ABSTRACT

Introduction

The COVID-19 pandemic has had exceptional effects on travel behaviour in the UK. This paper focuses specifically on the outdoor exercise trips of Scottish residents at several distinct points of the COVID-19 pandemic. Given the negative health consequences of limited exercise, this study aims to determine the sociodemographic and behavioural factors affecting frequency of outdoor exercise trips.

Methods

Using recent public survey data (n=6000), random parameters ordered probit models (with allowances for heterogeneity in the means of random parameters) are estimated for three points during the pandemic: the most stringent lockdown, modest restriction easing and further easing of restrictions.

Results

The survey data show frequent outdoor exercise in the early stages of the pandemic, with ~46% making six or more weekly trips during lockdown, reducing to ~39% during the first phase of restriction easing, and further to ~34% during the following phase of easing. The model estimations show that common factors, dominated by socioeconomic and demographic variables, influenced the frequency of outdoor exercise trips across most survey groups. The modelling framework also allowed insights into the impact of unobserved characteristics within several independent variables; for example, the lockdown exercise trip rates of those with a health problem or disability, and those over 65, were both found to be dependent on personal vehicle access.

Conclusions

The findings suggest that those with a health problem or disability, those who live in households' where the main income earner is employed in a semi-skilled/unskilled manual occupation or is unemployed and ethnic minority groups (i.e., any mixed, Asian, or Black background) were significantly more likely to complete no weekly outdoor exercise trips throughout the pandemic. As a result, we suggest that these groups are at higher risk of the negative health consequences associated with limited physical activity. Policy implications are discussed in terms of mitigating this effect, as well as reducing transport inequity related to vehicle accessibility.

Keywords: COVID-19; Outdoor exercise; Transport equity; Random parameters ordered probit; Unobserved heterogeneity

INTRODUCTION

The COVID-19 pandemic has had unprecedented effects on human behaviour across the globe. In the context of transportation, significant changes in travel behaviour have been observed during government-enforced lockdowns. Research has shown the trip purposes and mode preferences of individuals to vary significantly from normal, pre-lockdown levels (Abdullah, et al., 2020; Laverty, et al., 2020). During 2020 in Scotland, significant reductions in bus, rail and car journeys, and significant increases in active travel (walking and cycling) were recorded (Transport Scotland, 2020). However, the overall impact of social distancing measures, and the associated increase of telecommuting (working from home), on physical activity is not clear. It may be anticipated that the significant decline in commuting trips and use of public transport during COVID-19 lockdowns also reduced levels of physical activity. In fact, before COVID-19, commuting journeys made by public transport in England were shown to generate on average 21 minutes of physical activity through walking or cycling from the origin or destination of the trip to stops or hubs (Patterson, et al., 2019). 34% of public transport commuters achieved the recommended level of physical exercise while travelling to and from work. The UK Government's "stay-at-home" guidance significantly limits this daily component of physical activity. This limitation should be compensated for through adjusted behavioural patterns, thus avoiding the well-known negative consequences of limited exercise. For instance, past research has shown reliable causal relationships between reduced rates of exercise and increased incidence of serious physiological disorders, such as diabetes and cardiovascular disease (Anderson & Durstine, 2019) and increased rates of mental illness, including anxiety and depression (Camacho, et al., 1991).

Such compensation has been reflected in the recent study of Rogers et al. (2020), where some preliminary evidence suggested that pre-lockdown levels of physical activity may not greatly vary from those recorded during the March 2020 lockdown in the UK. During the lockdown in the UK, people were only permitted to leave their home once per day for outdoor exercise. This mobility restriction was considered an opportunity for exercise by a significant portion of the population in an effort to compensate for the lack of physical activity associated with the abrupt interruption of regular mobility patterns (e.g., trips for work, education, and so on). In this context, recent data from Sport England showed that during the first six weeks of lockdown, outdoor activity surged compared to pre-lockdown levels, with walking and cycling being among the most popular forms of outdoor activity (Sport England, 2020). The extent to which different population groups made use of lockdown to exercise more frequently may significantly vary based on various factors, such as: sociodemographic characteristics, level of access to public facilities (e.g., green spaces or public parks) and availability of transport links that may enable travel to destinations for outdoor exercise.

This study aims to further understand the relationship between sociodemographic characteristics and physical activity by analysing the frequency of outdoor exercise trips made by Scottish residents throughout the COVID-19 pandemic. To achieve this, we use data (n=6000) collected by Transport Scotland's triweekly 'COVID-19 Public Attitudes Surveys' (Transport Scotland, 2020). In addition to gathering information about respondents' travel choices, the survey data also include sociodemographic and behavioural characteristics of respondents, information about their travel behaviour, before and during the outbreak of COVID-19, as well as their attitudes and expectations about future mobility.

Recent research has shown health equality to be an issue throughout the COVID-19 pandemic, as individuals belonging to certain social groups (e.g., those in certain occupations or lower income groups) have been at greater risk of infection and mortality (Bambra, et al., 2020). Similarly, the mortality rate across the UK's most deprived areas has been approximately twice that of the rate recorded in the least deprived areas (Office for National Statistics, 2020). Analysis of infection and mortality rates also show a gulf in the health outcomes of those belonging to different ethnic backgrounds. In the UK, those from Black, Asian or other ethnic minority groups have faced significantly higher rates of infection and mortality than those from White ethnic backgrounds (Office for National Statistics, 2020), a phenomenon mirrored in the US (Centers for Disease Control and Prevention, 2021). These disparities are mostly attributable to engrained social inequalities, relating to occupation, income and education, and are not thought to be the result of pre-existing health conditions (Office for National Statistics, 2020). The analysis of trip rates throughout the pandemic will shed light on the environment that facilitated higher infection incidence among certain groups. The analysis of outdoor exercise trips in particular, will show the groups that have suffered from a lack of exercise and as a result are at higher risk of the associated mental and physical illnesses (Anderson & Durstine, 2019; Camacho, et al., 1991). Given the potentially dire consequences for public health, this study identifies the sociodemographic and behavioural factors affecting outdoor exercise trip frequencies, therefore allowing those groups at elevated risk of mental or physical illnesses to be identified. These findings may be used to develop targeted policies to mitigate the severity of future public health crises and to generally improve levels of physical activity.

To provide granular insights into potential equity issues related to travel for outdoor exercise trips during the COVID-19 pandemic, we adopt an advanced statistical modelling framework, specifically, the random parameters ordered probit model with allowances for heterogeneity in the means of random parameters (RPOPHM). This framework has the potential to account for the impact of various unobserved factors, thus enabling the identification of underlying relationships between trip rates and their influential factors, which could not be unveiled through conventional statistical approaches.

DATA

Transport Scotland, Scotland's government agency for transport, conducted triweekly public attitudes surveys to gauge the travel behaviour of Scottish residents throughout the government-enforced lockdown and subsequent phases of restriction easing (Transport Scotland, 2020). A consultancy was commissioned to conduct the different waves of the survey, of which there are nine at the time of writing. The sample frame was based on randomly selected postcodes, chosen considering Scottish Index of Multiple Deprivation (SIMD)[1] regional quotas. The surveys were conducted telephonically and were subject to the General Data Protection Regulation (GDPR) and Market Research Society (MRS) Code of Conduct. The MRS Code of Conduct provides a set of ethical and professional standards, based on the GDPR, that research practitioners must maintain (MRS, 2019). Telephone numbers (80% landline and 20% mobile) were chosen randomly from the households with a landline in the selected postcode areas. Any numbers that were identified as non-response, a business or refusal to participate were discarded.

The purpose of these surveys, which are still ongoing, is to monitor the impact of COVID-19 restrictions on travel behaviour in Scotland, as well as exploring perceptions regarding future travel intentions. We study the weekly rate of outdoor exercise trips, via respondents' answers to mobility-related questions during three distinct periods of the pandemic. The periods will be referred to as Survey Groups 1, 2 and 3, and can be defined as follows: Survey Group 1 includes two "survey waves" conducted during the most stringent lockdown (24th March 2020 – 27th May 2020); Survey Group 2 includes two survey waves conducted during "Phase 1" (28th May – 17th June 2020) and "Phase 2" (18th June – 8th July 2020) of the Scottish

[1] SIMD is the Scottish Government's standard approach for ranking relative deprivation in subareas of Scotland. SIMD considers multiple metrics that indicate different aspects of deprivation, including: income, employment, education, health access to services, crime rates and quality of housing (Scottish Government, 2020).

Government's "COVID-19 route map"; and Survey Group 3 contains five survey waves during "Phase 3" (9th July – 8th October 2020) of the route-map.

To contextualise the survey groups further, lockdown and subsequent phases can be outlined as follows: "lockdown" refers to the most stringent restrictions, where people living in Scotland were advised to stay at home with the exception of "essential work or travel"; "Phase 1" refers to the first phase of restriction easing, where the most significant alteration to restrictions was to allow those who could not work from home to return to work; "Phase 2" included further relaxations regarding the reopening of workplaces and physical distancing with people from other households; and "Phase 3" refers to the furthest stage of restriction easing, where many small businesses, workplaces and gyms reopened (Scottish Government, 2020). Throughout the pandemic, the Scottish Government promoted outdoor exercise within an individual's local area, which was initially limited to one trip per day during lockdown, however, this limit was removed during subsequent phases (Scottish Government, 2020). Table 1 shows the matching of survey waves into survey groups, where dates in parentheses are the duration of survey window (i.e., the period in which respondents were consulted) or the duration of a given phase of restrictions, while Table 2 shows the number of initial responses and complete responses for each survey group.

