Green space accessibility helps buffer declined mental health during the COVID-19 pandemic: Evidence from big data in the UK

Abstract

Accumulating evidence has highlighted a negative effect of the COVID-19 pandemic on public mental health, and we examined green space accessibility as a potential remedy for such an effect. Based on the mobility data from 2 million mobile phone users within London over the period of January 2019–December 2020, we found that, after the COVID-19 outbreak and during lockdowns, residential neighbourhoods whose edges are within 800 meters of the edge of the nearest green space recorded a 1–1.5 percentage point higher proportion of green space travellers out of all travellers when compared to other neighbourhoods. Next, using the multi-wave data with a sample of 4,998 individuals matched from the original sample of 19,020 respondents across UK towns and cities based on the UK Household Longitudinal Survey, we demonstrate that individuals who live within 800 meters of the nearest green space experienced much less mental distress (i.e., the mental distress score is 0.106 lower out of the average score of 2.31) than those who live farther away. Our findings provide suggestive evidence that accessibility to green spaces is important to the population's mental health, especially when their mobility is restricted. Enhancing green space accessibility for more residential neighbourhoods should thus be important to city planners and policymakers as they help citizens become more resilient to a similar future pandemic.

1. Introduction

Since the first known cases in late December 2019, the COVID-19 pandemic has posed unprecedented challenges for everyone worldwide. Due to the increased risk to public health, many countries have subsequently adopted policies to reduce mobility, such as lockdowns and safe-distancing measures. Although these policies are known to be effective both to alleviate the burden on intensive care units and to reduce the number of new COVID-19 infections,[1,2] recent research has identified them as a cause of many negative outcomes. For example, COVID-19 lockdowns pushed many individuals to experience high levels of adversities arising from social isolation, inactivity, decreased family and social support, and financial hardship.[3] Besides the negative economic and social consequences of population mobility restrictions due to COVID-19,[4] research also highlights the heightened issues of public mental health.[5-10]

Evidence produced from representative cohort studies provided us with a clear comparison of individuals' pre- and in-pandemic psychological state, which showed heightened psychological distress and a rise in the proportion of people experiencing significant levels of mental illness.[5-8, 10, 11] These findings are not completely surprising, considering similar findings in past epidemic events. For example, individuals experienced symptoms of depression and post-traumatic stress disorder during the quarantine order for the severe acute respiratory syndrome (SARS) epidemic.[12–14] Nevertheless, given the dilemma between the policy needs of mobility restrictions and their negative outcomes, we urgently need to identify potential tools to mitigate such outcomes and maintain the level of public (mental) health even during lockdowns.

Based on the review of twenty-four studies, scholars have pointed out a few solutions and highlighted that we should keep quarantine orders as short as possible while providing quarantined individuals with more information and support (e.g., reducing boredom with improved communication) and encouraging people to participate in voluntary precaution and mobility restriction.[15] Although the investigation of these quarantine orders is important, lockdown policies (i.e., stay-at-home orders) and compulsory social-distancing measures pose a substantial threat to a much larger number of people as their daily activities are fully or partially restricted. Therefore, it is still important for us to understand how we can successfully mitigate the detrimental effect of these measures.

To accomplish this goal, we explore research in environmental psychology, particularly on the effect of green space exposure on public mental health. Exposures to green spaces have been widely recognized to promote mental health and well-being for a variety of populations in different circumestances.[16–19] Previous research suggests the negative associations between green space exposure and psychological distress.[20–23] Accumulating research has also pointed out the potential beneficial effects of green spaces during COVID-19 when the mobility of the general public is restricted on a compulsory or voluntary basis.[24-26] Research has also showed that people change the time spent visiting green space and urban green infrastructure after COVID-19 and during lockdowns.[27-29] To contribute to this booming literature, this study seeks to better understand how the change in public mobility is related to the beneficial effects of green spaces on mental health during COVID lockdowns. We aim to adopt a more precise way of documenting the ecological-level mobility information of residents during COVID lockdown. Doing so can enable us to accurately observe mobile activities in a much smaller area as compared to other methods (e.g.. Google Mobility Reports).[28]

Meanwhile, research showed that living closer to green spaces helps support mental and general health and also prevents depression in young adults.[17] COVID-19 lockdowns highlighted the need for outdoor walks to nearby parks. In fact, Google searches for "go for a walk" significantly increased right after lockdown orders in many countries.[30] However, the surge in interest in going for short walks is not always matched with the supply of green spaces (e.g., parks and gardens), especially in high-density urban areas.[31, 32] This highlights another important question: Is the mental health of some individuals more adversely affected by the COVID-19 pandemic and lockdowns than others due to unequal accessibility to green spaces? In fact, recent BMJ commentary highlighted the importance of equal access to green spaces during the COVID-19 pandemic and called for more academic and political attention to this issue.[33] Research in the past three years have also responded and started to pay attention to the relationship between green space accessibility and mental health since the outbreak of COVID-19. Based on the Web of Science database, we found 241 empirical articles from various subject fields, including public health, environmental studies, urban studies, and planetary studies. Some have used panel data to examine the relationship, surveying individuals green space activities and mental status,[34, 35] and others have tried to examine the general mobility patterns during the COVID-19 pandemic.[36]

There is, however, little empirical testing that combines the evidence from the rigorous mobility data with that from the panel data of a relatively large, representative sample using a validated mental health scale. By adopting the mobility data from 2 million mobile phone users and the multi-wave longitudinal survey data, this study presents a thorough empirical examination of the relationship between mobility to green spaces and mental health status after COVID-19 and during lockdowns. Furthermore, our research highlights the accessibility to green spaces as a crucial feature for both green space travels and mental well-being, which has important implications for not only the mental health services but also urban planning and policymaking. We choose to examine this question in London, UK, as it provides us with a great opportunity to carry out large-scale, quasi-experimental analyses by uniquely utilizing mobile phone–based mobility data and multi-wave surveys during and after lockdown periods.

2. Data and Methods

2.1. Data Sources

Our data come from several sources (see Figure 1A for the summary of data sources, key indicators, and their links). The first is a dataset on the weekly bilateral flow information of 2 million mobile phone users from their residence (origin) to destination locations within London over the period of January 2019–December 2020. We were granted access to anonymized mobility data from

Telefónica that contain aggregated counts of travels between antenna points and do not include any personally identifiable information. The data consist of the number of travels and travel frequency between antenna points within London as well as the time spent in the destination location, where they stayed more than 1 hour to exclude temporary movements through car and/or public transportation. Existing research using mobile phone data suggests 1 or 1.5 hours as the threshold for stable detection of location changes.[37, 38] Also, as the difference in the number of travels between the thresholds of 30 minutes and 1 hour was not significant in our data, we believe that the 1-hour threshold is a reasonable choice and safer from possible noises. In our analysis, we define a "travel" as an event where a mobile phone user connects to a non-home antenna over 1 hour, using pre-identified information of the home antenna. This means that we do not account for the antennas connected on the way to destination antennas. Our data include travel information for both work hours (08:00–16:00 on working days) and non-work hours (16:00–24:00 on working days and 08:00–24:00 on weekends and bank holidays). To perform the analysis with resident characteristics at the temporally stable geographic level, we perform spatial interpolation from the origin-destination flows between antenna points to flows between the residential Lower layer Super Output Areas (LSOAs) and green/non-green space destinations. An LSOA is the smallest geographic unit available for the major UK administrative data and contains about 1,500 residents or 650 households, on average. A more detailed explanation of the mobility data processing is presented in Appendix 1.

Second, we mark the location information of a broad range of open spaces with good vegetation coverage including registered public parks, cemeteries, and town squares in London provided by Historic England in August 2021.[39] The data contain 1,699 entries in England and 168 listings in London as of August 2021. The advantage of using these data is that we could control for the level of attractiveness, accessibility, and maintenance of green spaces that are open to the public by focusing on registered green spaces instead of small, unregistered spaces that may be exclusive or specialized (e.g., community garden, golf course). More detailed explanations for our choice of green spaces are provided in Appendix 2. By identifying whether the destination locations belong to these green spaces based on the interpolated mobility flows, we obtain the ratio of the number of green space travellers relative to the number of total travellers from each residential LSOA in a given week. We use this ratio during non-work hours for our main analyses because travels to green spaces are recreational activities which do not occur frequently during work hours. Later, we show that results using the ratio of the number of green space travels out of total travels are consistent with those using the current measure. To account for demographic and socioeconomic characteristics at the LSOA level, we use the LSOA-level data on population characteristics for the years of 2019 and 2020 provided by the Office for National Statistics (ONS),[40] as well as the 2020 data on ethnic composition from the Consumer Data Research Centre (CDRC), which was obtained with special permission.[41] We also use the 2019 English indices of deprivation for the 4,835 LSOAs in London provided by the Ministry of Housing, Communities and Local Government (MHCLG).[42] The data include diverse neighbourhood indicators on income, employment, education, health, crime, barriers to housing affordability and local services, living environment, income deprivation affecting children and older people.

Our final dataset is generated from the UK Household Longitudinal Survey (UKHLS) in 2020 and 2021, provided by Understanding Society, to assess individuals' psychological distress levels.[43, 44] The data contain various information on respondents such as age, gender, race, family composition, income, and physical health conditions across eight different waves of COVID-19. After cleaning up the data with no or missing responses, we have unique respondents of 19,020 residing across cities and towns in the UK. The basic nature of this survey is a longitudinal study that follows the same sample of people over time, although each wave adds a small number of people into the sample with cross-sectional sampling weights. For our main analyses, we use the panel sample with longitudinal sampling weights. We also received special permission to obtain the residence LSOA information of respondents, which enables us to measure the distance of one's residence to the nearest green spaces to proximate their probability to travel to green spaces. As only 2,073 survey respondents reside in London, and this number becomes even smaller after matching, we use the UK sample for our main analyses and perform the robustness test with the London subsample. Full details on the recruitment, sampling, retention, and weighting of the sample are available in the UKHLS user guide (see Appendix 3).

2.2. Identification Strategies

Figure 1B shows how lockdown periods overlap with our other datasets of cell phone–based mobility in London as well as the UKHLS. During our sample period, the UK government imposed three national lockdowns that placed restrictions on movement; no person was allowed to leave the place where they live without a reasonable excuse. Lockdown laws in the UK encompass restrictions on movement and gatherings, as well as the closure of and restrictions on businesses. As restrictions on movement are the strongest regulation that affects travel behaviours, we focus on these phases for our research and call them *lockdowns*.[45] During these lockdowns, non-essential street businesses (e.g., cafes, restaurants, bars and pubs) were closed and people were asked to stay at home as much as possible and were strictly banned from gathering. People were, however, still allowed to do outdoor exercises either alone or with other household members or seek medical assistance.

For our statistical model of travels to green spaces at the neighbourhood level, we examine the threshold distance to green spaces that determines the significant changes in travel patterns after the COVID-19 pandemic (vs. before) and during the lockdown (vs. non-lockdown). We utilize straight-line distances between the edges of green spaces and residence LSOAs using a Geographic Information System (GIS). Figure 2 presents the gradient of the proportion of the number of green space travellers out of all travellers by the distance to the nearest green space. The distinct divergence at around the 800-meter radius suggests that people residing within 800 meters of green spaces show different changes in travel patterns to green spaces compared to those who live farther away. The 800-meter cut-off coincides with a walkable distance in existing literature.[46] As this is identified as an ideal spatial treatment, we generate a binary variable that captures whether the nearest green space is located within 800 meters of each residential LSOA.

