in trip frequency, similar to the present study. Nevertheless, issues such as congestion, exacerbated by the increase for outdoor spaces by Covid-19 during the time survey responses were coming in, would require further examination. As information around congestion was not available in the dataset this was not carried out; Timmins and Murdock (2007) suggest the use of an instrumental variable approach in the regression estimation to account for this endogeneity.

Social inequalities and deprivation in our findings either did not influence demand for visits to GNS (see Segment 1 respondents in Table 2) or had an inverse effect on demand for recreation (see Segment 2 respondents in Table 2). Our findings provide evidence that living in socially deprived areas does not decrease demand for recreation, suggesting that GNS recreation is a normal good for the English public. The results for Segment 2 are of particular importance, as they indicate that living in one of the approximately 3284 most socially deprived LSOAs in England positively affects demand for visits to GNS. Past studies on visits to outdoor spaces during the pandemic found differences between socially deprived groups and racial/ethnic groups (Lu et al., 2023) but this can be traced to the association between travel distance and access to such spaces, making travel cost and mode an important factor here. In our sample, focusing on those accessing GNS via motorised transport this effect was potentially eliminated.

Accounting for heterogeneity through a discrete finite mixture model produces large differences in CS. Differences are also observed when comparing welfare measures between continuous and finite mixture negative binomial regression models. Properly accounting for heterogeneity should acknowledge the variability in the frequency of visits which appears to be less sensitive to changes in travel cost or income for those who are frequent visitors (see the income and travel cost elasticity results in Table 3). Accounting for heterogeneity also determines the levels of welfare estimation, as evident from the results in Table 3 who are contingent on the statistical strength of the model. Such results indicate that over-estimation of consumer surpluses might be an issue in travel cost studies that fail to account for heterogeneity. Accounting for heterogeneity was carried out through using a finite mixture model which is not without issues (Tyllianakis, 2023). Such issues can be around the convergence of such models as they might arrive at local and not global maxima (Muthén & Muthén, 2008). Including random starts and draws can help with optimisation and this was carried out in this study but adds to computational burden and time. This study adds to the growing literature employing such methods to estimate travel demand and welfare estimates while using a diverse group of variables to inform the finite mixture model.

We find that visits to GNS are both cost and income inelastic, indicating that UK residents are less responsive to changes in travel cost that could be caused by increases in petrol prices, or in changes in their income. Despite that, the income coefficient, across models in Table 2, was positive, indicating that visits to GNS are always a normal good. Therefore, it appears that demand for visits to GNS is determined by other characteristics, with a small part of the population being committed to visiting the outdoors quite often (those belonging in Segment 2 from the FMM negative binomial regression) while the majority of the population is visiting GNS less than half of that time (the majority of the sample belongs in Segment 1). Our results are similar with other studies with respect to inelastic cost elasticities (Borzykowski et al., 2017; Englin & Mendelsohn, 1991). Lack of price (cost) sensitivity for visits to GNS indicates the importance of outdoor recreation for the English public, especially for the frequent visitors of such spaces. Such findings broadly confirm that the UK Government's efforts to incentivise outdoor recreation are resulting in only a small number of people visiting GNS frequently with most being casual visitors (UK Government, 2016). Incentivising outdoor visits for casual visitors such as those in Segment 1 could therefore require improving site quality through investing in site cleanliness and biodiversity richness which could in turn lead to an increase in the welfare values enjoyed by UK recreationists. Nevertheless, it is likely that the increase in visits to GNS across the UK is due to increase of casual visits (given the size of segments 1 and 2). Educational campaigns and web-based information systems for outdoor recreationists therefore become more imperative (Pröbstl-Haider et al., 2023).

GNS in the UK are expected to continue facing mounting problems from the increased demand for outdoor recreation in GNS. Particular challenges refer to issues such as rubbish left behind (D'Arco et al., 2021), threats to sensitive ecosystems such as peatlands (Byg et al., 2017) and overall threats to biodiversity and ecosystems (Gibbons et al., 2022). Possible management strategies can include increased budgets for national parks to deal with increased numbers, fencing off of areas and increase hiring of personnel (Mackenzie & Goodnow, 2021) while mitigation strategies can involve entrance fees for specific parks that meet certain characteristics to curb visits, similar to US parks (Ji et al., 2022). As this paper demonstrates, demand for visits to GNS does not depend heavily on travel cost, making visits to GNS contingent on other determinants. Therefore, more in-depth studies on the impact of increased demand to outdoor spaces is required, especially since most of the visitors might not be well-versed in interacting with nature given their infrequent visits to it.

CRediT authorship contribution statement

Emmanouil Tyllianakis: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors have no relevant financial or non-financial interests to disclose and no competing interests to declare that are relevant to the content of this article.

Data availability

Data will be made available on request.

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