Table 1 – Aggregation of survey waves to survey groups based on the Scottish Government's "route map"

Route map (Lockdown/Phase)	**Survey groups**	**Survey waves**
Lockdown (24/03/20 – 27/05/20)	Group 1 (05/05/20 – 25/05/20)	Wave 1 (05/05/20 – 13/05/20) Wave 2 (18/05/20 – 25/05/20)
Phase 1 (28/05/20 – 17/06/20) Phase 2 (18/06/20 – 08/07/20)	Group 2 (01/06/20 – 27/06/20)	Wave 3 (01/06/20 – 07/06/20) Wave 4 (24/06/20 – 27/06/20)
Phase 3 (09/07/20 – 08/10/20)	Group 3 (08/07/20 – 06/10/20)	Wave 5 (08/07/20 – 13/07/20) Wave 6 (22/07/20 – 28/07/20) Wave 7 (19/08/20 – 25/08/20) Wave 8 (08/09/20 – 16/09/20) Wave 9 (30/09/20 – 06/10/20)

Table 2 – Number of initial and complete observations per survey group

Survey group	**Initial observations**	**Complete observations**
Group 1	2000	1605
Group 2	1500	1169
Group 3	2500	1924
Total	6000	4698

The verbatim survey question, which is the key dependent variable for this paper, was as follows: "In the past 7 days how many times have you left your home to go for outdoor exercise (e.g. going for a walk or hike, run or cycle, dog walking)". The weekly trip rates were recorded as discrete, ordered outcomes (zero, one, two-three, four-five, six-seven, and more than seven trips). To account for low variability for several of these categories across the sample, the outcomes of the dependent variables (i.e., the weekly trip frequencies across survey groups) were aggregated as follows: Level 1 (no trips), Level 2 (one, two or three trips), Level 3 (four or five trips) and Level 4 (six or more trips). Kolmogorov-Smirnov tests were conducted to verify the assumption that the distribution of responses for grouped waves (as shown in Table 1) was similar. All test results were insignificant, therefore, there is no significant variation in the distributions of grouped waves (e.g., in Survey Group 1, there is no significant variation in the distributions of survey waves 1 and 2). Further Kolmogorov-Smirnov tests were conducted for the distributions of the survey groups; all results were statistically significant (p-value < 0.05) as shown in Table 3, hence, there is significant variation in the distribution of outdoor exercise trips among the survey groups.

Table 3 – Matrix displaying p-values for Kolmogorov-Smirnov tests between survey groups

	Survey Group 1	**Survey Group 2**	**Survey Group 3**
Survey Group 1	–	0.001	2.058×10^{-11}
Survey Group 2	0.001	–	0.047
Survey Group 3	2.058×10^{-11}	0.047	–

Figure 1 shows the distribution of outdoor exercise trips for Survey Group 1 (n=1605), Survey Group 2 (n=1169) and Survey Group 3 (n=1924). At any stage of the pandemic, about 1 in 3 respondents did not complete any outdoor exercise trips. The trips frequencies are reasonably well distributed among the levels of dependent variable, however, for every survey group Level 1 (no trips) and Level 4 (six or more trips) are the most popular responses. The majority of respondents belong to the lowest or highest rank, which suggests stark differences in outdoor exercise experiences during the pandemic. Interestingly, the number of respondents making six or more trips decreases consistently (46.42% to 38.75% to 33.52%) as restrictions ease, suggesting a particular enthusiasm or availability to exercise frequently in the early stages of the pandemic, which falters over time. The reopening of gyms in Phase 3 may also be a factor contributing to reduced outdoor exercise among Survey Group 3 respondents.

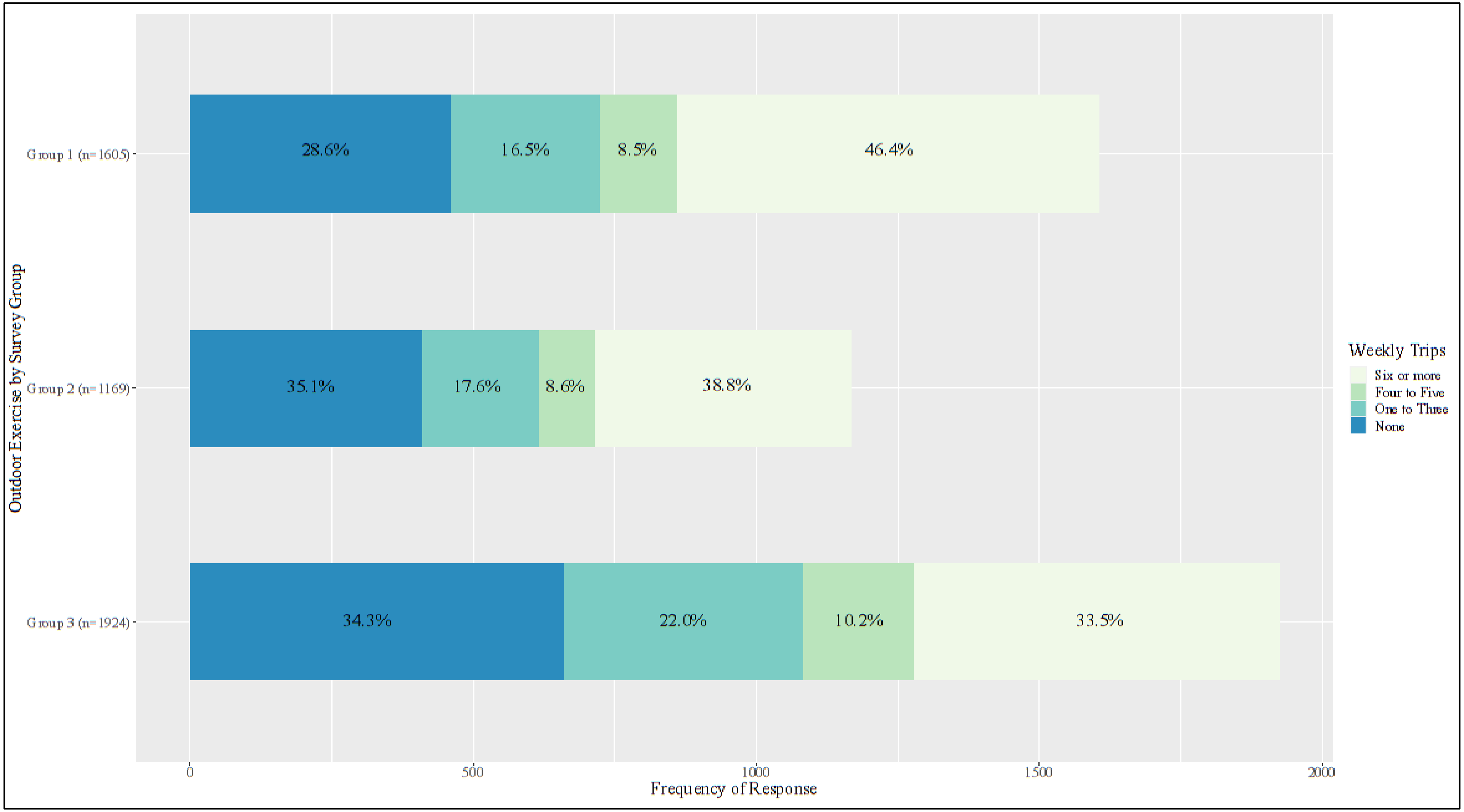

Figure 1 – Weekly outdoor exercise trips made by Scottish residents in Survey Groups 1, 2 & 3

A variety of other factors may also be influencing the frequency of outdoor exercise trips, including risk perceptions of travel modes, changes in commuting behaviour and meteorological variability. In Scotland, and across the EU, the risk of transmitting or contracting COVID-19 is thought to have decreased usage of public transport (Jenelius & Cebecauer, 2020; Przybylowski, et al., 2021), as individuals opted to travel on-foot or by bicycle instead. Another contributing factor may be that people living in Scotland, many of whom were furloughed (particularly during Lockdown, Phase 1 and Phase 2) or telecommuting, had greater freedom to travel actively and exercise frequently; a trend often observed among those with fewer work commitments (Cook & Gazmararian, 2018).

The survey data also include respondents' demographic (e.g., gender, age, disability and ethnic background), socioeconomic (current working situation, employment status and social grade based on the occupation type of the household's main income earner) and behavioural characteristics (mode of travel, and altered personal behaviour as a result of COVID-19). UK Government definitions of social grades are as follows: Social AB (households whose main earners are in managerial/professional occupations), Social C1 (main earners in supervisory/junior managerial occupations or in full-time education), Social C2 (main earners in skilled manual occupations) and Social DE (main earners in semi/unskilled manual occupations or unemployed) (Scottish Government, 2018). Since the social grade variable captures information for the household's main income earner, it will be referred to as "household social grade" from here on. The surveys used SIMD quota restraints to return samples that were almost exactly representative of Scotland's demographic strata, for example, the gender, ethnic background, household social grade and regional data for Scottish residents were all accurately represented among the survey groups.

METHODOLOGY

Statistical methods are widely adopted to analyse survey data in transportation research (Eker, et al., 2020a; Barbour, et al., 2020) and, specifically, trip rate data (Sultana, et al., 2018). In recent years, an increasing number of studies have shown the merits of accounting for the potential effects of unobserved heterogeneity in survey data (Eker, et al., 2020a; Mannering, et al., 2016; Paleti & Balan, 2017). Unobserved heterogeneity refers to unobserved characteristics within independent variables, which may reflect unobserved tastes, preferences or experience of the respondents that are often difficult to identify through survey questions. If the effects of unobserved heterogeneity are left unaccounted for, the statistical analysis may lead to unreliable inferences and, subsequently, to erroneous policy implications (Eker, et al., 2020b; Fountas, et al., 2019; Mannering, et al., 2016).