Next, to minimize potential confounding issues and provide a causal interpretation for our model of the role of proximity to green space to mental distress, we adopt a standard logic of a counterfactual causal inference design. Consistent with the above analysis on neighbourhood-level mobility, we identify green space proximity using the distance limit of 800 meters for each survey respondent. Our potential treatment group is comprised of all UKHLS survey respondents residing in LSOAs within 800 meters of the nearest green space, and those who reside in LSOAs that are farther belong to the potential comparison group. Among the pool of survey respondents in the potential comparison group, we select the closest match for each individual residing within 800 meters of the nearest green space by using the propensity score matching (PSM) procedures. Our final sample size after matching is 2,496 individuals for the treatment group and 2,496 for the comparison group, both of which are highly homogeneous with respect to age, race, family composition, earnings, and drinking/smoking habits (see Appendix 3 for the detailed matching process and the quality of the matched sample).

Finally, we pay attention to the UKHLS data where psychological distress was measured using 12 questions from the General Health Questionnaire (GHQ), a well-validated tool used to screen and diagnose generalized anxiety disorder in clinical practice and research.[47] It uses a four-point scale, where higher point values indicate a more deteriorated condition (“not at all”/“same as usual” were give a score of 0; "more than usual"/"much more than usual," a score of 1). We then convert the total score into the measure with 12 points (asymptomatic [score 0], sub-clinically symptomatic [1-3], symptomatic [4-6], and highly symptomatic [7-12]).[47]

Figure 1A: Summary of Data and Sources

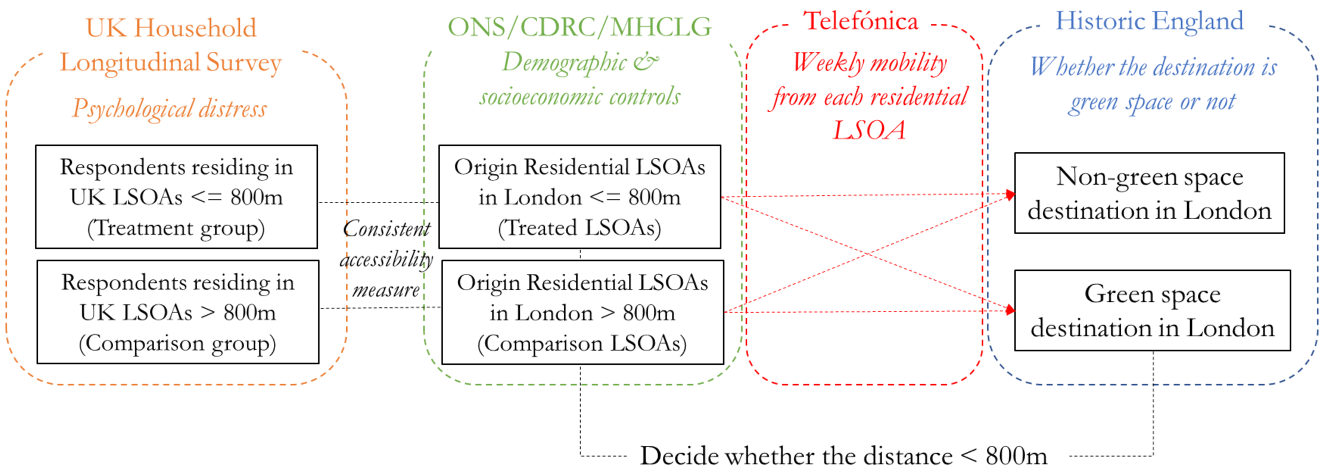


Figure 1B: Differences in Total Number of Travels for Each Week in 2020 Compared to the Corresponding Week in 2019 (Year-over-Year Change) along with the Timeline of COVID-19 and Lockdowns in London

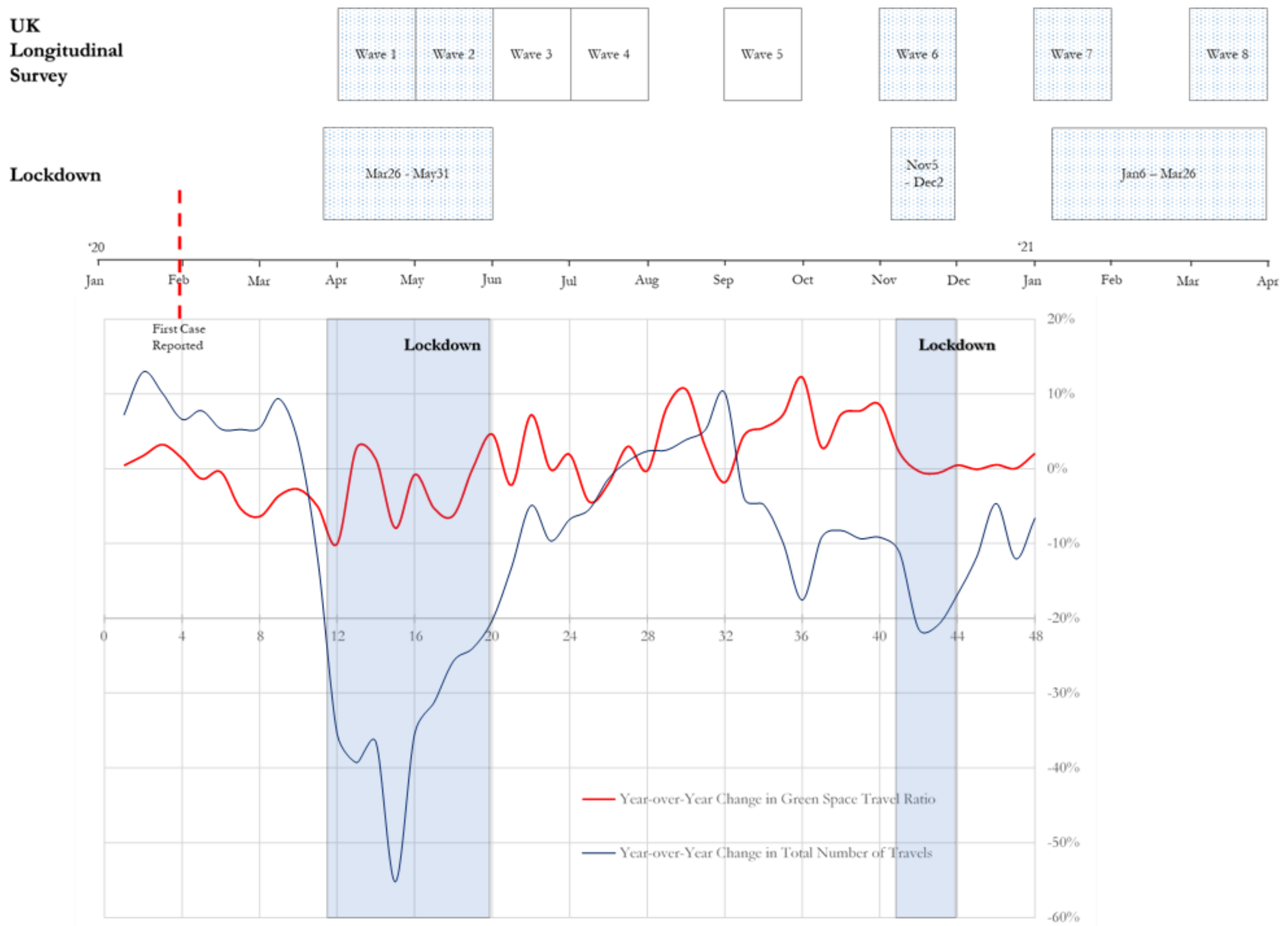
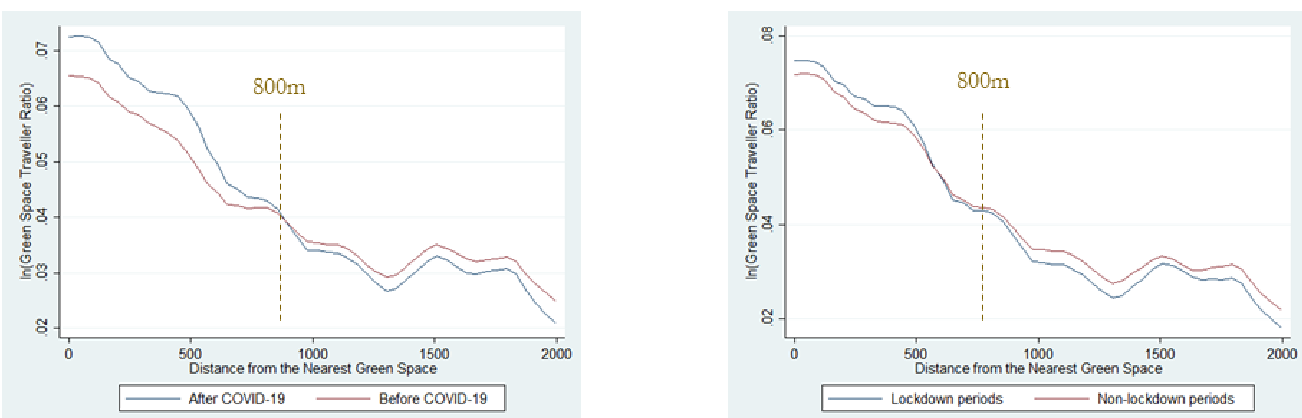


Figure 2: Green Space Distance Gradient for the Proportion of the Number of Green Space Travellers out of All Travellers during Non-Work Hours in London



2.3. Empirical Models

First, we adopt a difference-in-difference (DID) analytical approach using variations in the distance from green spaces and in pre-post periods of the COVID-19 outbreak or lockdown event. We employ the DID model as follows:

$$V_{jt} = \beta D_{jt}^{800} + \theta D_{jt}^{800} \times Post_{jt} + \delta Post_{jt} + X_j'\gamma + \varphi_m + \alpha_l + \varepsilon_{jt}. \quad [1]$$

where V_{jt} is the proportion of the number of travellers to green spaces out of all travellers in LSAO j in week t, D_{jt}^{800} is a binary indicator of whether there is a green space within an 800-meter radius of LSAO j, and $Post_{jt}$ is a binary indicator that travel behaviours in week t occurred after the COVID-19 outbreak or during lockdown periods. θ picks up how the proportion of green space travellers in LSOAs located within 800 meters of the nearest green space changes after COVID-19 or during lockdown periods compared to the pre-pandemic or non-lockdown periods. X is a control vector of LSOA-specific characteristics such as population size, gender (men vs. women), racial groups (White, Asian, Black, others), age groups (under 18 years,18–29, 30–45, 46–59, 60-89, over 89), as well as a wide range of neighbourhood indices related to income, employment, education, health disability, crime, barriers to housing and services, and living environment. We include month fixed effects and local authority fixed effects to control for unobserved heterogeneity. ε_{jt} is an error term. To account for the potential serial correlation of residuals within an LSOA, we cluster standard errors at the LSOA level.

