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Green space accessibility helps buffer declined mental health during the COVID-19 pandemic: evidence from big data in the United Kingdom

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Given accumulating evidence that highlights the negative effect of the COVID-19 pandemic on public mental health, we examine green space accessibility as a potential mitigator. Based on mobility data from 2 million mobile phone users within London between January 2019 and December 2020, we found that, after the COVID-19 outbreak and during lockdowns, residential neighbourhoods within 800 m of the nearest green space had a higher proportion of green-space travellers (0.9–1.4 percentage points) compared with other neighbourhoods. Next, using multiwave data with a matched sample of 4,998 individuals across towns and cities in the United Kingdom, we demonstrate that individuals who lived close to green spaces experienced much less mental distress than those who lived farther away during lockdown periods. We imply that enhancing green space accessibility for residential neighbourhoods can help citizens become more resilient to future pandemics with mobility restrictions.

Since the first known cases in late December 2019, the COVID-19 pandemic has posed unprecedented challenges for everyone worldwide. Owing 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 effective in alleviating the burden on intensive care units and reducing the number of new COVID-19 infections[1,2], recent research has identified many consequent negative outcomes. For example, COVID-19 lockdowns resulted in 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 (ref. [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 states, 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 a review of 24 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 (for example, reducing boredom with improved communication) and encouraging people to participate in voluntary precaution and mobility restriction[15]. Although the

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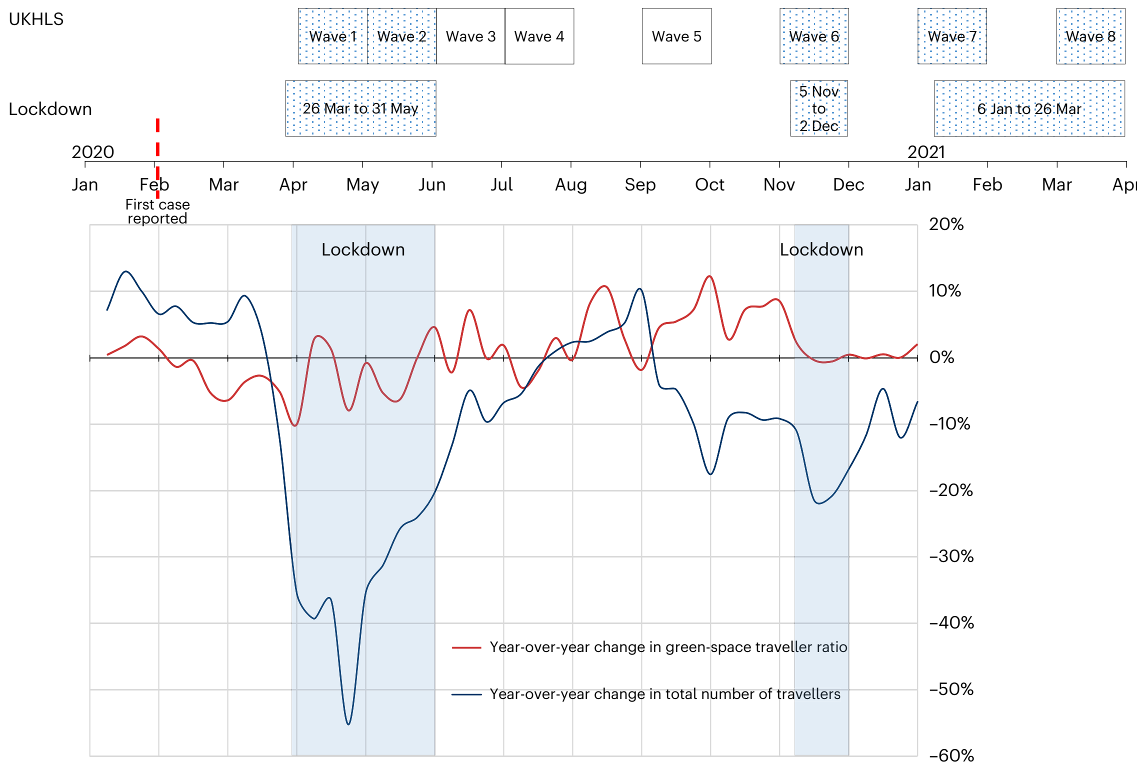

Fig. 1 | Differences in travellers per week in 2020 compared with the corresponding week in 2019 in London alongside the timeline of COVID-19 lockdowns and UKHLS waves. For the UKHLS, each wave of the survey was conducted for 1 month and some waves overlapped with lockdown periods (dotted boxes). With the mobility data available for the period of January 2019 to December 2020, we calculated the change in the number of travellers in each week of 2020 relative to the same week of 2019 (year-over-year change). We did the same calculation for the ratio of travellers to green spaces out of total travellers.