Given the discrete, ordered nature of the dependent variable, discrete outcome modelling, in particular the ordered probit modelling framework, was deemed appropriate for the statistical analysis (Washington, et al., 2020). In this study, the random parameters technique is also incorporated in the ordered modelling framework; this integrated approach differs from the standard ordered probit, as it allows for the potential effects of unobserved heterogeneity within the observed independent variables to be captured (Mannering, et al., 2016). From here on, the methodological formulation of the modelling framework is in accordance with Washington et al., 2020. The ordered probit model can be defined as follows:

$$z_n = \boldsymbol{\beta}\mathbf{X}_n + \varepsilon \,, \tag{1}$$

where $\boldsymbol{\beta}$ is a vector of estimable parameters, $\mathbf{X}$ is a vector of independent variables dictating the discrete ordering for an observation, n, and ε is random disturbance – assumed to be normally distributed across observations, with mean = 0 and variance = 1. Using the previous equation, the ordered data, y, for each observation can be defined as follows:

$$y = 1 \text{ if } z \leq \boldsymbol{\mu}_0$$

$$y = 2 \text{ if } \boldsymbol{\mu}_0 < \text{z} \leq \boldsymbol{\mu}_1$$

$$y = \text{"} \ldots \text{"}$$

$$y = I \text{ if z} \geq \boldsymbol{\mu}_{I-1} \,, \tag{2}$$

where $\boldsymbol{\mu}_i$ are estimable parameters that explain *y*, which corresponds to integer ordering where *I* is the highest integer response. Estimable parameters, $\boldsymbol{\mu}_i$, are estimated in conjunction with model parameters, $\boldsymbol{\beta}$.

To account for the effects of unobserved heterogeneity, the coefficients $\boldsymbol{\beta}$ are allowed to vary across observations for selected independent variables. Past research has shown that this approach, known as random parameters ordered probit (RPOP) modelling, often significantly improves the explanatory power of the framework (Anastasopoulos & Mannering, 2009; Mannering, et al., 2016; Seraneeprakarn, et al., 2017; Yu, et al., 2020), when compared to the traditional fixed parameters ordered probit (FPOP). To optimize the layers of unobserved heterogeneity captured by the modelling framework, allowances are also made for heterogeneity in the means of random parameters; hence, the complete modelling approach used for the statistical analysis is referred to as the Random Parameters Ordered Probit with Heterogeneity in the Means of random parameters (RPOPHM). This approach is considered a more comprehensive way of capturing unobserved heterogeneity, as random parameters are allowed to vary by explanatory variables (Seraneeprakarn, et al., 2017; Yu, et al., 2020). The revised framework can be written as follows:

$$\boldsymbol{\beta}_n = \boldsymbol{\beta} + \boldsymbol{\Theta}\mathbf{Z}_n + \boldsymbol{\xi}_n \,, \tag{3}$$

where $\boldsymbol{\beta}_n$ is a vector of estimable parameters that may vary across observations, *n*, $\boldsymbol{\beta}$ is the vector of mean parameter estimates across the dataset, $\mathbf{Z}_n$ is a vector of explanatory variables from observation *n*, that influence the mean of $\boldsymbol{\beta}_n$, $\boldsymbol{\Theta}$ is a vector of estimable parameters and $\boldsymbol{\xi}_n$ is a vector of random distributed terms. The calculation of the probabilities for RPOP models is particularly cumbersome, therefore, a simulation-based maximum likelihood is used for model estimation (Washington, et al., 2020). For this process, Halton draws are often considered a more effective alternative to random draws (Halton, 1960), as such we use Halton draws for model calibration in this paper.

The average marginal effects, which are the change in the levels of the dependent variable as a result of a one unit change in the independent variable, can be calculated to gauge the influence of independent variables on interior categories (Washington, et al., 2020). For variables that generate statistically significant random parameters, observation-specific parameters ($\boldsymbol{\beta}_n$) can be used for the calculation of the marginal effects, significantly enhancing their robustness (Anastasopoulos, 2016). Observation-specific parameters can be derived through a built-in capability of the modelling software (R package: 'Rchoice' (Sarrias, 2020)).

MODEL ESTIMATION RESULTS

Table 4 displays the descriptive statistics for the independent variables that were found to have statistically significant influence in the RPOPHM models. A variety of other independent variables were trialled during modelling (see Appendix – Table A1 for all available independent variables), however, those excluded from Table 4 were insignificant. Tables 5, 6 and 7 display the RPOPHM model estimations for Survey Groups 1, 2 and 3[2], respectively. It should be noted that the final model for Survey Group 2 is referred to as an RPOP model, as no instances of heterogeneity in the means of random parameters were discovered. The average marginal effects are presented in each table, accompanying the parameter estimates of their respective models. The model parameters can be interpreted as follows: an independent variable with a significantly positive coefficient (*t*-stats > 1.65 = >90% level of confidence (l.o.c.), *t*-stats > 1.96 = >95% l.o.c.) increases the likelihood of belonging to the highest variable

[2] It should be noted that only the final RPOPHM/RPOP models are presented in the results, as these models were shown to have significantly superior explanatory power (verified by Likelihood Ratio Tests following each results table) than their FPOP counterparts.

rank ([y=4], 6 or more trips per week), while a significantly negative coefficient increases the likelihood of belonging to the lowest rank ([y=1], no trips per week).[3] The average marginal effects enhance understanding of the effect of a given independent variable across all outcomes of the dependent variable, including interior categories ([y=2], 1-3 trips and [y=3], 4-5 trips).

Table 4 – Descriptive statistics for key independent variables for Survey Groups 1, 2 & 3

Variable Description	**Survey Group 1**	**Survey Group 2**	**Survey Group 3**
Socioeconomic characteristics			
Household social grade (1 if managerial/professional occupation, 0 otherwise)	35.95%	30.97%	36.80%
Household social grade (1 if semi-skilled/unskilled manual occupation or unemployed, 0 otherwise)	20.31%	–	19.28%
Current working situation (1 if furloughed, 0 otherwise)	15.64%	9.24%	4.31%
Current working situation (1 if full-time education, 0 otherwise)	–	4.28%	–
Current working situation (1 if self-employed, 0 otherwise)	–	–	8.04%
Demographic characteristics			
Age indicator (1 if over 65, 0 otherwise)	19.44%	21.13%	21.05%
Health problem or disability (1 if yes, 0 if no)	20.31%	27.89%	25.73%
Gender (1 if male, 0 otherwise)	47.17%	–	49.84%
Ethnic background (1 if ethnic minority group (any mixed, Asian, or Black background), 0 otherwise)	1.43%	–	3.27%
Ethnic background (1 if White British, 0 otherwise)	88.91%	–	84.30%
Directly affected by COVID-19 (1 if yes, 0 if no)	22.99%	–	–
Behavioural characteristics			
Mode of travel prior to lockdown (1 if active travel used frequently, 0 if not used frequently)	13.71%	14.46%	16.84%
Mode of travel prior to lockdown (1 if personal vehicle used frequently, 0 if not used frequently)	83.43%	76.48%	–

[3] It should be noted that *t*-stats >1.96 (threshold for 95% l.o.c.) provide stronger evidence of statistical significance for the corresponding independent variables compared to *t*-stats ranging from 1.65-1.95, which suggest statistical significance for the corresponding independent variables at a 90% l.o.c. Despite the milder evidence provided by the latter, this threshold is still considered to be useful for identifying statistically significant relationships (Washington et al., 2020).

Table 5 – Outdoor exercise trips (Survey Group 1): RPOPHM model estimation and average marginal effects [4]

Variable Description	**RPOPHM Model**		**Marginal Effects**			
	Coefficient	***t*-stat**	**[y = 1]**	**[y = 2]**	**[y = 3]**	**[y = 4]**
Constant	0.780	9.488	–	–	–	–
Household social grade (1 if managerial/professional occupation, 0 otherwise)	0.285	3.338	-0.0855	0.0024	0.0093	0.0739
Household social grade (1 if semi-skilled/unskilled manual occupation or unemployed, 0 otherwise)	-0.305	-2.850	0.0921	-0.0079	-0.0117	-0.0735
Mode of travel prior to lockdown (1 if active travel used frequently, 0 if not used frequently)	0.491	4.321	-0.1415	-0.0059	0.0119	0.1355
Ethnic background (1 if ethnic minority group, 0 otherwise)	-0.825	-2.652	0.2457	-0.0489	-0.0368	-0.1600
Gender (1 if male, 0 otherwise) *Standard deviation of parameter density function*	0.131 *0.728*	1.511 *3.347*	-0.0412	-0.068	0.0028	0.0452
Health problem or disability (1 if yes, 0 if no) *Standard deviation of parameter density function*	-1.854 *1.566*	-4.775 *4.327*	0.3228	-0.0954	-0.0522	-0.1751
Current working situation (1 if furloughed, 0 otherwise) *Standard deviation of parameter density function*	0.326 *0.805*	2.282 *2.613*	-0.0960	-0.0052	0.0083	0.0929
Age indicator (1 if over 65, 0 otherwise) *Standard deviation of parameter density function*	-0.552 *1.083*	-2.059 3.618	0.0342	-0.0123	-0.0062	-0.0157
Directly affected by COVID-19 (1 if yes, 0 if no) *Standard deviation of parameter density function*	0.563 *0.519*	1.952 *1.660*	-0.0122	-0.0026	0.0004	0.0144
Heterogeneity in the mean of RP Health problem or disability : Mode of travel used prior to lockdown – personal vehicle	0.877	2.343	-0.0960	-0.0052	0.0083	0.0929
Heterogeneity in the mean of RP Age indicator (over 65) : Mode of travel used prior to lockdown – personal vehicle	0.503	1.676	-0.0283	0.0070	0.0047	0.0167
Heterogeneity in the mean of RP Directly affected by COVID-19 : White British ethnic background	-0.582	-1.994	0.0390	0.0036	-0.0027	-0.0399
Threshold 1	0.656	11.856	–	–	–	–
Threshold 2	0.958	13.124	–	–	–	–
Number of observations	1605		–	–	–	–
$LL_{CONSTANT}$ / $LL(\beta_{FPOP})$	-1960.04 / -1858.02		–	–	–	–
LL at convergence, $LL(\beta_{RPOPHM})$	-1835.36		–	–	–	–
$AIC_{CONSTANT}$ / AIC_{FPOP}	3926.08 / 3740.04		–	–	–	–
AIC at convergence, (AIC_{RPOPHM})	3710.72		–	–	–	–

LRT (I): RPOPHM > FPOP with > 99.99% l.o.c.; LRT (II): RPOPHM > RPOP with > 99.90% l.o.c.