Next, we attempt to compare the level of mental distress between individuals residing in LSOAs that are within 800 meters of the nearest green spaces and those residing in farther LSOAs but within the same city. We employ a DID model similar to equation (1) as follows:

$$M_{iw} = \beta D_{iw}^{800} + \theta D_{iw}^{800} \times LD_{iw} + \delta LD_{iw} + X_i'\gamma + \varphi_w + \alpha_c + \varepsilon_{iw}. \quad [2]$$

where M_{iw} is the mental distress score of individual respondent i from the matched sample in wave w, D_{iw}^{800} is a binary indicator of whether there is a green space within an 800-meter radius of the residence of respondent i, and LD_{iw} is a binary indicator that a mental health survey in wave w is conducted during lockdown periods. θ picks up how the mental health score changes for those who reside within 800 meters of the nearest green space during lockdown periods. X is a control vector of demographic and economic variables such as age, gender (men vs. women), racial groups (White, Black, other), number of household members, number of children, whether living with a partner, household/individual monthly earning, and whether having financial difficulties as well as health status such as whether having long-term health issues, whether infected with COVID-19, number of days doing moderate activities, whether drinking moderately or heavily, and whether smoking. We include wave fixed effects and city fixed effects to control for unobserved heterogeneity and uneven distribution of green spaces across cities. ε_{iw} is an error term.

3. Results

With a sample of mobile location records of 4,835 LSOAs, Figure 1A shows that the total number of travellers within London significantly decreased after the COVID-19 outbreak by 25% as compared to the pre-COVID-19 period. The most significant drop of 55% was seen when the first lockdown was imposed. Meanwhile, starting from April 2020, the individual's probability to travel to green space relative to other places increased compared to the same week in 2019. Interestingly, even during lockdowns, more people tended to travel to green spaces than to other spaces while the general mobility showed a significant downward trend. We attempt to perform spatial analyses and identify which LSOAs within London experienced higher or lower increases in the proportion of green space travellers during lockdowns compared to the average amount in 2019. Figure 3 shows that LSOAs in the red colour (increasing probability of green space travels during lockdowns compared to pre-COVID-19 periods) mainly cluster around major green spaces in London. This implies that LSOAs closer to green spaces were much more likely to see an increase in the share of the number of travellers to such spaces than other LSOAs.

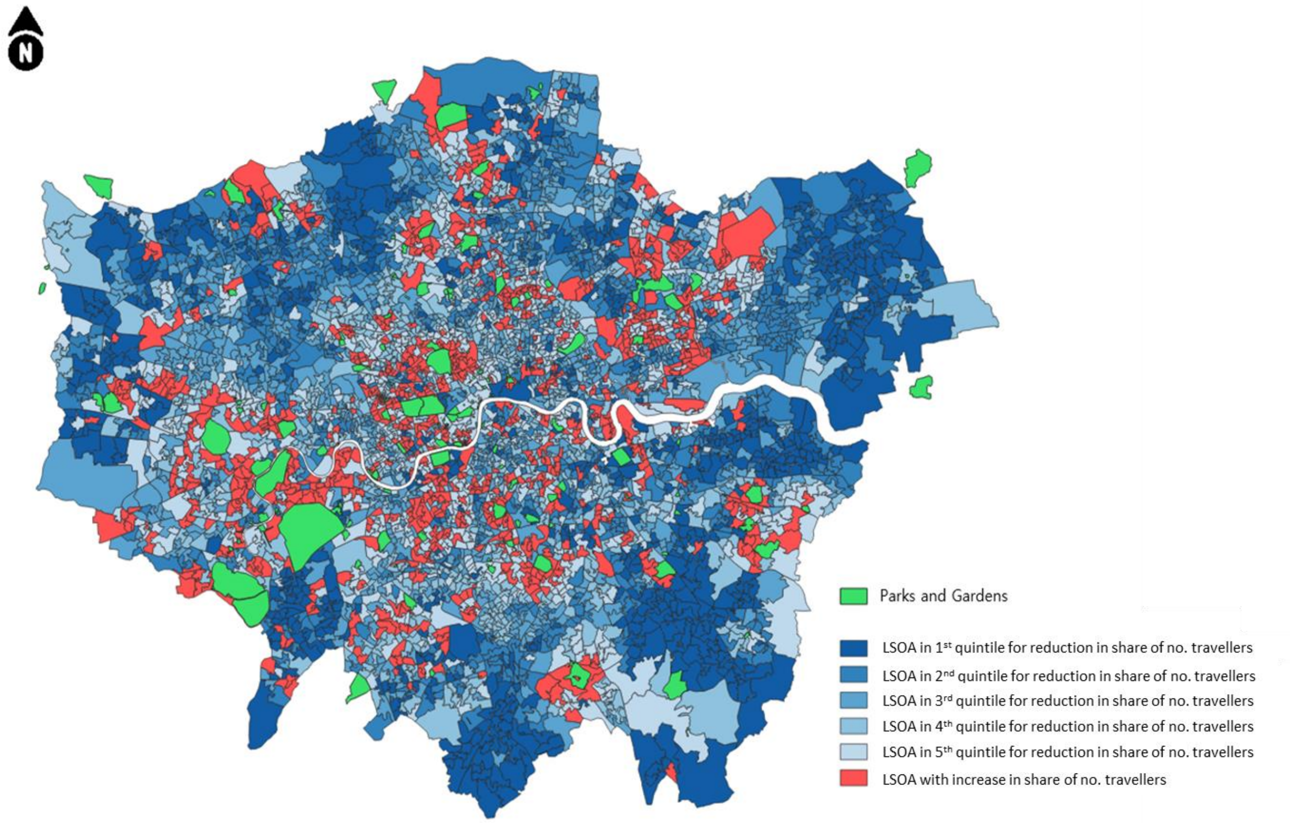
Table 1 provides summary statistics for the sample of LSOAs in London for our mobility analysis. Neighbourhoods whose edges were within 800 meters of a green space edge (treated LSOAs) had a higher ratio of green space travels than neighbourhoods further away from green spaces (comparison LSOAs). In line with Figure 2 and Figure 3, those residing in the treated LSOAs were also much more likely to travel to green spaces, and their probability of visiting green spaces relative to non-green spaces within London was double compared with residents residing in other LSOAs. This difference in travel behaviours by proximity to green spaces was most significant when people were stuck at home. After the COVID-19 outbreak, residents in the treated LSOAs increased their travel to green spaces while those in the comparison LSOAs decreased green space travels. During the lockdowns, those living closer to the green space travelled more to green spaces while those living farther travel less compared to non-lockdown periods. While demographic characteristics were quite similar for the treated and comparison LSOAs, residents in treated neighbourhoods were more likely to be whites. Deprivation indices suggest that while the treated LSOAs were less deprived in general than a comparison neighbourhood, they were slightly worse in terms of health desirability, crime, and living environment, potentially because planned green spaces were more likely to be located in higher density areas.

Table 1. Descriptive Statistics of Travel Data in London

Variables	LSOAs within 800 m of the nearest green space (Treated LSOAs)		LSOAs farther from the nearest green space (Comparison LSOAs)	
	Mean	Std. Dev	Mean	Std. Dev
Total number of travellers during non-work hours	1,316·92	1559·24	1,234·88	1431·24
Total number of green space travellers during non-work hours	78·33	287·04	36·27	102·09
Proportion of the no. green space travellers out of all travellers during non-work hours	5·96%	10·95%	2·90%	2·90%
Proportion of the no. green space travellers out of all travellers before COVID-19	5·67%	5·67%	3·01%	4·84%
Proportion of the no. green space travellers out of all travellers after COVID-19	6·31%	12·85%	2·77%	5·70%
Proportion of the no. green space travellers out of all travellers during non- lockdown periods after COVID-19	6·26%	12·07%	2·84%	2·84%
Proportion of the no. green space travellers out of all travellers during lockdown periods after COVID-19	6·46%	14·94%	2·58%	6·46%
Demographic characteristics (2019, 2020)				
Population	1,867·71	441·81	1,849·58	527·33
Share of male population	0·46	0·50	0·43	0·50
Share of population under 18 years old	0·22	0·05	0·24	0·05
Share of population of 18 to 39 years old	0·35	0·10	0·32	0·09
Share of population of 40 to 59 years old	0·26	0·04	0·26	0·03
Share of population of 60 to 89 years old	0·16	0·06	0·17	0·06
Share of population over 89 years old	0·01	0·01	0·01	0·01
Share of White	0·73	0·15	0·68	0·18
Share of Asian	0·16	0·14	0·21	0·17
Share of Black	0·06	0·05	0·07	0·06
Share of other races	0·04	0·02	0·03	0·02
Socioeconomic characteristics (English indices of deprivation 2019)				
Index of multiple deprivation (IMD) score	20·67	10·77	22·16	10·97
Income score (rate)	0·13	0·08	0·14	0·07
Employment score (rate)	0·08	0·05	0·09	0·05
Education, skills and training score	10·25	8·84	15·31	10·26
Health deprivation and disability score	-0·44	0·79	-0·34	0·63
Crime score	0·27	0·58	0·25	0·56
Barriers to housing and services score	30·03	9·18	32·89	9·99
Living environment score	31·81	10·96	27·15	10·37
Income deprivation affecting children index (IDACI) score (rate)	0·17	0·10	0·18	0·09
Income deprivation affecting older people index (IDAOPI) score (rate)	0·23	0·14	0·23	0·13
Number of LSOAs	2,149		2,686	
Number of LSOAs*weeks (96 weeks)	206,063		257,198	

Note 1: Non-work hours are defined as 16:00–24:00 on working days and 08:00–24:00 on weekends and bank holidays.
Note 2: The English indices of deprivation 2019 comprises seven different domains which are combined and weighed to generate the LSOA's IMD score out of 100. The higher score means more deprivation. IDACI and IDAOPI are supplementary indices for income. For more detailed descriptions of the data, refer to online guidance of the data (https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019).

Figure 3. Differences in Share of Number of Travellers to Green Spaces during Lockdowns Compared to Share of Green Space Travellers during Pre-COVID Periods



Note: The colours are selected as blue for decrease and red for increase, aligning with the common sense of the heatmap, and each hexile has approximately the same number of LSOAs.

Our empirical model results report the effect of being located closer to green spaces on the probability of traveling to green spaces. Cross-sectional estimates show pre-existing conditions that the proportion of green space travellers out of all travellers within London is about 1.4 percentage points higher in neighbourhoods within 800 meters of the nearest green space than in neighbourhoods located farther (Table 2, columns 1). If we only account for post-COVID-19 periods, the difference in this proportion is slightly larger at 1.6 percentage points, implying the increasing importance of the distance to green spaces for the travel patterns to green spaces (column 3). Table 2 then shows the estimation results of the DID specification introduced in equation (1). In general, the proportion of travellers to green spaces relative to other places decreased by 0.3 and 0.2 percentage points after the COVID-19 outbreak in London (column 2) and during lockdowns (column 4). However, the probability of traveling to green spaces from these neighbourhoods was approximately 0.9 percentage points higher compared to other London neighbourhoods with similar characteristics but located farther from green spaces (column 2). Similarly, during the lockdowns, neighbourhoods that were closer to green spaces experienced an additional increase of 0.5 percentage points in the proportion of green space travellers (column 4). These increases are much greater than the general reduction in the proportion of green space travellers after COVID-19 and during the lockdowns (0.3 and 0.2 percentage points, respectively). Given that the average proportion of green space travellers out of all travellers in London was about 6% (see Table 1), these increases after COVID-19 and during lockdown periods are significant. Our results suggest that people residing closer to green spaces were much more likely to travel to green spaces than those residing farther even when they faced strict restrictions on movement. Note that for our robustness test, we use the ratio of the number of travels to green spaces out of total travels and the results are consistent (Appendix 4).