investigation of these quarantine orders is important, lockdown policies (that is, 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. Exposure to green spaces have been widely recognized to promote mental health and wellbeing for a variety of populations in different circumstances[16–19]. Previous research suggests 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 was restricted on a compulsory or voluntary basis[24–26]. Research has also shown that people changed the amount of 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 the COVID-19 lockdowns. We aim to adopt a more precise way of documenting the ecological-level mobility information of residents during COVID-19 lockdowns. Doing so can enable us to accurately observe mobile activities in a much smaller area compared with other methods (for example, Google Mobility Reports)[28].

Research has shown that living closer to green spaces supports mental and general health and also helps prevent 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 by the supply of green spaces (for example, 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 access to green spaces? A 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 over the past three years has responded and started to pay attention to the relationship between green space accessibility and mental health since the outbreak of COVID-19. From 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 general mobility patterns during the COVID-19 pandemic[36].

There is, however, little empirical testing that combines rigorous mobility data with panel data of a relatively large, representative sample using a validated mental health scale. By adopting mobility data from 2 million mobile phone users and the multiwave 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 accessibility to green spaces as a crucial feature for both green-space travel and mental wellbeing, which has important implications for not only mental health services but also urban planning and policymaking. We choose to examine this question in London, United Kingdom (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 multiwave surveys during and after lockdown periods.

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	s.d.	Mean	s.d.
Total number of travellers during non-work hours	1,316.92	1,559.24	1,234.88	1,431.24
Total number of green-space travellers during non-work hours	78.33	287.04	36.27	102.09
Proportion of green-space travellers during non-work hours	5.96%	10.95%	2.90%	2.90%
Proportion of green-space travellers before COVID-19	5.67%	5.67%	3.01%	4.84%
Proportion of green-space travellers after COVID-19	6.31%	12.85%	2.77%	5.70%
Proportion of green-space travellers during non-lockdown periods after COVID-19	6.26%	12.07%	2.84%	2.84%
Proportion of green-space 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
Male	45.62%	49.81%	43.15%	49.53%
Under 18 years old	21.50%	5.24%	23.69%	4.78%
18–39 years old	35.22%	10.19%	32.35%	8.77%
40–59 years old	26.28%	3.82%	26.46%	3.12%
60–89 years old	16.33%	5.99%	16.82%	6.10%
Over 89 years old	0.68%	0.60%	0.67%	0.58%
White	73.44%	15.31%	68.50%	17.94%
Asian	15.80%	13.57%	20.72%	16.94%
Black	6.44%	5.36%	7.43%	5.99%
Other races	4.30%	2.39%	3.33%	2.11%
Socioeconomic characteristics (English Indices of Deprivation 2019)				
Index of Multiple Deprivation 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 score	0.17	0.10	0.18	0.09
Income Deprivation Affecting Older People Index 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	

Non-work hours include 16:00–24:00 on working days and 08:00–24:00 on weekends and bank holidays. The English Indices of Deprivation 2019 comprises seven different domains that are combined and weighed to generate the LSOA's Index of Multiple Deprivation score out of 100. A higher score means more deprivation. Income Deprivation Affecting Children Index and Income Deprivation Affecting Older People Index are supplementary indices for income. For more detailed descriptions of the data, refer to online guidance[61].

Results

We used a sample of mobile location records from 4,835 residential lower layer super output areas (LSOAs, defined as neighbourhoods in this paper), which are the smallest geographic units available for major UK administrative data and contain about 1,500 residents on average. Figure 1 shows that the total number of travellers within London significantly decreased after the COVID-19 outbreak by 25% compared with the pre-COVID-19 period. The most significant drop of 55% was seen when the first lockdown was imposed. Interestingly, even during lockdowns, more people tended to travel to green spaces than to other spaces while general mobility showed a significant downward trend. Starting from April 2020, the probability that an individual would travel to green space relative to other places increased compared with the same week in 2019. 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 with the average amount in 2019. Extended Data Fig. 1 shows that LSOAs in red (those with increasing probability of travel to green spaces during lockdowns compared with 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 proportion of travellers to green spaces than other LSOAs.