[4] RP = random parameter, LL = log-likelihood, AIC = Akaike Information Criterion, *t*-stats > 1.65 are significant at >90% l.o.c., *t*-stats > 1.96 are significant at >95% l.o.c., grey fill = heterogeneity in the mean of random parameters (where the term preceding “ : ” is the random parameter and the succeeding term is the exogenous influence) and their associated “indirect” marginal effects, LRT = Likelihood Ratio Test

Tables 5, 6 and 7 show that a wide range of factors significantly affected the rates of outdoor exercise trips made by Scottish residents throughout the COVID-19 pandemic. Influential independent variables capture mainly socioeconomic (e.g., household social grade and current working situation), demographic (e.g., disability, ethnic background and age) and behavioural (e.g., mode of travel choices) features of the respondents.

Several instances of significant heterogeneity in the means of random parameters were found in Survey Group 1 (Table 5) and Survey Group 3 (Table 7). We also estimate marginal effects for variables capturing heterogeneity in the means of random parameters; this is achieved by calculating the impact of a unit change of these variable on the means of the random parameters, and subsequently on the probabilities of the outcomes of the dependent variable. For example, in the model for Survey Group 1 (Table 5), the variable 'mode of travel used prior to lockdown – personal vehicle' affects the mean of the 'health problem or disability' random parameter variable, suggesting that the frequency of outdoor exercise trips made by those with a health problem or disability is dependent upon personal vehicle use. Given the associated positive coefficient, the personal vehicle variable increases the proportion of respondents with a health problem or disability who complete frequent outdoor exercise. If a respondent frequently used a personal vehicle to travel prior to lockdown, it is implicit that they also have access to a personal vehicle. Hence, it can be inferred that those with a health problem or disability and access to a personal vehicle are significantly more likely to complete frequent outdoor exercise than those with no personal vehicle access. The marginal effects of the personal vehicle variable provide further insights into how a unit change in the heterogeneity in the means variable (which is not a direct predictor of the dependent variable) can affect the outcome probabilities.

The employed modelling approaches are evaluated and justified in terms of goodness-of-fit (GOF) metrics. The AICs for competing frameworks are displayed in each table, where a decrease in AIC at convergence is consistent with improved GOF. Across all survey groups, the final AICs show considerable reductions compared to their $AIC_{CONSTANT}$ and AIC_{FPOP} counterparts, thus suggesting improved statistical performance for the approaches featuring random parameters. Likelihood Ratio Tests (LRTs) provide further means to compare the statistical fit of competing models (Washington, et al., 2020). All LRTs show, with at least 99.9% l.o.c., that the final frameworks (RPOPHM or RPOP) have significantly superior explanatory power compared to the fixed parameters alternatives (see 'LRT (I)', 'LRT (III)' and 'LRT (IV)'). In Survey Groups 1 and 3, it was also shown, with at least 96.0% l.o.c., that the RPOPHM framework provided significantly enhanced explanatory power compared to the RPOP framework (see 'LRT (II)' and 'LRT (V)'). GOF and statistical fit metrics justify the inclusion of random parameters and consideration for heterogeneity in the means of random parameters, reinforcing the merits of accounting for unobserved heterogeneity in survey data.

Table 6 – Outdoor exercise trips (Survey Group 2): RPOP model estimations and average marginal effects [5]

Variable Description	**RPOP Model**		**Marginal Effects**			
	Coefficient	***t*-stat**	**[y = 1]**	**[y = 2]**	**[y = 3]**	**[y = 4]**
Constant	0.394	3.821	–	–	–	–
Household social grade (1 if managerial/professional occupation, 0 otherwise)	0.274	3.259	-0.0890	0.0020	0.0083	0.0788
Current working situation (1 if furloughed, 0 otherwise)	0.236	1.862	-0.0756	0.0001	0.0064	0.0690
Mode of travel prior to lockdown (1 if active travel used frequently, 0 if not used frequently)	0.348	3.085	-0.1109	-0.0012	0.0089	0.1031
Mode of travel prior to lockdown (1 if personal vehicle, 0 otherwise)	0.171	1.711	-0.0561	0.0035	0.0060	0.0466
Health problem or disability (1 if yes, 0 if no) *Standard deviation of parameter density function*	-1.005 *1.157*	-6.673 *4.182*	0.3464	-0.0819	-0.0514	-0.2131
Current working situation (1 if full-time education, 0 otherwise) *Standard deviation of parameter density function*	0.192 *1.581*	0.574 *2.311*	-0.0622	-0.0031	0.0044	0.0610
Age indicator (1 if over 65, 0 otherwise) *Standard deviation of parameter density function*	-0.024 *0.804*	-0.212 *2.778*	0.0064	-0.0041	-0.0016	-0.0007
Threshold 1	0.577	13.569	–	–	–	–
Threshold 2	0.844	16.204	–	–	–	–
Number of observations	1169		–	–	–	–
$LL_{CONSTANT}$ / $LL(\beta_{FPOP})$	-1463.74 / -1398.81		–	–	–	–
LL at convergence, $LL(\beta_{RPOP})$	-1390.30		–	–	–	–
$AIC_{CONSTANT}$ / AIC_{FPOP}	2933.48 / 2817.62		–	–	–	–
AIC at convergence, (AIC_{RPOP})	2806.60		–	–	–	–

LRT (III): RPOP > FPOP with > 99.93% l.o.c.

[5] LL = log-likelihood, AIC = Akaike Information Criterion, *t*-stats > 1.65 are significant at >90% l.o.c., *t*-stats > 1.96 are significant at >95% l.o.c., LRT = Likelihood Ratio Test

Table 7 – Outdoor exercise trips (Survey Group 3): RPOPHM model estimation and average marginal effects [6]

Variable Description	**RPOPHM Model**		**Marginal Effects**			
	Coefficient	***t*-stat**	**[y = 1]**	**[y = 2]**	**[y = 3]**	**[y = 4]**
Constant	0.593	9.363	–	–	–	–
Household social grade (1 if managerial/professional occupation, 0 otherwise)	0.198	3.011	-0.0656	0.0112	0.0108	0.0436
Household social grade (1 if semi-skilled/unskilled manual occupation or unemployed, 0 otherwise)	-0.251	-2.919	0.0830	-0.0180	-0.0142	-0.0507
Gender (1 if male, 0 otherwise)	-0.142	-2.504	0.0467	-0.0082	-0.0077	-0.0308
Mode of travel prior to lockdown (1 if active travel, 0 otherwise)	0.369	4.707	-0.1213	0.0149	0.0187	0.0877
Ethnic background (1 if ethnic minority group, 0 otherwise)	-0.386	-2.394	0.1251	-0.0317	-0.0220	-0.0714
Current working situation (1 if furloughed, 0 otherwise)	0.335	2.416	-0.1092	0.0116	0.0163	0.0812
Health problem or disability (1 if yes, 0 if no) *Standard deviation of parameter density function*	-0.815 *1.245*	-7.033 *5.868*	0.2661	-0.0997	-0.0494	-0.1169
Current working situation (1 if self-employed, 0 otherwise) *Standard deviation of parameter density function*	0.049 *0.856*	0.376 *2.993*	-0.0163	0.0007	0.0023	0.0133
Age indicator (1 if over 65, 0 otherwise) *Standard deviation of parameter density function*	-0.219 *0.965*	-0.875 *4.523*	-0.0831	0.0012	0.0120	0.0699
Heterogeneity in the mean of RP Age indicator (over 65) : White British ethnic background	0.543	2.032	-0.0383	0.0077	0.0067	0.0239
Threshold 1	0.716	20.022	–	–	–	–
Threshold 2	1.045	23.816	–	–	–	–
Number of observations	1924		–	–	–	–
$LL_{CONSTANT}$ / $LL(\beta_{FPOP})$	-2501.16 / -2413.12		–	–	–	–
LL at convergence, $LL(\beta_{RPOPHM})$	-2391.07		–	–	–	–
$AIC_{CONSTANT}$ / AIC_{FPOP}	5008.32 / 4850.24		–	–	–	–
AIC at convergence, (AIC_{RPOPHM})	4814.14		–	–	–	–

LRT (IV): RPOPHM > FPOP with > 99.99% l.o.c.; LRT (V): RPOPHM > RPOP with > 96.04% l.o.c.

For the random parameters across the survey groups, model coefficients and marginal effects cannot reveal the unobserved heterogeneity in the effects of the corresponding variable, therefore, the distributional effects of the random parameters are shown in Table 8. The values in Table 8 can be interpreted as in the following example: for the health problem and disability

[6] RP = random parameter, LL = log-likelihood, AIC = Akaike Information Criterion, *t*-stats > 1.65 are significant at >90% l.o.c., *t*-stats > 1.96 are significant at >95% l.o.c., grey fill = heterogeneity in the mean of random parameters (where the term preceding " : " is the random parameter and the succeeding term is the exogenous influence) and their associated "indirect" marginal effects, LRT = Likelihood Ratio Test

variable in Survey Group 1, 88.18% of respondents with a health problem or disability are likely to make no outdoor exercise trips (i.e., the attribute increases the likelihood of the lowest outcome of the dependent variable), while the remaining 11.82% are likely to make outdoor exercise trips frequently (i.e., the attribute increases the likelihood of the highest outcome of the dependent variable). The positive (>0) and negative (<0) distributional effects of the random parameters can be visualised in Figures 2, 3 and 4, where the dashed red line red indicates the threshold between positive and negative effects. The visualisation of the random parameters allows the full range of their variability to be observed. Random parameters shown in Figures 2-4 correspond to their respective 'RP (random parameter) Code' as presented in Table 8.