Table 2. Empirical Estimation of Impact of Proximity to Green Spaces on the Proportion of Green Space Travellers

	(1)			(2)			(3)			(4)		
	Cross-sectional			Difference-in-Difference			Cross-sectional (post-COVID-19 periods)			Difference-in-Difference (post-COVID-19 periods)		
	Coef.	S.E.	P	Coef.	S.E.	P	Coef.	S.E.	P	Coef.	S.E.	P
LSOAs located within 800 meters of the nearest green space	0·014	0·002	0·000	0·010	0·002	0·000	0·016	0·003	0.000	0·015	0·002	0·000
After COVID-19 outbreak				-0·003	0·000	0·000						
Lockdown										-0·002	0·000	0·000
LSOAs within 800 meters of the nearest green space & After COVID-19				0·009	0·001	0·000						
LSOAs within 800 meters of the nearest green space & lockdown										0·005	0·001	0·000
Observations	463,261			463,261			212,411			212,411		
R-squared	0·227			0·232			0·237			0·237		
Demographic characteristics	Yes			Yes			Yes			Yes		
Socioeconomic characteristics	Yes			Yes			Yes			Yes		
Local authority fixed effects	Yes			Yes			Yes			Yes		
Month fixed effects	Yes			Yes			Yes			Yes		

Note: Standard errors are clustered at the LSOA level.

After establishing the evidence on the significant role of proximity to green spaces to the higher probability of traveling to green spaces after the COVID-19 outbreak and during lockdowns, we move to our next analysis of the mental distress of residents. With the sample of 4,998 individuals matched from the original sample of 19,020 survey respondents and their residential location information, Table 3 shows that people reported higher mental distress during the lockdowns compared with post-COVID-19 non-lockdown periods. In particular, residents living farther than 800 meters from green spaces (comparison group) experienced a more substantial increase in their mental distress score during the lockdowns. Their mental distress score was 0.5 higher on average during the lockdown compared with post-COVID-19 non-lockdown periods, while those living closer to green spaces (treatment group) experienced an average increase of 0.35 in the score. As individuals in the treatment and comparison groups showed quite homogenous characteristics after matching (Table 3), this difference in the change in mental destress scores is likely to be attributable to the proximity of one's residence to green spaces. The treated individuals tended to earn more than their matched counterparts even after matching and this is potentially because green spaces in our data are planned spaces that are more likely to be concentrated in cities with higher productivity.

Table 3. Descriptive Statistics of Matched Household Survey Data in the UK

Variables	Individuals living within 800 m of the nearest green space (Treatment)		Individuals living farther from the nearest green space (Comparison)	
	Mean	Std. Dev	Mean	Std. Dev
Total score of mental distress	2·36	3·32	2·26	3·29
Total score of mental distress during lockdown periods	2·49	3·33	2·45	3·35
Total score of mental distress during non-lockdown periods	2·14	3·30	1·95	3·17
Demographic characteristics				
Age	54·21	16·94	54·96	16·33
Gender (male vs· female)	0·43	0·49	0·42	0·49
White	0·03	0·16	0·02	0·13
Black	0·87	0·34	0·91	0·29
Number of household members	1·63	1·25	1·64	1·22
Number of children	0·38	0·80	0·35	0·73
Having a partner	0·71	0·45	0·72	0·45
Economic characteristics				
Household monthly earning	4,189·67	14,503·48	3,415·81	12,780·11
Individual monthly earning	1,716·01	6,298·52	1,414·13	5,310·86
Having financial difficulties	0·04	0·19	0·05	0·21
Health status				
Having long-term health issues	0·40	0·49	0·41	0·49
COVID-19 infection	0·01	0·08	0·01	0·09
Number of days doing moderate activities	2·69	2·60	2·61	2·57
Moderate/heavy drinker	0·46	0·50	0·47	0·50

Smoker	0·07	0·25	0·07	0·26
Number of individuals	2,496		2,496	
Number of individuals × survey waves	15,529		15,730	

Table 4 first shows the mental distress score is not statistically different for individuals residing within 800 meters of the nearest green space (treatment group) and their matched counterparts that have similar attributes and reside farther from green spaces (comparison group; column 1). These cross-sectional results suggest a null effect of the proximity to green spaces on mental health in pre-existing conditions. When we use the DID specification shown in equation (2), the difference in the average mental health scores between the treatment and comparison groups remain statistically insignificant at the 10% level (column 2). Then, results report that the mental distress score is 0.605 higher during lockdowns compared to non-lockdown periods (column 2), which is substantial given the average score is only 2.31 for our matched sample. Nonetheless, individuals residing close to green spaces were able to offset this increased mental distress score by 0.106 more than those in the comparison groups (column 2). Finally, we perform the robustness test with the matched subsample of London residents. Results (column 3) demonstrate that the increase in the mental distress score during lockdowns is even higher for London residents (0.734 for London vs. 0.605 for the UK). Also, green space accessibility plays a more important role in reducing this score for London residents (0.378 for London vs. 0.106 for the UK). These results suggest that while the urban environment with higher density may be more vulnerable to mental distress during lockdowns, enhancing green space accessibility could be a great remedy to such a risk.. In addition, we observe that treated individuals had less volatile psychological distress scores between lockdown and non-lockdown periods than their matched counterparts. In particular, in the last wave of the UKHLS, which falls in the lockdown period, the treatment group showed a much lower median mental distress score than the comparison group, suggesting that people living closer to green spaces were able to better stabilize their mental status during lockdowns (see Appendix 5).

Table 4. Empirical Estimation of Impact of Living Closer to Green Spaces on Psychological Distress

	(1)			(2)			(3)		
	Cross-sectional			Difference-in-Difference (all UK respondents)			Difference-in-Difference (London respondents)		
	Coef.	S.E.	P	Coef.	S.E.	P	Coef.	S.E.	P

Living within 800 meters of the nearest green space	0·071	0·072	0·324	0·129	0·080	0·109	0·405	0·251	0·106
Lockdown				0·605	0·059	0·000	0·734	0·190	0·000
Living within 800 meters of the nearest green space & Lockdown				-0·106	0·050	0·035	-0·378	0·163	0·021
Observations		31,259			31,259			3,314	
R-squared		0·097			0·112			0·134	
Demographic characteristics		Yes			Yes			Yes	
Economic characteristics		Yes			Yes			Yes	
Health status		Yes			Yes			Yes	
City fixed effect		No			Yes			Yes	
Wave fixed effect		No			Yes			Yes	

4. Discussion

This study first examined how London's population mobility to green spaces changed after COVID-19 and during lockdowns and then explored how better access to green spaces could affect psychological distress with a longitudinal cohort sample during lockdowns. The overall number of travellers within London has significantly decreased after the COVID-19 outbreak as compared to the same weeks in 2019, and the most significant drop was seen when the first lockdown was imposed. This trend was similarly discovered by many studies in other contexts. For example, the average time spent in non-residential locations decreased by 40% in response to various mobility restriction policies across 80 countries globally.[48] Our study built an empirical model that considers population mobility patterns derived from anonymous mobile phone data. This approach is arguably better than using other available mobility data (including air and rail travel records, GPS loggers, Google records, apps, or other social media sources) as the latter could only capture the trajectories of subpopulations who use specific transport tools or mobile applications.[49] By contrast, the comprehensive coverage of mobile phone users aged 15–65 years with a market share of 25% can help obtain a more representative sample for the whole population in London, and an accurate reflection of movement patterns between their residences and high-frequency destinations. Additionally, this study integrated the location information of registered green spaces in London and examined whether the antenna polygon of the travel destination of mobile phone users from different residential neighbourhoods overlaps with green spaces. Such investigation unveiled that the individuals' probability to travel to green spaces than other places has increased as compared to the same period in 2019, and the tendency to increase travels to green spaces continued during lockdowns even when the general mobility decreased.

While the COVID-19 outbreak has substantially affected population mobility patterns within London due to people's voluntary precautionary behaviours, lockdown orders have brought an even higher reduction in mobility. When people were ordered not to leave home without a reasonable excuse, they immediately reduced more than half of their travels.[50, 51] Even with this reduced mobility, the probability of travelling to green spaces relative to other places showed a quick recovery about one week after the first lockdown order. Also, lockdown measures appeared to have different effects on populational mobility across different stages of the outbreak. In the period of our sample, we observed a much higher reduction in the year-over-year mobility changes during the first lockdown order than during the second lockdown. A potential reason could be that the second order (27 days) was much shorter than the first (91 days), and moving around would have been a more appealing option if allowed during the first order when the weather was more suitable for movement and outdoor activities (i.e., summertime) than the second (i.e., wintertime). In addition, people likely adjusted their travel behaviours from the continuing pandemic by the time they reached the second order. In terms of travels to green spaces, we found a more stable trend during the second lockdown, which could again be attributable to travel behaviour adjustment. The probability of traveling to green spaces instead of other places during the second lockdown is consistently higher than in the same weeks in 2019.

More importantly, this study examined how the proximity from residence to green spaces can affect individuals' mobility during the lockdowns. After the COVID-19 outbreak and during the lockdowns, individuals who lived close to green spaces were more likely to visit those spaces than other non–green spaces. These findings echo the discoveries from some of the urban sustainability and environmental studies. For example, previous studies found that stressed individuals like to access green spaces more than other spaces[52], that neighbourhood greenery can help to facilitate social support[53], and that publicly accessible neighbourhood nature can be associated with residents' increased sense of community belonging, which in turn improves mental health outcomes.[54] Additionally, a previous review in environmental research has also pointed out the benefits of accessing green space on improving well-being, by reducing exposure to environmental stressors, restoring capacities, and building capacities.[19] Recently, urban research also showed that green infrastructure across cities can interplay with respondents' residential location, as well as their socio-demographic profiles and lockdown policies, to predict residents' outdoor recreation behavior.[55] In fact, the unequal access to green spaces presents a troubling picture to policymakers, as individuals who live more than 800 meters away from green spaces tended to travel less to green spaces than those who have better access. This by itself might not be an issue as the mobility restriction measures were meant to reduce social interactions and population mobility. However, this study highlighted the potential issue in regards to impaired psychological well-being.