Table 1 provides summary statistics for the subsamples of LSOAs whose edges were within 800 m of a green space edge (treated LSOAs) and those further away from green spaces (comparison LSOAs). The probability that people residing in treated LSOAs travel to green spaces relative to non-green spaces within London was double compared with residents in other LSOAs. This difference in travel behaviours by

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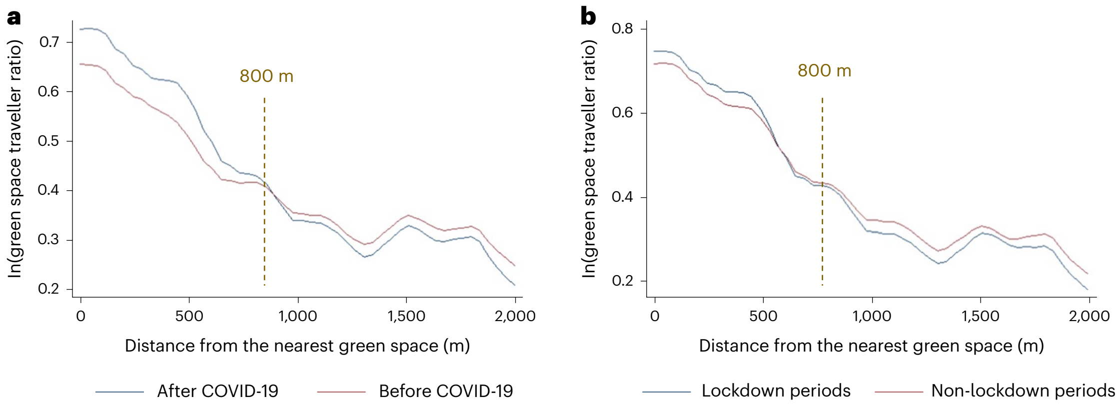

Fig. 2 | Green-space distance gradient for the ratio of green-space travellers during non-work hours in London. a, Green-space traveller ratio before and after COVID-19 outbreak. **b**, Green-space traveller ratio during non-lockdown and lockdown periods

proximity to green spaces was most significant when people were stuck at home. After the COVID-19 outbreak, more residents in the treated LSOAs travelled to green spaces while fewer in the comparison LSOAs did so. During the lockdowns, more people living closer to green spaces travelled to green spaces while fewer living farther did so, compared with non-lockdown periods. Figure 2 shows consistent results, with the green space distance gradient for the proportion of green-space travellers. While demographic characteristics were quite similar for the treated and comparison LSOAs, residents in treated neighbourhoods were more likely to be white. While the treated LSOAs were less deprived in general than comparison neighbourhoods, they were slightly worse in terms of health desirability, crime and living environment, potentially because planned green spaces are more likely to be located in higher density areas.

Our empirical model results report the effect of being located closer to green spaces on the probability of travelling to green spaces. Cross-sectional estimates show pre-existing conditions that the proportion of green-space travellers within London is about 1.4 percentage points higher in neighbourhoods within 800 m of the nearest green space than in neighbourhoods located farther (Table 2). 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. Table 2 also shows the estimation results of the difference-in-difference (DID) specification that adds the temporal variations (before versus after the COVID-19 outbreak and lockdown versus non-lockdown). 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 and during lockdowns. However, the probability of travelling to green spaces from LSOAs that were closer to green spaces was approximately 0.9 percentage points higher compared with other London neighbourhoods with similar characteristics but located farther from green spaces. During the lockdowns, these neighbourhoods experienced an additional increase of 0.5 percentage points in the proportion of green-space travellers. Given that the average proportion of green-space travellers in London was 4.2%, the total increase of 1.4 percentage points during lockdown periods is significant. Additionally, the increase is 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). Our results suggest that green space accessibility plays an even more important role in travel to green spaces when people face strict restrictions on movement. Note that for our robustness test, we use the ratio of green-space travel out of total travel counts and the results are consistent (Extended Data Table 1).

After establishing the evidence on the significant role of proximity to green spaces in the higher probability of travelling to green spaces after the COVID-19 outbreak and during lockdowns, we next analysed the mental distress of residents. From a sample of 4,998 individuals matched from the original sample of 19,020 survey respondents from the UK Household Longitudinal Study (UKHLS), Table 3 shows that people reported higher mental distress during the lockdowns compared with post-COVID-19 non-lockdown periods. In particular, respondents living farther than 800 m 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 lockdowns compared with post-COVID-19 non-lockdown periods. 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 homogeneous characteristics after matching (Table 3), this difference in the change in mental distress 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 4 shows that the mental distress score is not statistically different for individuals residing within 800 m of the nearest green space (treatment group) and their matched counterparts who have similar attributes but reside farther from green spaces (comparison group). These results with only the spatial variation suggest a null effect of the accessibility to green spaces on mental health in pre-existing conditions. When we use the DID specification, adding the temporal variation between lockdowns and non-lockdowns, the difference in the average mental health scores between the treatment and comparison groups remains statistically insignificant at the 10% level. Then, results report that the mental distress score is 0.605 higher during lockdowns compared with non-lockdown periods, 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. Finally, we performed a robustness test with the matched subsample of London residents. The results demonstrate that the increase in the mental distress score during lockdowns is even higher for London residents (0.734 for London versus 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 versus −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 mitigate 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 fell in a lockdown period, the