Table 8 – Distributional effect of random parameters for outdoor exercise trips models

Variable as random parameter	**RP Code**	**Negative Effect**	**Positive Effect**
Survey Group 1	–	–	–
Gender (1 if male, 0 otherwise)	G1_GEN	42.86%	57.14%
Health problem or disability (1 if yes, 0 if no)	G1_HPD	88.18%	11.82%
Current working situation (1 if furloughed, 0 otherwise)	G1_FUR	34.28%	65.72%
Age indicator (1 if over 65, 0 otherwise)	G1_O65	69.49%	30.51%
Directly affected by COVID-19 (1 if yes, 0 if no)	G1_COV	13.90%	86.10%
Survey Group 2	–	–	–
Health problem or disability (1 if yes, 0 if no)	G2_HPD	80.75%	19.25%
Current working situation (1 if full-time education, 0 otherwise)	G2_EDU	45.17%	54.83%
Age indicator (1 if over 65, 0 otherwise)	G2_O65	51.19%	48.81%
Survey Group 3	–	–	–
Health problem or disability (1 if yes, 0 if no)	G3_HPD	74.36%	25.64%
Current working situation (1 if self-employed, 0 otherwise)	G3_SEM	47.72%	52.28%
Age indicator (1 if over 65, 0 otherwise)	G3_O65	58.98%	41.02%

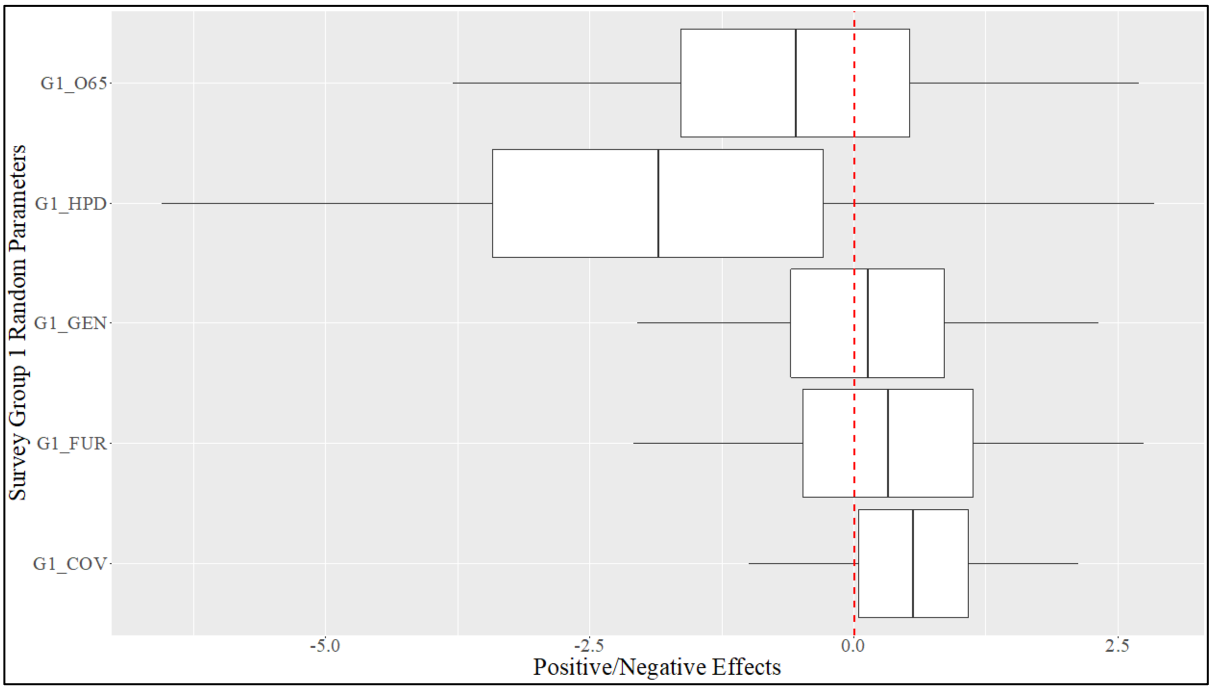

Figure 2 – Boxplot representation of distributional effects for random parameters from Survey Group 1

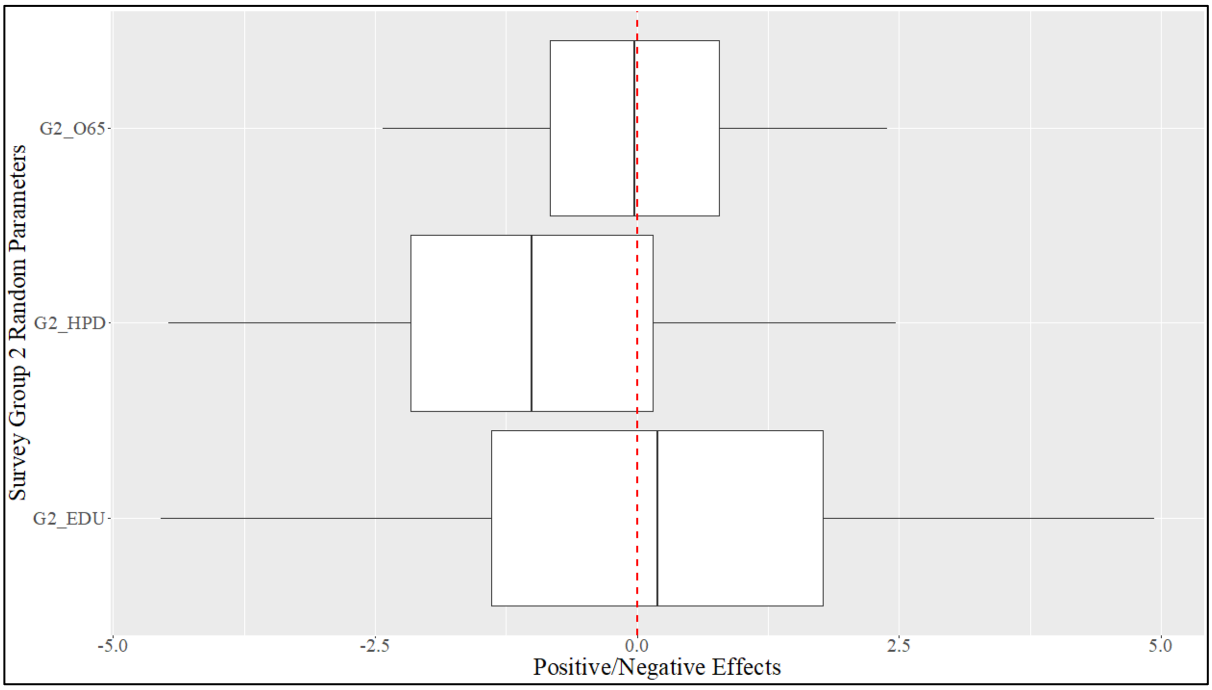

Figure 3 – Boxplot representation of distributional effects for random parameters from Survey Group 2

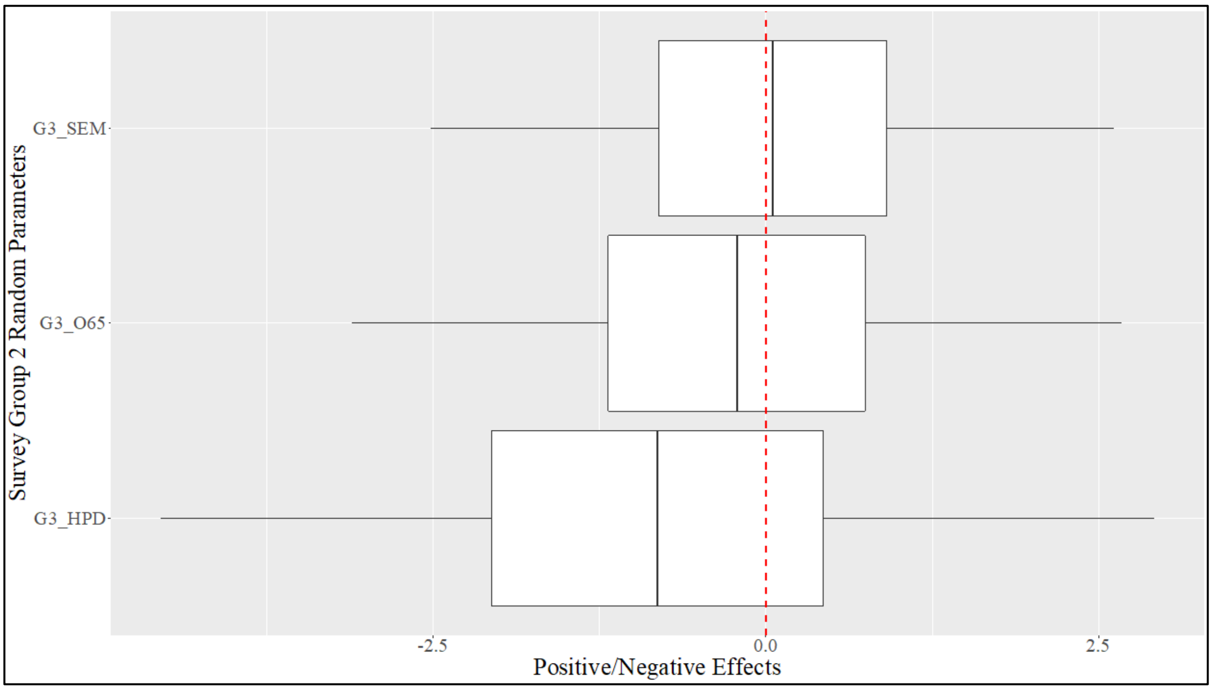

Figure 4 – Boxplot representation of distributional effects for random parameters from Survey Group 3

The discovery of multiple random parameters across all models suggests highly heterogeneous effects on outdoor exercise trip rates throughout the pandemic for the variables shown in Table 8. The health problem or disability and age indicator (over 65) variables were consistently significant as random parameters in all survey groups. Interestingly, both were influenced by the same exogenous variable ('mode of travel used prior to lockdown – personal vehicle') in Survey Group 1 (i.e., during lockdown). Two further instances of heterogeneity in the means of random parameters were discovered within the 'directly affected by COVID-19' variable in Survey Group 1 and the 'age indicator (over 65)' variable in Survey Group 3.