By using the longitudinal household sample in the UK to track temporal changes in national mental health from before COVID-19 to the subsequent lockdown period, this study examined how individuals' psychological well-being was affected during the pandemic with detailed time series data. Unlike previous inquires with similar data,[6, 56] we associated the survey data with the individuals' residence information and further investigated whether living close to green spaces helped individuals battle the negative influence of lockdown on their psychological well-being. Similar to a previous study,[6] we found that individuals were significantly distressed during the lockdowns (vs. non-lockdown period) after accounting for all relevant factors. Specially, we observed a 0.605 increase in the psychological distress score.

Importantly, supporting our hypothesis, we found that, during lockdowns, individuals who lived close to green spaces (i.e., within 800 meters) saw a much smaller increase in the distress score than those who lived farther away from green spaces (i.e., more than 800 meters) after controlling for all other potential determinants of mental health known in the literature. We also found that psychological states, as represented by the GHQ scores, were much more stable for individuals who lived close to green spaces than those who lived farther away. This is particularly interesting as we identified a potential group of the population that had a higher volatility of psychological distress during lockdowns. Unlike the prior studies that focused on examining effects of the individual characteristics—such as gender, age, educational attainment and socioeconomic position, Black, Asian, and minority ethnic (BAME) backgrounds, and living conditions (e.g., living alone)[57-60]—this study identified an environmental factor that can provide policymakers with an opportunity to intervene. Building from the seminal work that has shown the positive effect of simply having a window view of a natural setting on the speed of recovery and quality of postoperative experiences,[60] this study suggested that residing in a place close to public green spaces could also have a significantly positive impact on individuals' mental health, especially when their mobility is restricted by lockdown orders.

Additionally, lockdown measures in the COVID-19 pandemic provided a better context to examine the effects of green space accessibility than quarantines in previous epidemics. For the majority of residents in London during lockdowns, certain travels outside of the home were permitted so they could travel to green spaces. Because quarantines of previous epidemics posed stronger mobility restrictions and the number of affected individuals was typically smaller compared to an entire city lockdown, they provided no opportunity to observe public mobility, especially to green spaces. To our knowledge, this is one of the first studies to combine public mobility data with the longitudinal household survey and systematically examine how lockdowns affect the level of public mental distress with a focus on exposure to green spaces. The unique datasets enabled the long-term tracking of public mobility and mental health before and during COVID-19. Although we didn't test this proposition directly for those who cannot travel outside of their residences at all during lockdowns (e.g., someone with quarantine orders), we have a reason to believe that providing a place with a view of green spaces, [61] incorporating vertical greenery (i.e., the integration of vegetation onto the vertical structures of buildings),[62] or even a plasma display of nature view,[63] could be beneficial for the mental well-being of such individuals.

5. Conclusion

Overall, these findings suggested that when mobilities were restricted by lockdown measures during the COVID-19 pandemic, London residents increased their travels to green spaces. That is especially true for residents who lived closer to green spaces. This echoes prior research on how green spaces can help restore psychological distress and even reduce pain. Furthermore, individuals could greatly benefit from visiting green spaces, as such activities reduce the chance of experiencing psychological distress during lockdowns. We observed a higher level of aggravating psychological distress for those who cannot access green space easily (i.e., those living in areas not within walking distance). As countries and cities around the world face the risks of future lockdowns, these findings emphasize the importance of supporting and paying attention to individuals who have inferior access to green spaces. Some cities like Paris and Singapore have already begun plans to enhance accessibility to green spaces for more residential neighbourhoods and they are likely to be in a good position to prevent excessive mental illnesses during similar future pandemics.[64, 65] Besides creating more quality green spaces, policymakers can consider expanding trails and green networks to provide better environments for walking to larger green spaces and to ensure more equal access to green spaces for all citizens during lockdowns. It is a key to supporting more vulnerable groups during the current pandemic and those in the future.

This work has limitations, which could spark future research. First, because of the data limitations, our two analyses were performed with different samples and at different geographic scales (i.e., mobility analysis in London and mental distress analysis in the UK). Ideally, we would have wanted to have travel information of individual survey respondents so that we could directly associate their travel patterns to green spaces with their mental well-being. Next, although we believe that we have done our best to identify individual mobility and associate that with green space location, there still could be some miscalculation on the location of the individuals given that the size of the antenna could potentially cover areas with both green and non-green spaces. Finally, our analyses on mental health do not fully account for potential confounders related with the built environment such as walkability, bikeability, the level of noise, which could be important for mental health of residents, especially when they stay longer in their residences after COVID-19 and during lockdown. Future research would benefit from further investigating clearer underlying mechanisms through which green spaces mitigate negative impacts of COVID-19 on mental health. Also, as lockdown measures vary significantly by countries and regions, more comparative analyses would be useful to generalize empirical results.

Declaration of interests

We declare no competing interests.

Data sharing

Ethics approval for UKHLS was granted by the University of Essex Ethics Committee for the COVID-19 web and telephone surveys (ETH1920-1271), and we obtained approval from the University of Essex to access this data. Anonymous data can be requested from the University of Essex. Due to the non-disclosure agreement with Telefónica, we are not allowed to share the mobility data. Other anonymous datasets can be requested from the relevant agencies.

References

1. Alfano, V. & Ercolano, S. The Efficacy of Lockdown Against COVID-19: A Cross-Country Panel Analysis. *Appl. Health Econ. Health Policy.* **18**, 509–517 (2020).
2. Cauchemez, S. *et al.* Lockdown impact on COVID-19 epidemics in regions across metropolitan France. *The Lancet* **396**, 1068–1069 (2020).
3. Witteveen, D., Sociodemographic inequality in exposure to COVID-19-induced economic hardship in the United Kingdom. *Res. Soc. Stratif. Mobil.* **69**, 100551 (2020).
4. Bonaccorsi, G. *et al.* Economic and social consequences of human mobility restrictions under COVID-19. *Proc. Natl. Acad. Sci.* **117**, 15530–15535 (2020).
5. Moreno, C. *et al.* How mental health care should change as a consequence of the COVID-19 pandemic. *Lancet Psychiatry* **7**, 813–824 (2020).
6. Pierce, M. *et al.* Mental health before and during the COVID-19 pandemic: a longitudinal probability sample survey of the UK population. *Lancet Psychiatry* **7**, 883–892 (2020).
7. Pancani, L. *et al.* Forced social isolation and mental health: a study on 1,006 Italians under COVID-19 lockdown. *Front. Psychol.* **12**, 663799 (2021).
8. Passos, L. *et al.* Impact on mental health due to COVID-19 pandemic: cross-sectional study in Portugal and Brazil. *Int. J. Environ. Res. Public Health* **17**(18), 6794 (2020).
9. Mariani, R. *et al.* The impact of coping strategies and perceived family support on depressive and anxious symptomatology during the coronavirus pandemic (COVID-19) lockdown. *Front. Psychol.* **11**, 587724 (2020).

10. Simon, J. *et al.* Impacts of the Covid-19 lockdown and relevant vulnerabilities on capability well-being, mental health and social support: an Austrian survey study. *BMC Public Health*, **21**(1), 1-12 (2021).

11. Shanahan, L. *et al.* Emotional distress in young adults during the COVID-19 pandemic: evidence of risk and resilience from a longitudinal cohort study. *Psychological Medicine* **52**, 1-10 (2020).

12. Hawryluck, L. *et al.* SARS control and psychological effects of quarantine, Toronto, Canada. *Emerg. Infect. Dis.* **10**, 1206 (2004).

13. Reynolds, D. *et al.* Understanding, compliance and psychological impact of the SARS quarantine experience. *Epidemiology & Infection* **136**, 997-1007 (2008).

14. Liu, X. *et al.* Depression after exposure to stressful events: lessons learned from the severe acute respiratory syndrome epidemic. *Comprehensive Psychiatry*, **53**(1), 15-23 (2012).

15. Brooks, S. K. *et al.* The psychological impact of quarantine and how to reduce it: rapid review of the evidence. *The Lancet* **395**, 912–920 (2020).

16. Barton, J. & Rogerson, M. The importance of greenspace for mental health. *BJPsych Int.* **14**, 79–81 (2017).

17. Astell-Burt, T. & Feng, X. Association of urban green space with mental health and general health among adults in Australia. *JAMA Netw. Open* **2**, e198209–e198209 (2019).

18. Torres Toda, M. *et al.* Residential surrounding greenspace and mental health in three Spanish areas. *Int. J. Environ. Res. Public. Health* **17**, 5670 (2020).

19. Markevych, I. et al. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environ. Res.* **158**, 301-317 (2017).

20. Sallis, J. F. *et al.* An ecological approach to creating active living communities. *Annu Rev Public Health* **27**, 297–322 (2006).

21. Wolch, J. R., Byrne, J. & Newell, J. P. Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landsc. Urban Plan.* **125**, 234–244 (2014).

22. Hartig, T., Mitchell, R., De Vries, S. & Frumkin, H. Nature and health. *Annu. Rev. Public Health* **35**, 207–228 (2014).

23. Lee, A. C. & Maheswaran, R. The health benefits of urban green spaces: a review of the evidence. *J. Public Health* **33**, 212–222 (2011).

24. Heo, S. *et al.* Impact of changed use of greenspace during COVID-19 pandemic on depression and anxiety. *Int. J. Environ. Res. Public Health* **18**(11), 5842 (2021).

25. Robinson J. M. *et al.* Nature's role in supporting health during the covid-19 pandemic: a geospatial and socioecological study. *Int. J. Environ. Res. Publ. Health* **18**(5), 1–21 (2021).

26. Vos, S., *et al.* Residential green space is associated with a buffering effect on stress responses during the COVID-19 pandemic in mothers of young children, a prospective study. *Environ. Res.* **208**, 112603 (2022).

27. Burnett, H. *et al.* Change in time spent visiting and experiences of green space following restrictions on movement during the COVID-19 pandemic: A nationally representative cross-sectional study of UK adults. *BMJ Open* **11**(3), 044067 (2021).

28. Dobbie, L. J. *et al.* The impact of the COVID pandemic on mobility trends and the associated rise in population-level physical inactivity: insights from international mobile phone and national survey data. *Front. Sports Act. Living* **80** (2022).

29. Venter, Z. S. *et al.* Back to nature: Norwegians sustain increased recreational use of urban green space months after the COVID-19 outbreak. *Landsc. Urban Plan* **214**, 104175 (2021).

30. Kleinschroth, F. & Kowarik, I. COVID-19 crisis demonstrates the urgent need for urban greenspaces. *Front. Ecol. Environ.* **18**, 318 (2020).

31. Boulton, C., Dedekorkut-Howes, A., & Byrne, J. Factors shaping urban greenspace provision: A systematic review of the literature. *Landscape and Urban Planning* **178**, 82-101 (2018).

32. Haaland, C. & van Den Bosch, C. K. Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban For. Urban Green* **14**, 760–771 (2015).

33. Gray, S. & Kellas, A. COVID-19 has highlighted the inadequate, and unequal, access to high quality green spaces. *BMJ Opin.* **3**, (2020).

34. Das, A. & Gailey, S. Green exercise, mental health symptoms, and state lockdown policies: A longitudinal study. *J. Environ. Psychol.* **82**, 101848 (2022).

35. Narea, M. *et al.* The Effect of COVID-19 Lockdowns on Maternal Mental Health and Parenting Practices Moderated by Urban Green Space. *Clin. Psychol. Sci.* (2022).

36. Marcelo, G. T. *et al.* Do we have enough recreational spaces during pandemics? An answer based on the analysis of individual mobility patterns in Switzerland. *Landsc. Urban Plan*, **221**, (2022).

37. Bonnel, P. *et al.* Passive mobile phone dataset to construct origin-destination matrix: potentials and limitations. *Transportation Research Procedia* **11**, 381-398 (2015).

38. Calabrese, F. *et al*. Estimating Origin-Destination flows using opportunistically collected mobile phone location data from one million users in Boston Metropolitan Area. *IEEE Pervasive Comput.* **10**, 36-44 (2011).
39. Data source: https://historicengland.org.uk/listing/the-list/
40. Data source: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates
41. Data source: https://data.cdrc.ac.uk/dataset/cdrc-modelled-ethnicity-proportions-la-geography
42. Data source: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019
43. For the study user guide, please see the following link: https://doc.ukdataservice.ac.uk/doc/8644/mrdoc/pdf/8644_ukhls_covid19_user_guide_v10.0.pdf;
44. For more study details, please see the following link: https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=8644#!/details
45. The Health Protection (Coronavirus, Restrictions) (England) (No. 4) Regulations 2020. https://www.legislation.gov.uk/uksi/2020/1200/contents/made.
46. Timperio, A. *et al.*. Perceptions about the local neighborhood and walking and cycling among children. Prev Med **38**, 39-47 (2004).
47. Batty, G. D., Russ, T. C., Stamatakis, E. & Kivimäki, M. Psychological distress in relation to site specific cancer mortality: pooling of unpublished data from 16 prospective cohort studies. *bmj* **356**, (2017).
48. Ilin, C. *et al.* Public mobility data enables covid-19 forecasting and management at local and global scales. *Sci. Rep.* **11**, 1–11 (2021).
49. Finger, F. *et al.* Mobile phone data highlights the role of mass gatherings in the spreading of cholera outbreaks. *Proc. Natl. Acad. Sci.* **113**, 6421–6426 (2016).
50. Galeazzi, A. *et al.* Human mobility in response to COVID-19 in France, Italy and UK. *Sci. Rep.* **11**, 1–10 (2021).
51. Borkowski, P., Jażdżewska-Gutta, M. & Szmelter-Jarosz, A. Lockdowned: Everyday mobility changes in response to COVID-19. *J. Transp. Geogr.* **90**, 102906 (2021).
52. Stigsdotter, U. K. & Grahn, P. Stressed individuals' preferences for activities and environmental characteristics in green spaces. *Urban For. Urban Green.* **10**, 295–304 (2011).
53. Dzhambov, A. M. *et al.* Does greenery experienced indoors and outdoors provide an escape and support mental health during the COVID-19 quarantine?. *Environ. Res.* **196**, 110420 (2021).
54. Rugel, E. J. *et al.* Exposure to natural space, sense of community belonging, and adverse mental health outcomes across an urban region. *Environ. Res.* **171**, 365-377 (2019).
55. Fagerholm, N. *et al.* Analysis of pandemic outdoor recreation and green infrastructure in Nordic cities to enhance urban resilience. *npj Urban Sustain.* **2**(1), 1-14 (2022).
56. Fancourt, D. *et al.* Trajectories of anxiety and depressive symptoms during enforced isolation due to COVID-19 in England: a longitudinal observational study. *Lancet Psychiatry* **8**, 141–149 (2021).
57. Proto, E. *et al.* COVID-19 and Mental Health Deterioration Among Bame Groups in the UK. *CESifo Working Paper No. 8449*, Available at SSRN: https://ssrn.com/abstract=3662057 (2020).
58. Wright, L. *et al.* Are we all in this together? Longitudinal assessment of cumulative adversities by socioeconomic position in the first 3 weeks of lockdown in the UK. *J. Epidemiol Community Health* **74**(9), 683-688 (2020).
59. D'Angelo, S. *et al.* Pre-pandemic socio-economic status and changes in employment during the first lockdown (2020) on the health of middle-aged people in England: a longitudinal study. *BMC Public Health* **22**(1), 1-10 (2022).
60. Raj, T., & Bajaj, A. Living alone in lockdown: impact on mental health and coping mechanisms among young working adults. *Curr. Psychol.* 1-13, (2021).
61. Ulrich, R. S. View through a window may influence recovery from surgery. *Science* **224**, 420–421 (1984).
62. Chan, S. H. M. *et al.* Vertical greenery buffers against stress: evidence from psychophysiological responses in virtual reality. *Landsc. Urban Plan.* **213**, 104127 (2021).
63. Kahn Jr, P. H., et al. A plasma display window? - The shifting baseline problem in a technologically mediated natural world. *J. Environ. Psychol.* **28**(2), 192-199 (2008).
64. See https://www.citiesforum.org/news/15-minute-city/ for the Paris' 15-minute City Plan.
65. See hthttps://www.greenplan.gov.sg/key-focus-areas/key-targets#city-in-nature for the Singapore's SG Green Plan 2030.

Appendix 1. Mobility Data Processing Details

Appendix 1A: Mobility Data Source.

The data set used in this study is developed based on the network access logs over the period of January 2019–December 2020, provided by Telefónica, one of the largest mobile phone companies in the UK, accounting for a market share of 25%. The network access logs track the antennas that a mobile device is connected to. All access events of mobile devices to the cellular network, which occur whenever a device establishes or updates a channel with the network, are recorded. For example, when the device attaches to or detaches from the network, or the device is handed over between antennas. The mobile device typically connects to an antenna that is physically proximal to the mobile device for greater bandwidth and smaller last-mile latency.

While the raw data include personal identifiers, the data we use for this study are aggregated data, which completely removed the personal identifiers. This is to comply with the legal standards of personal data (i.e., GDPR) and internal privacy policies that prohibit any type of analysis targeted towards an individual or a group of people. To put it simply, the data used for the analysis are the aggregate counts of visits made between antenna points, and the scale of our data (e.g., number of subjects living in an area) is large enough to make personal identification impossible.

In comparison to the data sources employed in prior studies of large-scale mobility, our data are distinguished in terms of consistently capturing fine-grained mobility activity across space and time and representing the general population. Various data sources including Call Detail Records (CDRs), geo-social media, and public transportation logs have been used. For instance, CDRs log the antennas that mobile phones connect to in the same way, and prior works have used them to predict mobility,[1] segregation,[2] and socioeconomic status.[3,4] An important drawback of CDRs is that they only record phone calls and SMS messages and, therefore, are inherently limited in their ability to accurately identify trip destinations and daily mobility due to the sparsity of records across different time spans. This issue is further compounded by the increasing usage of messaging apps instead of SMS, which are not recorded in CDRs. On the other hand, although geo-social media data (e.g., Foursquare) allow GPS-level spatial accuracy,[5] the temporal sparsity described above for CDRs is similarly problematic here. In addition, social media sources are likely to be prone to a demographic bias as active users are not typically representative of the general population.[6] Moreover, as individuals' habits to use social media could have a significant temporal variation, the data may not represent routine mobility activities.[7] Lastly, while public transportation logs have been used in a few studies,[8] the data are restricted to the users of a particular mode of transportation.

Appendix 1B. Home detection.

The residential neighbourhoods of all device users are estimated and we use them as the origin of the mobility flows. Methods for identifying residences from mobility traces commonly aim to identify routine activities during the evening and/or weekends.[9] Likewise, a method for home antenna detection is developed based on this intuition. For each day over a month, devices that remain in the same antenna's polygon during the evening (midnight–8 a.m.) for a substantial number of days are identified. The method first selects the set of antennas to which a device connects during the evening each day. Finally, the method classifies the home antenna of a device as the one with the maximum connection time for at least 14 days during the month, and the devices that do not have a home antenna that satisfies these criteria are excluded from the data sample.

Appendix 1C. Travel.

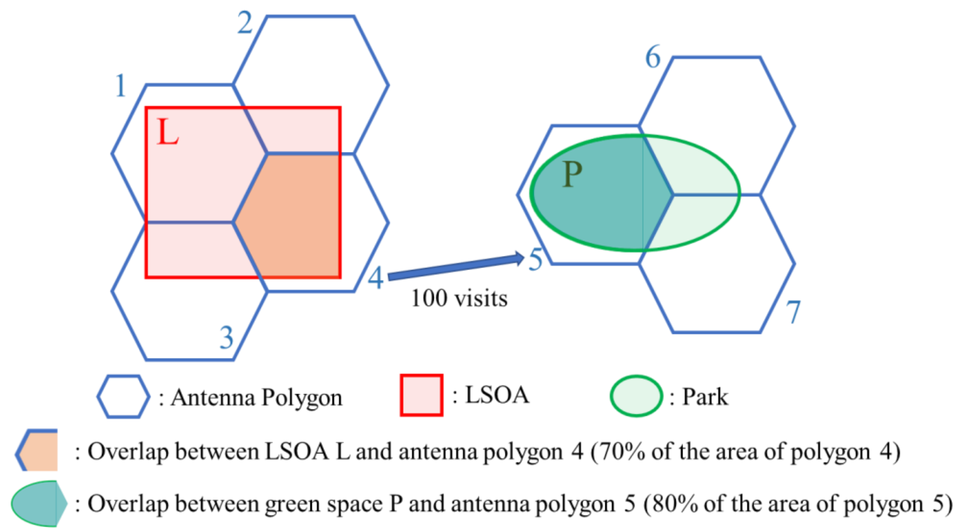
In our analysis, we define a "travel" as an event where the person connects to a non-home antenna (for longer than the time threshold), which implies that the person is not at home. Of course, we pre-identify the home antenna of all individual phone users for a given month as described in Appendix 1B. With this information of home antenna, we could identify the location of the non-home antenna and the length of time the user stayed in this location. More specifically, based on the antenna connection records of an individual phone user, the computation logic aggregates the time spent by each antenna and checks whether the antenna is the home antenna or not. Hence, when someone is connected to an antenna that is not home and stays there more than 1 hour (our threshold), it is considered a "travel".

We carefully chose the time threshold for travels by considering the trade-off between different lengths of time. A longer threshold has the risk of neglecting short visits to green space. On the other hand, a short threshold has the risk of greater noise, which is counting the people who are simply passing by. Our choice of 1 hour is based on the prior literature and an analysis of the impact of different thresholds with our data. Previous research frequently cited in the transportation literature suggests similar values for a stable detection of a change of locations with mobile phone data (e.g., Bonnel et al. suggests 1 hour, and evaluates the validity with other methods such as travel surveys and commute data.,[10] and Calabrase et al. suggests 1.5 hours or a lower value for detecting the changes [11]). We also studied the impact of the threshold specific to the antennas covering the green spaces by varying the value from 15 minutes and increasing it by 15 minutes up to 4 hours. Although the majority of travels were detected with the lowest threshold (15 minutes which has the obvious risk of counting people who are simply passing by), we found that the difference between the thresholds of 30 minutes and 1 hour was not significant. The 1-hour threshold was capturing only about 5% fewer travels compared to the 30-minute threshold, thus we chose 1 hour which is safer from possible noises.