DISCUSSION OF RESULTS

Table 9 – Summary of significant variables affecting outdoor exercise trips across survey groups 1-3 [7]

Variable Description	Group 1 RPOPHM	Group 2 RPOP	Group 3 RPOPHM
Socioeconomic characteristics			
Household social grade (1 if managerial/professional occupation, 0 otherwise)	↑↑	↑↑	↑
Household social grade (1 if semi-skilled/unskilled manual occupation or unemployed, 0 otherwise)	↓↓	–	↓↓
Current working situation (1 if furloughed, 0 otherwise)	[↑↑]	↑↑	↑↑
Current working situation (1 if full-time education, 0 otherwise)	–	[↑]	–
Current working situation (1 if self-employed, 0 otherwise)	–	–	[↑]
Demographic characteristics			
Health problem or disability (1 if yes, 0 if no)	[↓↓↓]	[↓↓↓]	[↓↓↓]
Age indicator (1 if over 65, 0 otherwise)	[↓]	[↓]	[↓↓]
Ethnic background (1 if ethnic minority group, 0 otherwise)	↓↓↓	–	↓↓
Gender (1 if male, 0 otherwise)	[↑]	–	↓↓
Directly affected by COVID-19 (1 if yes, 0 if no)	[↑]	–	–
Behavioural characteristics			
Mode of travel prior to lockdown (1 if active travel, 0 otherwise)	↑↑	↑↑	↑↑
Mode of travel prior to lockdown (1 if personal vehicle, 0 otherwise)	–	↑	–
Heterogeneity in the means of random parameters			
Heterogeneity in the mean of random parameter Health problem or disability : Mode of travel used prior to lockdown – personal vehicle	↑↑	–	–
Heterogeneity in the mean of random parameter Over 65 : Mode of travel used prior to lockdown – personal vehicle	↑	–	–
Heterogeneity in the mean of random parameter Directly affected by COVID-19 : White British ethnic background	↓	–	–
Heterogeneity in the mean of random parameter Over 65 : White British ethnic background	–	–	↑

An overview of the effects identified in all models is displayed in Table 9. A range of socioeconomic, demographic and behavioural factors significantly affected weekly outdoor exercise trip frequencies throughout the COVID-19 pandemic in Scotland. As discussed in

[7] Table key: "↑" or "↓" denote a variable with a significantly positive or negative coefficient, respectively, "[↑]" or "[↓]" indicate a variable which is significant as a random parameter with a significantly positive or negative coefficient, respectively, "–" indicate that a variable was trialled for a given model, however, the variable's effect was insignificant. The number of arrows, regardless of direction, correspond to the strength of marginal effects (displayed in model estimation tables), where: ↑ = 0.0000-0.0749; ↑↑ = 0.0750-0.1499; ↑↑↑ = >0.1499

‘Data’, the outdoor exercise trip rates of Scottish residents varied significantly at distinct points of the pandemic, hence the three separate models estimated for lockdown (Survey Group 1), Phases 1 and 2 (Survey Group 2), and Phase 3 (Survey Group 3). Table 9 allows the changes in significant independent variables affecting outdoor exercise trips at distinct points of the pandemic to be better understood. Additionally, the relative magnitude of the marginal effects per independent variable are given in Table 9, such that one arrow indicates a moderate effect, two arrows a strong effect and three arrows a very strong effect.

Many of the effects are consistent in direction and magnitude across the survey groups, for example: the ‘health problem or disability’ variable has a very strong negative effect on the likelihood of frequent outdoor exercise trips (y=4) in all groups, and the ‘current working situation (furloughed)’ variable has a consistently strong positive effect across all groups. There are, however, several instances where the strength of an independent variable changes over time, for example: ‘household social grade (managerial/professional occupation)’ has a strong positive effect on the probability of frequent outdoor exercise trips in Survey Groups 1 and 2, while the strength is only moderate in Survey Group 3; the ‘ethnic background (ethnic minority groups)’ variable has a very strong negative effect in Survey Group 1, no significant effect in Survey Group 2, and a strong negative effect in Survey Group 3; and the ‘gender (male)’ variable, induces heterogeneous effects in Survey Group 1, has no effect in Survey Group 2, and has a strong negative effect in Survey Group 3. The behavioural variability of these demographics throughout the pandemic is likely the result of changing government restrictions, however, it may also be related to other factors. For example, in how the risk of COVID-19 infection is perceived may lead to altered behaviour (restriction easing is typically preceded by lower infection rates in the community), or variation in weather (which may be captured as unobserved variations in some of the random parameters generated by the demographic characteristics).

Influential socioeconomic factors include household social grade and current working situation. If the extremities of the dependent variable are described as no outdoor exercise (y=1) and frequent outdoor exercise (y=4), their specific effects were as follows: those who live in households where the main income earner is employed in a managerial/professional occupation were found to be significantly more likely than those with other occupation types to complete frequent outdoor exercise in all survey groups, while respondents who live in households where the main income earner is employed in a semi/unskilled manual occupation or is unemployed were significantly more likely to complete no outdoor exercise.

This difference between these household types emphasises experiential disparities of COVID-19 that are based on occupational factors. A possible explanation may be that those in managerial/professional occupations are more able to telecommute, and as a result, have greater freedom to exercise frequently. Similarly, furloughed respondents were significantly more likely to complete outdoor exercise frequently compared to other groups with different working situations (i.e., key workers, retired, in full-time education or self-employed). Intuitively, this may be explained by the fact that furloughed respondents had greater freedom and availability to exercise than the remaining respondents. A pre-COVID-19 study by Cook & Gazmararian (2018) found similar trends in the US, as those who worked fewer hours had more time for physical activity and were less likely suffer from obesity. The socioeconomic influences identified in this study reiterate the stark inequalities in British society, which have been highlighted and exacerbated by the pandemic (Office for National Statistics, 2020). The long-term effects of this are hard to predict, however, it is within reason to suggest that those who live in households where the main income earner is employed in a semi/unskilled manual occupation or is unemployed are more likely to suffer the mental and physical health issues associated with limited exercise (Anderson & Durstine, 2019; Camacho, et al., 1991).

A variety of demographic characteristics, including: health problem or disability, age, ethnic background and gender were found to significantly affect outdoor exercise trip frequencies. The effect was particularly pronounced among those with a health problem or disability, who were significantly more likely than those without a health problem or disability to complete no outdoor exercise across all survey groups. As mentioned in the previous section, the 'health problem or disability' variable was consistently significant as a random parameter, suggesting highly heterogeneous effects on outdoor exercise among this demographic. Table 9 shows that in one instance (Survey Group 1) significant heterogeneity in the mean of the health problem or disability random parameter was discovered. An exogenous variable, 'mode of travel used prior to lockdown – personal vehicle', explained some of the unobserved heterogeneity, such that those who have a health problem or disability and access to a personal vehicle were significantly more likely to exercise frequently during lockdown, compared to those with no personal vehicle access. This suggests that features of transport equity, related to personal vehicle ownership and accessibility, influenced the ability of those with a health problem or disability to complete frequent outdoor exercise. For those aged over 65 in Survey Group 1, a similar trend was discovered. Respondents over the age of 65, and with access to a personal vehicle, were significantly more likely to complete frequent outdoor exercise compared to those with no access. A possible explanation is that among those with a health problem or disability and those over 65, there is a hesitancy to exercise in densely populated areas where the risk of contracting COVID-19 is higher. As a result, those with access to a personal vehicle may have driven to more secluded areas to complete their outdoor exercise, while those with no personal vehicle access may have felt uncomfortable exercising in densely populated environments.

Ethnic minority groups were found to be significantly more likely to complete no outdoor exercise trips in Survey Groups 1 and 3, in comparison to those from other ethnic backgrounds

(White British and any other White background). This may be explained by socioeconomic influences, particularly occupation, or factors related to the quality of built environment characteristics, for example, lower income neighbourhoods often suffer from a lack of high quality, local green space (Sport England, 2015; UK Government, 2020). As discussed in the introduction, ethnic minority groups have experienced disproportionate levels of COVID-19 infection and mortality (Office for National Statistics, 2020). These effects are experienced immediately, however, we suggest that ethnic minority groups may also be at increased risk of longer-term mental and physical health problems associated with prolonged periods of limited exercise.