Appendix 1D. Spatial Interpolation.

The mobile network log allows approximating the location of the user holding the device based on the coverage area of the antennas, and it has been widely used for various spatial analyses in the prior literature, including transportation pattern analysis, [12] migration analysis,[13] and urban hotspot detection.[14] Spatial interpolation is a typical method used to link the mobile network estimates to other geographical units; for instance, to estimate the real-time population of neighbourhoods, where the boundaries of the neighbourhoods and the antenna coverage areas are not aligned.[15] In addition to the mobile network data, spatial interpolation has been used for other data in the geography literature such as population,[16] agriculture,[17] rainfall,[18] and atmosphere.[19]

As mentioned above, we estimate the ratio of travels to green space for every LSOA. First, Voronoi tesselation was performed for antenna coverage estimation, which is commonly used in the literature using mobile phone–based big data[9] to model the coverage area of every antenna as a polygon. Second, for the mobility flow between every pair of antennas, the origin of the flow is interpolated to LSOAs while the destination interpolated to green spaces. We use the figure below to give an example.

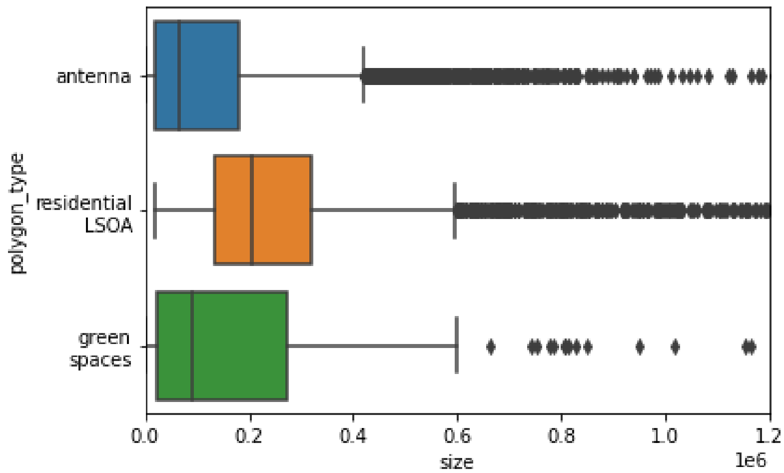


The figure depicts an LSOA and a green space, and the antenna polygons that overlap with them. Assume 100 travels were observed from antenna polygon 4 to antenna polygon 5. As mentioned, the origin is first interpolated. Considering that 70% of the area of antenna polygon 4 overlaps with LSOA L, the spatial interpolation estimates 70 travels are from LSOA L. As for the destination, since 80% of antenna polygon 5's area overlaps with green space P, we estimate 56 travels (80% of 70 travels) were made to P from LSOA L.

The same process is applied for all the flows that originate from antenna polygons 1 to 4 (which overlap with L) and end at polygons 5 to 7 (that overlap with P). As the final step, all the interpolated flows are grouped by their origin (residential LSOAs). Then, we calculate the number of travels/travellers to green spaces and the total number of travels/travellers so that we can simply compute the ratio of green space travels/travellers from each LSOA.

Appendix 1E. Potential Concerns.

We here discuss two potential concerns on our mobility data and how we try to address them. The first is that the locations are approximated based on antenna polygons instead of a phone user's exact location. We believe that the mobile network data are suitable since our focus is on aggregate-level mobility from different residential LSOAs to green spaces and the antenna polygons are much finer grained than these target areas. The figure below shows the distribution of the size of different areas in box plots. The average size of an antenna polygon is less than a half of an average LSOA, also less than a half of the average size of the green spaces. The scale of our sample (2 million users) and timespan of our study (weekly panel data over 2 years) also make it resilient to possible errors from individual events. For example, the mobility estimates were highly consistent across weeks in a given month, which indicates that the data are not driven by noises. We sampled different weeks of a month and compared the travel frequency between all pairs of antenna polygons between the sampled weeks. The travel frequencies showed very high correlation: for example, for all the week pairs among the four weeks of October 2019, the correlation was all above .97.



Next, while the interpolation method itself does not add new noise to the antenna-based measurements, it assumes that the visits of an antenna polygon are evenly spread within the polygon (e.g. the travels to an antenna polygon with a larger overlap with a green space are likely to contribute more to the green space travels than travels to other nearby antennas). Therefore, our final measure (the ratio of green space travels from each LSOA) may be under- or over-estimated depending on the skew of travels within antenna polygons and the overlaps with the target area. We try to address this potential concern with multiple approaches. For example, we use the temporal threshold for travel identification to filter out the events where users simply pass by as well as the algorithm that only detects travels to non-home antennas to avoid repetitive miscounting for people who live near green spaces.

Reference:

1. Zhang, Y. User mobility from the view of cellular data networks. I*EEE INFOCOM 2014-IEEE Conference on Computer Communications* 1348–1356 (2014).
2. Dannemann, T. *et al.* The time geography of segregation during working hours. *Royal Society open science* **5**, 180749 (2018).
3. Silm, S. & Ahas, R. The temporal variation of ethnic segregation in a city: Evidence from a mobile phone use dataset. *Soc. Sci. Res.* **47**, 30–43 (2014).
4. Smith-Clarke, C. *et al.* Poverty on the cheap: Estimating poverty maps using aggregated mobile communication networks. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* 511–520 (2014).
5. Wang, Q. *et al.* Urban mobility and neighborhood isolation in America's 50 largest cities. *Proc. Natl. Acad. Sci.* **115**, 7735–7740 (2018).
6. Jiang, Y. *et al.* Understanding demographic and socioeconomic biases of geotagged Twitter users at the county level. *Cartogr. Geogr. Inf. Sci.* **46**, 228–242 (2019).
7. Lindqvist, J. *et al.* I'm the mayor of my house: examining why people use foursquare-a social-driven location sharing application. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* 2409–2418 (2011).
8. Lathia, N. *et al.* The hidden image of the city: sensing community well-being from urban mobility. *International Conference on pervasive computing* 91–98 (Springer, 2012).
9. Park, S. *et al.* Mobinsight: A framework using semantic neighborhood features for localized interpretations of urban mobility. *ACM Trans. Interact. Intell. Syst.* **8**, 1–25 (2018).
10. Bonnel, P. *et al.* Passive mobile phone dataset to construct origin-destination matrix: potentials and limitations. *Transp. Res. Rec.* **11**, (2015): 381-398.
11. Calabrese, F. *et al.* Estimating Origin-Destination flows using opportunistically collected mobile phone location data from one million users in Boston Metropolitan Area. *IEEE Pervasive Comput.* **10**, 36–44 (2011).
12. Rojas IV, M. B. *et al.* Comprehensive review of travel behavior and mobility pattern studies that used mobile phone data. *Transp. Res. Rec.* **2563**, 71-79 (2016).

13. Hankaew, S. *et al.* Inferring and modeling migration flows using mobile phone network data. *IEEE Access* **7**, 164746-164758 (2019).
14. Louail, T. *et al.* From mobile phone data to the spatial structure of cities. *Sci. Rep.* **4**, 1-12 (2014).
15. Bergroth, C. *et al.* A 24-hour population distribution dataset based on mobile phone data from Helsinki Metropolitan Area, Finland. *Sci. Data* **9**, 1-19 (2022).
16. Jia, P. & Gaughan, A. E. *et al.* Dasymetric modeling: A hybrid approach using land cover and tax parcel data for mapping population in Alachua County, Florida. *Appl. Geogr.* **66**, 100-108 (2016).
17. Comber, A. *et al.* The creation of a national agricultural land use dataset: combining pycnophylactic interpolation with dasymetric mapping techniques. *Trans. GIS* **12**, 775-791 (2008).
18. Goovaerts, P. Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. *J. Hydrol.* **228**, 113-129 (2000).
19. Joseph, J. *et al.* Application of validation data for assessing spatial interpolation methods for 8-h ozone or other sparsely monitored constituents. *Environ. Pollut.* **178**, 411-418 (2013).

Appendix 2. Green Space Data

Our data for green spaces are based on listings provided by Historic England. The data contain 1,699 entries in England and 168 listings in London as of August 2021 and they encompass a broad range of planned open spaces including registered public parks, cemeteries, and town squares. The figure below presents the proportion of different categories of green spaces that are used for our analysis in London. We can see that the majority of listings are parks and gardens.

Green Space Type	Count
Parks and gardens	132
Town squares	17
Cemeteries	19

Even town squares and cemeteries included for our analyses have good enough vegetation coverage so that they could be regarded as green spaces. For example, according to Historic England, town squares refer to gardens of a particular arrangement (e.g., bounded by trees and includes grass plats and walking paths) and cemeteries refer to landscapes with burial grounds (and often with religious monuments and plantings) that reflect the space design patterns of different historic periods. The below figures provide some visual examples of these listings.

Left: Russel square (town square)
Source: Historic England

Right: Kensal Green Cemetery (cemetery)
Source: Kensal Green Cemetery website

On the other hand, there are small green spaces in residential neighbourhoods that we considered but did not include in our study. The main reason for this is because these are spaces may be used only for specific activities or an exclusive group of people. For example, although they have vegetation coverage, small green spaces including allotments, community gardens, and private backyards were excluded because they are not open to the public. Golf courses and tennis courts were also excluded as the spaces are used for the purpose of specific sports. Lastly, there are many (un-registered) green spaces with the vegetation coverage near the boundary of London, which are wild. We did not include these areas (mostly greenbelt areas and/or farms) because they have fewer inhabitants nearby and are far from the majority of residential neighbourhoods in London. According to the 2019 census, the population density per square meter of the LSOAs near those areas is about 200 whereas the average of the LSOAS in London is roughly 4,400.

We admit that there are pros and cons for our selection. We try to control for the level of attractiveness, accessibility, and maintenance of green spaces accessible to the public by focusing on registered green spaces instead of small, unregistered spaces that may be exclusive or specialized. The designation of registered green spaces is based on their significance and quality. And because the statutory designation encourages appropriate long-term management, these green spaces are likely to be better maintained. On the other hand, by doing so, we may have missed some small green spaces that are accessible by the public. We think the former issue is more critical than the latter. And if the distribution of such small green spaces does not significantly vary across high-density London neighbourhoods, we believe this will not be a critical issue.