Those over the age of 65 were found to be significantly more likely than other age groups to have completed no outdoor exercise during lockdown. As discussed previously, the outdoor exercise trip frequencies of over 65s were found to be significantly influenced by personal vehicle access during lockdown. In Survey Groups 1, 2 and 3 the over 65 variables were significant as random parameters, while in two instances (Survey Group 1 and 3) heterogeneity in the means of the random parameters were discovered. It is worth noting that the coefficients of the over 65 variables were not significantly negative in Survey Group 2 and 3, in other words, the exercise trips of this demographic were most severely affected during Survey Group 1 (lockdown). Among over 65s in Survey Group 3, it was found that those from a White British ethnic background were significantly more likely to complete frequent outdoor exercise trips compared to other ethnicities. This finding corroborates with a recent report by Sport England (2015), where it was found that the physical activity levels of different ethnic backgrounds were often dependent on factors, such as the quality of surrounding infrastructure and access to local green space. The same report also found that ethnic minority groups in particular, tended to live in more deprived communities where access to local green space was scarcer or the spaces were of poorer quality (Sport England, 2015). In comparison, more affluent communities, where White British is the most common ethnic background (UK Government, 2020), often have a greater abundance of local green space (Sport England, 2015). Particularly in the context of a pandemic, it may be that this availability of local green space allowed White British over 65s to complete frequent outdoor exercise trips.

The gender variable was significant as a random parameter in Survey Group 1, suggesting significantly heterogeneous outdoor exercise trip frequencies. In Survey Group 3, males were significantly more likely to complete no outdoor exercise trips compared to other genders (female and non-binary). The varying effect of the gender variable may be the result of changing working situations, for example, women are more likely to be key workers (58% female, 42% male (Office for National Statistics, 2020)), therefore, it is likely that some females were unable or unwilling to exercise frequently in the early stages of the pandemic because of work commitments. During Phase 3 of restriction easing (Survey Group 3), a significant proportion of males may have reverted to more regular daily activity patterns (e.g., returning to work), therefore the need for frequent outdoor exercise may not be as evident as during the more stringent lockdown phases.

One behavioural characteristic, relating to mode usage prior to COVID-19, was also found to significantly affect the frequency of outdoor exercise trips. Those who frequently used active modes (on-foot or by bicycle) prior to lockdown, were significantly more likely to complete frequent outdoor exercise trips in all models, in comparison to those who did not use active travel modes. It is likely that people who already used active modes live in an area, or have access to equipment (e.g. bicycles), that facilitates active travel, hence, these individuals are able to continue with their pre-COVID-19 behavioural patterns. More interestingly, those who travelled frequently by a personal vehicle prior to lockdown were significantly more likely to have completed frequent outdoor exercise trips in Survey Group 2, in comparison to those who did not frequently use a personal vehicle. This may be related to previous findings, which showed that the outdoor exercise trips of those with a health problem or disability, and of those over 65, were dependent on personal vehicle use prior to lockdown. A possible explanation is that among the entire Survey Group 2 sample, vehicle access is a factor determining the frequency of outdoor exercise trips. As discussed previously, it may be that those who have personal vehicle access, but who live in an undesirable exercise area (e.g., because the area is densely populated, there is a lack of active travel routes, or local green space is limited or of poor quality), may travel to a more desirable area to complete outdoor exercise. However, this finding requires deeper investigation, as the original variable gauges personal vehicle use as opposed to ownership, and therefore may include those who car share or rideshare.

Finally, those who were "directly affected by COVID-19" were found to be significantly more likely to have completed frequent outdoor exercise trips during lockdown than those who were not directly affected; this factor was also found to induce heterogeneous effects, as it resulted in a statistically significant random parameter. It should be noted that "direct affect" is not strictly defined in the questionnaire, and as a result, it may have been interpreted in different ways by respondents. We make the assumption that "direct affect" is someone who has personally contracted COVID-19, or whose close family or friends have been infected. The propensity of most respondents who feel "directly affected by COVID-19" to complete frequent exercise trips, may reflect their determination to follow the widely circulated advice of various healthcare (e.g., NHS) or scientific (e.g., World Health Organisation) bodies, to stay active and maintain their wellbeing during lockdown. Furthermore, individuals who feel affected by COVID-19 but did not considerably amend their activity patterns during the lockdown, may have done so due to their cultural beliefs or personal attitudes. The heterogeneous effects within this variable could be linked to how people's perceived risk of COVID-19 changed following direct affectation, for example, some individuals belonging to this group may have acted more cautiously as a result of being directly affected by COVID-19, thus making less trips for any reason. Significant heterogeneity in the mean of the random parameter was also detected, suggesting that among directly affected respondents, those from a White British ethnic background were more likely to have completed no outdoor exercise than those directly affected and from other ethnic backgrounds. This finding may be related to the effect of cultural identity (e.g., nationality or religion) on COVID-19 risk perceptions, such that certain groups may act more cautiously after being directly affected. Although recent studies have explored this theory, the factors affecting people's perceived risk of COVID-19 were in fact dominated by social values, such as: trust in government advice, trust in science and political ideology (e.g. individualist or collectivist worldviews) (Dryhurst, et al., 2020).

CONCLUSION

This paper uses public survey data to show how the frequency of outdoor exercise trips made by Scottish residents changed throughout the COVID-19 pandemic. The proportion of respondents who made six or more outdoor exercise trips per week decreased consistently, from 46.4% during lockdown, to 38.8% during Phase 1 & 2, to 33.5% during Phase 3. We suggest that this is most likely the result of an initial conscientiousness, or availability – due to increased telecommuting or the introduction of the furlough scheme – to complete frequent outdoor exercise trips during lockdown. In Phases 1 and 2, and Phase 3, around 35% of respondents made no weekly outdoor exercise trips, whereas the proportion who made no trips during lockdown was comparatively smaller (28.6%). This also suggests that Scottish residents were more able to exercise in the earlier stages of the pandemic or that their working circumstances facilitated this behaviour. The polarisation of exercise behaviour was also starkest during lockdown, as ~75% of respondents completed either no trips or six or more trips. It may be that the strictness of government restrictions during the lockdown period exacerbated polarisation of exercise behaviour, thus government's may wish to consider ad-hoc policies to counteract this effect for potential future lockdowns.

We show through statistical modelling that a variety of socioeconomic, demographic and behavioural variables affected weekly rates of outdoor exercise trips. The most consistent respondent characteristics that significantly increased the likelihood of frequent outdoor exercise trips (six or more) across all survey groups were as follows: households where the main income earner is employed in a managerial/professional occupation, those who were furloughed, and those who frequently used active travel modes prior to COVID-19. All of the aforementioned groups have in fact benefitted from high exercise rates during the pandemic. Conversely, those with a health problem or disability, ethnic minority groups and those who live in households where the main income earner is employed in a semi-skilled/unskilled manual occupation or is unemployed were all significantly more likely to have completed no weekly outdoor exercise, in at least two, if not all survey groups. As a result, these groups are likely to be at higher risk of the mental and physical illnesses associated with limited physical activity.

POLICY IMPLICATIONS

It is the recommendation of this paper that policymakers use public information campaigns to promote exercise among the previously identified low activity groups. Future research may also be conducted to determine the barriers preventing these groups from exercising frequently. A conduit for further research may explore whether these low exercise rates are attributable to the pandemic, or whether they are in fact an endemic social issue related to infrastructural impediments, such as a lack of local green space or active travel infrastructure. This is particularly important among groups who may require additional provision to complete outdoor exercise, for example, those with mobility limiting conditions. Issues of transport inequity discovered in this paper, specifically, that the lockdown outdoor exercise trip rates of those with a health problem or disability, and of those over 65, were both dependent on personal vehicle access, may provide similarly intriguing areas for further research. It is the recommendation of this study that these inequities are investigated further through targeted consultation of disabled and/or elderly individuals, thereby informing the direction of future policy with regards to an equitable transport system.

Future research may also investigate the relationship between future commuting intentions and physical activity. For example, if more people telecommute following the pandemic there may be detrimental effects on physical activity levels, which in the past have been incorporated into commuting trips (i.e. walking to a workplace, or walking to a public transport connection). If this proves to be the case, walk and cycle to work schemes are likely to be less effective methods for encouraging physical activity, therefore, we recommend that governments take pre-emptive action to ensure exercise levels do not suffer as telecommuting increases in popularity. This may come in the form of government policies to enhance built environment characteristics (e.g., creation of new, high-quality green space, improving the walkability of streets and enhancing active travel infrastructure), particularly in lower income neighbourhoods. The government may also consider subsidisation schemes for equipment that facilitates active lifestyles (e.g., gym memberships and bike ownership).

LIMITATIONS

Several limitations should be noted. Firstly, the survey data gauged respondents' region of residence, however, it did not contain in-depth details about the areas of residence (e.g., postcodes or local neighbourhood information). As a result, built environment characteristics, such as, the prevalence of public transport links, availability of cycle paths and access to green space, which have all previously been shown to significantly affect physical activity levels, cannot be accurately accounted for in the analysis. Secondly, the relative impact of COVID-19 on outdoor exercise levels cannot be accurately gauged, as limited data exist for the pre-pandemic exercise patterns of Scottish residents. As a result, it cannot be inferred whether the pandemic has improved or hindered general levels of physical activity in Scotland. Finally, given that the survey was conducted telephonically, the sample does not include those who do not have access to a landline or a mobile phone.

ACKNOWLEDGMENTS

The authors would like to thank Transport Scotland, and in particular, Mr. Paul Sloan, for providing access to this detailed and timely dataset.