Appendix 3. Propensity Score Matching Process for the UK Household Longitudinal Survey Sample

Appendix 3A: Summary statistics before matching

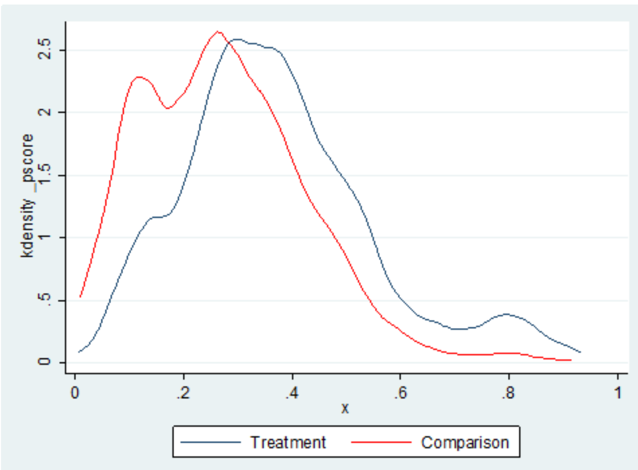
Variables	Individuals living within 800 m of the nearest green space (Treatment)		Individuals living farther from the nearest green space (Comparison)		Diff (Treatment – Comparison)		
	Mean	Std. Dev	Mean	Std. Dev	Diff	T (z)	Sig.
Total Score of General Health Questionnaire-12	12·289	5·945	12·255	5·921	0·034	0·861	
Total Score of Batty et al· (2017)	2·380	3·354	2·326	3·342	0·054	2·408	**
Wave falling in the lockdowns	0·517	0·5	0·515	0·500	0·002	0·656	
Demographic characteristics							
Age	53·894	16·814	54·295	16·316	-0·401	-3·635	***
%male	0·409	0·492	0·418	0·493	-0·009	-2·770	***
%White	0·857	0·350	0·903	0·296	-0·046	-21·777	***
%Black	0·030	0·170	0·024	0·153	0·006	5·595	***
Number of household members	1·634	1·284	1·680	1·27	-0·046	-5·433	***
Number of children	0·381	0·788	0·417	0·796	-0·036	-6·678	***
%couple	0·685	0·465	0·708	0·455	-0·023	-7·656	***
Economic characteristics							
Household monthly earning	4,025·395	14,688·38	3,150·657	11,908·63	874·738	10·208	***
Individual monthly earning	1,712·841	6,878·399	1,411·296	5,403·278	301·545	7·657	***
%having financial difficulties	0·046	0·209	0·043	0·203	0·003	2·122	**
Health status							
%feeling lonely often	0·364	0·481	0·363	0·481	0·001	0·159	
%having long-term health issues	0·402	0·490	0·413	0·492	-0·011	-3·324	***
%COVID-19 infection	0·008	0·086	0·008	0·089	0·000	-0·809	
Number of days doing moderate activities	2·600	2·603	2·551	2·590	0·049	2·823	**
%moderate/heavy drinker	0·439	0·496	0·422	0·494	0·017	5·097	***
%smoker	0·072	0·259	0·081	0·273	-0·009	-4·972	***
Number of individuals	5,724		13,296				
Number of individual*survey waves	31,843		74,186				

Notes: Appendix 2A reports summary statistics of the unmatched sample of 19,020 distinct survey respondents or 106,029 individual*waves.
*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

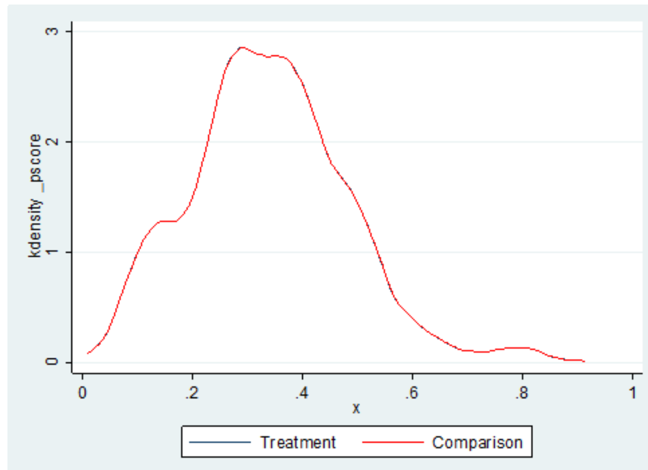
Appendix 3B: Application of Propensity Score Matching

In Appendix 3B, we would like to demonstrate that the distributions of propensity scores are very homogeneous after matching. Therefore, we have a panel of reasonably balanced treatment and comparison respondents, which allows us to claim that any observed treatment effect on mental well-being is not biased by observed differences between treatment and comparison groups in individual attributes.

Before Matching



After Matching



Notes: To estimate the propensity score based on the first wave of the survey, we use the logit model, in which the dependent variable is the nearest green space (1 for living within 800 m and 0 for otherwise) and the independent variables include age, gender, race, family composition, earnings, and health status as well as the city of their residence. These are the variables that could potentially affect mental well-being. We also apply longitudinal sampling weights for this model. Then, we use one-to-one matching with no replacement closest in the propensity score within a 0.003 caliper width to improve covariate balance and reduce bias. During the matching process, we lost some respondents in our treatment groups who were left unmatched because no one in the comparison group had a propensity score within a 0.003 caliper width of these individuals' scores.

Appendix 3C: Quality of propensity score matching (PSM) sample

		Treatment: living within 800 m of the nearest green space	Comparison: living farther from the nearest green space	Difference	%reduction	Difference in means as proportion standard deviation	Cochran's rule of thumb
Age	Unmatched	53·894	54·295	-0·401	3·567	0·056	y
	Matched	52·159	53·121	-0·962			
%male	Unmatched	0·409	0·418	-0·009	-20·73	0·014	y
	Matched	0·429	0·422	0·007			
%White	Unmatched	0·857	0·903	-0·046	0·582	0·14	y
	Matched	0·84	0·888	-0·048			
%Black	Unmatched	0·03	0·024	0·006	-1818	0·046	y
	Matched	0·028	0·021	0·007			
No. hh members	Unmatched	1·634	1·68	-0·046	-160·7	0·029	y
	Matched	1·948	1·908	0·04			
No. children	Unmatched	0·381	0·417	-0·036	-186·1	0·056	y
	Matched	0·449	0·403	0·046			
%partner	Unmatched	0·685	0·708	-0·023	89·5	0·006	y

	Matched	0·712	0·715	-0·003			
HH earning	Unmatched	4025·395	3150·657	874·738	5·401	0·04	y
	Matched	3782·9	3313·1	469·8			
Ind earning	Unmatched	1712·841	1411·296	301·545	-106·4	0·055	y
	Matched	1454	1206·9	247·1			
%fin difficulty	Unmatched	0·046	0·043	0·003	-18·36	0·053	y
	Matched	0·048	0·06	-0·012			
% lonely	Unmatched	0·364	0·363	0·001	20·1	0·005	y
	Matched	0·348	0·345	0·003			
%health issues	Unmatched	0·402	0·413	-0·011	-16·02	0·057	y
	Matched	0·49	0·518	-0·028			
%COVID-19	Unmatched	0·008	0·008	0	51·55	0·011	y
	Matched	0·001	0·002	-0·001			
No. activity	Unmatched	2·6	2·551	0·049	99·05	0	y
	Matched	2·517	2·517	0			
%drinker	Unmatched	0·439	0·422	0·017	-8·797	0·039	y
	Matched	0·473	0·492	-0·019			
%smoker	Unmatched	0·072	0·081	-0·009	-19·2	0·008	y
	Matched	0·076	0·078	-0·002			

Notes: Appendix 2C compares the statistics of the unmatched sample of 106,029 individual*waves and the matched sample of 31,259 individual*waves (15,529 treatment and 15,730 comparison groups) or 4,992 distinct individuals. The column "*% reduction*" shows the percentage reduction in the mean difference between treatment and comparison groups. "*Cochran's rule of thumb*" reports whether the mean difference of a variable with the matched sample is less than a quarter of a standard deviation of the respective variable ("y" indicates that the mean difference is smaller than this threshold, suggesting that good balance is achieved after matching).

Appendix 3D. UK Household Longitudinal Survey User Guide

For the study user guide, please see the following link:
https://doc.ukdataservice.ac.uk/doc/8644/mrdoc/pdf/8644_ukhls_covid19_user_guide_v10.0.pdf

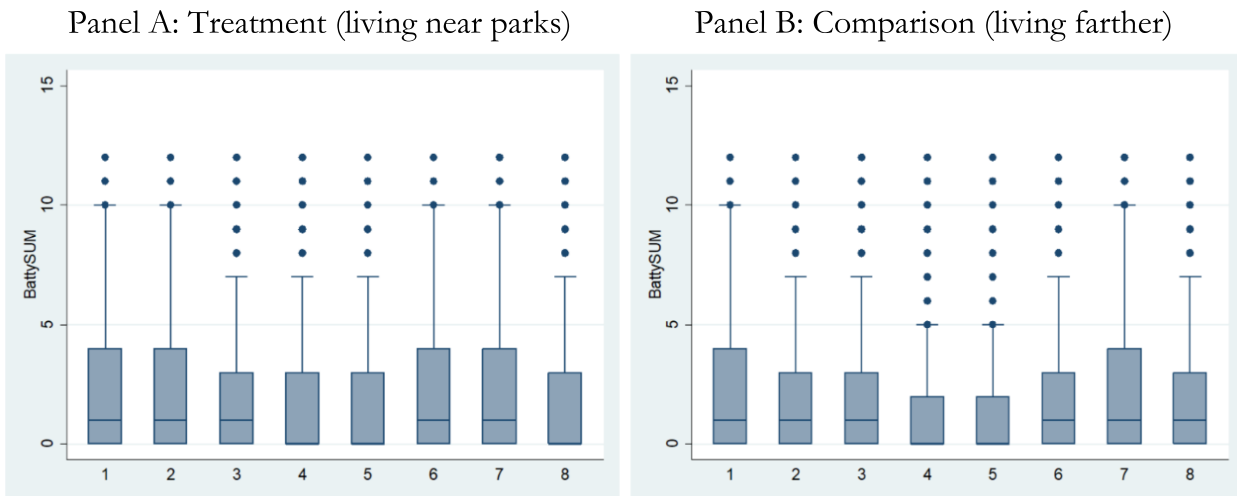
For more study details, please see the following link:
https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=8644#!/details

Appendix 4. Robustness Test for Table 2 with the Travel Frequency Measure (rather than number of travellers)

	(1)			(2)			(3)			(4)		
Dependent Variable	Proportion of Green Space Travels			Proportion of Green Space Travels			Proportion of Green Space Travels (post-COVID-19 periods)			Proportion of Green Space Travels (post-COVID-19 periods)		
	Coef.	S.E.	P	Coef.	S.E.	P	Coef.	S.E.	P	Coef.	S.E.	P
LSOAs located within 800 m of the nearest green space	0·023	0·004	0·000	0·020	0·003	0·000	0·023	0·004	0.000	0·023	0·004	0·000
After COVID-19 outbreak				-0·003	0·001	0·000						
Lockdown										-0·001	0·000	0·013
LSOAs within 800 m of the nearest green space & After COVID-19				0·005	0·001	0·000						
LSOAs within 800 m of the nearest green space & lockdown										0·002	0·001	0·011
Observations	463,261			463,261			212,411			212,411		
R-squared	0·143			0·143			0·150			0·150		
Demographic characteristics	Yes			Yes			Yes			Yes		
Socioeconomic characteristics	Yes			Yes			Yes			Yes		
Local authority fixed effects	Yes			Yes			Yes			Yes		
Month fixed effects	Yes			Yes			Yes			Yes		

Note: Standard errors are clustered at the LSOA level.

Appendix 5. Boxplot of Mental Distress Level by Different Waves for Treatment vs. Comparison Groups



Notes: Note than Wave 1, 2, 6, 7, 8 fall into the lockdown periods in the UK.