APPENDIX

Table A1 – Independent variables available for modelling

Variable No.	Variable Description
1	**Gender**: Male, Female, Non-binary
2	**Age**: Under 16, 16-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85+
3	**Ethnic background**: White British, Any other White background, Any mixed background, Indian, Pakistani, Bangladeshi, Chinese, Any other Asian background, Caribbean, African, Any other Black background, Any other background
4	**Region of Scotland**: Argyll & Bute, Ayrshire & Arran, Edinburgh and South East Scotland, Forth Valley, Glasgow City, Highlands and Islands, North East Scotland, Scottish Borders, South West Scotland, Tay Cities Region
5	**Health problem or disability that limits day-to-day activities**: Yes (a lot), Yes (a little), No
6	**Employment status (of the household's main income earner)**: Higher managerial, administrative, or professional; Intermediate managerial, administrative or professional; Supervisory, clerical, junior managerial, administrative or professional; Skilled manual workers; Semi and unskilled manual worker; Unemployed/currently not working; Housewife/husband; State pensioner/retired; Student
7	**Household social grade (based on the employment status of the household's main income earner)**: AB (higher/intermediate managerial, administrative or professional occupations), C1 (supervisory, clerical, junior managerial, administrative or professional, and students), C2 (skilled manual workers), DE (semi/unskilled manual worker or unemployed)
8	**Current working situation**: Any form of self-employment, Any form of employment (not furloughed), Currently employed but furloughed, Full-time education, Retired, Unemployed, Long-term sick/disabled/looking after household
9	**Directly affected by COVID-19**: Yes, No
10	**Most frequently used modes of travel before COVID-19**: Public transport (bus, train or tram), Personal vehicle (car, van or taxi), Active travel (on-foot, by wheelchair or by bicycle)
11	**Mode of travel before and during COVID-19**: E.g. Public transport frequently used before COVID-19 but used less during COVID-19

REFERENCES

Abdullah, M., Dias, C., Muley, D. & Shahin, M., 2020. Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives,* November, Volume 8, p. 100255.

Anastasopoulos, P. C., 2016. Random parameters multivariate tobit and zero-inflated count data models: Addressing unobserved and zero-state heterogeneity in accident injury-severity rate and frequency analysis. *Analytic methods in accident research,* September, Volume 11, pp. 17-32.

Anastasopoulos, P. C. & Mannering, F. L., 2009. A note on modeling vehicle accident frequencies with random-parameters count models. *Accident Analysis & Prevention,* 41(1), pp. 153-159.

Anderson, E. & Durstine, J. L., 2019. Physical activity, exercise, and chronic diseases: A brief review. *Sports Medicine and Health Science,* December, Volume 1, pp. 3-10.

Bambra, C., Riordan, R., Ford, J. & Matthews, F., 2020. The COVID-19 pandemic and health inequalities. *Journal of epidemiology and community health,* November, 74(11), p. 214401.

Barbour, N., Zhang, Y. & Mannering, F., 2020. An exploratory analysis of the role of socio-demographic and health-related factors in ridesourcing behavior. *Journal of Transport and Health,* March, Volume 16, p. 100832.

Camacho, T. et al., 1991. Physical Activity and Depression: Evidence from the Alameda County Study. *American Journal of Epidemiology,* 15 July, 134(2), p. 220–231.

Centers for Disease Control and Prevention, 2021. *Health Equity Considerations and Racial and Ethnic Minority Groups.* [Online]
Available at: https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/race-ethnicity.html
[Accessed February 2021].

Cook, M. A. & Gazmararian, J., 2018. The association between long work hours and leisure-time physical activity and obesity. *Preventative Medicine Reports,* June, Volume 10, pp. 271-277.

Dryhurst, S. et al., 2020. Risk perceptions of COVID-19 around the world. *Journal of Risk Research,* May, 23(7-8), pp. 994-1006.

Eker, U., Fountas, G. & Anastasopoulos, P., 2020b. An exploratory empirical analysis of willingness to pay for and use flying cars. *Aerospace Science and Technology,* Volume 104, p. 105993.

Eker, U., Fountas, G., Anastasopoulos, P. & Still, S., 2020a. An exploratory investigation of public perceptions towards key benefits and concerns from the future use of flying cars. *Travel Behaviour and Society,* April, Volume 19, pp. 54-66.

Fountas, G., Pantangi, S., Hulme, K. & Anastasopoulos, P., 2019. The effects of driver fatigue, gender, and distracted driving on perceived and observed aggressive driving behavior: A correlated grouped random parameters bivariate probit approach. *Analytic Methods in Accident Research,* Volume 22, p. 100091.

Halton, J., 1960. On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals. *Numerische Mathematik,* Volume 2, pp. 84-90.

Jenelius, E. & Cebecauer, M., 2020. Impacts of COVID-19 on public transport ridership in Sweden: Analysis of ticket validations, sales and passenger counts. *Transportation Research Interdisciplinary Perspectives,* November, Volume 8, p. 100242.

Laverty, A., Millett, C. & Majeed, A., 2020. COVID-19 presents opportunities and threats to transport and health. *Journal of the Royal Society of Medicine,* July, 113(7), pp. 251-254.

Mannering, F. L., Shankar, V. & Bhat, C. R., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic methods in accident research,* September, Volume 11, pp. 1-16.

MRS, 2019. *Code of Conduct.* [Online]
Available at: https://www.mrs.org.uk/standards/code-of-conduct
[Accessed September 2021].

Office for National Statistics, 2020. *Coronavirus and key workers in the UK.* [Online]
Available at:
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/articles/coronavirusandkeyworkersintheuk/2020-05-15
[Accessed 5 March 2021].

Office for National Statistics, 2020. *Deaths involving COVID-19 by local area and socioeconomic deprivation: deaths occurring between 1 March and 31 May 2020.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/bulletins/deathsinvolvingcovid19bylocalareasanddeprivation/deathsoccurringbetween1marchand31may2020
[Accessed 15 January 2021].

Office for National Statistics, 2020. *Why have Black and South Asian people been hit hardest by COVID-19?.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/articles/whyhaveblackandsouthasianpeoplebeenhithardestbycovid19/2020-12-14
[Accessed February 2021].

Paleti, R. & Balan, L., 2017. Misclassification in travel surveys and implications to choice modeling: application to household auto ownership decisions. *Transportation,* December, 46(4), pp. 1467-1485.

Patterson, R., Webb, E., Millett, C. & Laverty, A., 2019. Physical activity accrued as part of public transport use in England. *Journal of Public Health,* June, 41(2), pp. 222-230.

Przybylowski, A., Stelmak, S. & Suchanek, M., 2021. Mobility Behaviour in View of the Impact of the COVID-19 Pandemic—Public Transport Users in Gdansk Case Study. *Sustainability,* January, Volume 13, p. 364.

Rogers, N. T. et al., 2020. Behavioral Change Towards Reduced Intensity Physical Activity Is Disproportionately Prevalent Among Adults With Serious Health Issues or Self-Perception of High Risk During the UK COVID-19 Lockdown. *Frontiers in Public Health,* September, Volume 8, p. 575091.

Sarrias, M., 2020. *Rchoice: Discrete Choice (Binary, Poisson and Ordered) Models with Random Parameters.* [Online]
Available at: https://cran.r-project.org/web/packages/Rchoice/Rchoice.pdf
[Accessed 1 July 2020].

Scottish Government, 2018. *Social grade (approximated).* [Online]
Available at: https://www.scotlandscensus.gov.uk/social-grade-approximated
[Accessed 10 January 2021].

Scottish Government, 2020. *Coronavirus (COVID-19): Scotland's route map.* [Online]
Available at: https://www.gov.scot/collections/coronavirus-covid-19-scotlands-route-map/
[Accessed 5 January 2021].

Scottish Government, 2020. *Scottish Index of Multiple Deprivation 2020.* [Online]
Available at: https://www.gov.scot/collections/scottish-index-of-multiple-deprivation-2020/?utm_source=redirect&utm_medium=shorturl&utm_campaign=simd
[Accessed 1 September 2021].

Seraneeprakarn, P. et al., 2017. Occupant injury severities in hybrid-vehicle involved crashes: A random parameters approach with heterogeneity in means and variances. *Analytic methods in accident research,* September, Volume 15, pp. 41-55.
Sport England, 2015. *Getting Active Outdoors: A study of Demography, Motivation, Participation and Provision in Outdoor Sport and Recreation in England.* [Online]
Available at: https://sportengland-production-files.s3.eu-west-2.amazonaws.com/s3fs-public/outdoors-participation-report-v2-lr-spreads.pdf
[Accessed 20 January 2021].
Sport England, 2020. *Surge in appreciation of exercise and activity during lockdown.* [Online]
Available at: https://www.sportengland.org/news/surge-appreciation-exercise-and-activity-during-lockdown
[Accessed 15 January 2021].
Sultana, Z. et al., 2018. Modeling frequency of rural demand response transit trips. *Transportation research. Part A, Policy and practice,* December, Volume 118, pp. 494-505.
Transport Scotland, 2020. *COVID-19 Transport Trend Data - 14 - 19 April 2020.* [Online]
Available at: https://www.transport.gov.scot/publication/covid-19-transport-trend-data-14-19-april-2020/
[Accessed 17 December 2020].
Transport Scotland, 2020. *Publications - COVID-19.* [Online]
Available at: https://www.transport.gov.scot/publications/?topic=63625
[Accessed 1 December 2020].
UK Government, 2020. *People living in deprived neighbourhoods.* [Online]
Available at: https://www.ethnicity-facts-figures.service.gov.uk/uk-population-by-ethnicity/demographics/people-living-in-deprived-neighbourhoods/latest
[Accessed 20 January 2021].
Washington, S., Karlaftis, M. G. & Mannering, F. L., 2020. *Statistical and Econometric Methods for Transportation Data Analysis.* 3rd Edition ed. s.l.:CRC Press LLC.
Yu, M., Zheng, C., Ma, C. & Shen, J., 2020. The temporal stability of factors affecting driver injury severity in run-off-road crashes: A random parameters ordered probit model with heterogeneity in the means approach. *Accident analysis and prevention,* September, Volume 144, pp. 105677-105677.