Table 2 | Empirical estimation of the impact of proximity to green spaces on the proportion of green-space travellers

	Cross-sectional			DID			Cross-sectional (post-COVID-19)			DID (post-COVID-19)		
	Coef.	s.e.m.	P	Coef.	s.e.m.	P	Coef.	s.e.m.	P	Coef.	s.e.m.	P
LSOAs located within 800 m 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 m of the nearest green space and after COVID-19				0.009	0.001	0.000						
LSOAs within 800 m of the nearest green space and lockdown										0.005	0.001	0.000
Observations	463,261			463,261			212,411			212,411		
R^2	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		

Standard errors (s.e.m.) are clustered at the LSOA level. The analysis uses two-sided statistical tests.

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 (Extended Data Fig. 2).

Discussion

This study first examined how London's population mobility to green spaces changed after COVID-19 outbreak 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 with 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[37]. 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 that use specific transport tools or mobile applications[38]. 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 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 an individual's probability to travel to green spaces rather than other places has increased compared with the same period in 2019, and the tendency to increase travel to green spaces continued during lockdowns even when general mobility decreased.

While the COVID-19 outbreak has substantially affected population mobility patterns within London owing 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 travel activities[39,40]. 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. Additionally, 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 (that is, summertime) than the second (that is, wintertime). In addition, people likely adjusted their travel behaviours from the continuing pandemic by the time they reached the second order. In terms of travel 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 travelling 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 proximity between residence and green spaces can affect individuals' mobility during 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[41], that neighbourhood greenery can help to facilitate social support[42], and that publicly accessible neighbourhood nature can be associated with residents' increased sense of community belonging, which in turn improves mental health outcomes[43]. Additionally, a previous review in environmental research has also pointed out the benefits of accessing green space on improving wellbeing, 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 locations, as well as their socio-demographic profiles and lockdown policies, to predict residents' outdoor recreation behaviour[44]. In fact, the unequal access to green spaces presents a troubling picture to policymakers, as individuals who live more than 800 m away from green spaces tended to travel less to green spaces

Table 3 | Descriptive statistics of matched 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	s.d.	Mean	s.d.
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 versus female)	42.80%	49.48%	42.07%	49.37%
White	86.88%	33.76%	90.92%	28.73%
Black	2.50%	15.63%	1.82%	13.38%
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	71.43%	45.17%	71.50%	45.14%
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	3.81%	19.15%	4.58%	20.90%
Health status				
Having long-term health issues	39.95%	48.98%	41.35%	49.25%
COVID-19 infection	0.67%	8.16%	0.76%	8.67%
Number of days doing moderate activities	2.69	2.60	2.61	2.57
Moderate/heavy drinker	46.42%	49.87%	46.54%	49.88%
Smoker	6.70%	25.01%	7.23%	25.90%
Number of individuals	2,496		2,496	
Number of individuals × survey waves	15,529		15,730	

Treatment and comparison groups for this matched sample are derived by the PSM procedures. The purpose of PSM is to ensure individuals in treatment and comparison groups to be highly homogeneous with respect to their demographic, economic, and health attributes.

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 regard to impaired psychological wellbeing.

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 wellbeing was affected during the pandemic with detailed time series data. Unlike previous inquiries with similar data[6,45], we associated the survey data with the individual's residence information and further investigated whether living close to green spaces helped individuals battle the negative influence of lockdown on their psychological wellbeing. Similar to a previous study[6], we found that individuals were significantly distressed during the lockdowns (versus non-lockdown periods) after accounting for all relevant factors. In particular, we observed a 0.605 increase in the psychological distress score.

Supporting our main hypothesis, we found that, during lockdowns, individuals who lived close to green spaces (that is, within 800 m) saw a much smaller increase in the distress score than those who lived farther away after controlling for all other potential determinants of mental health known in the literature. We also found that mental distress states, as represented by the General Health Questionnaire 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 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 backgrounds; and living conditions (for example, living alone)[46–49]—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[49], 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 during 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 travel outside of the home was 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 than an entire city lockdown, they provided no opportunity to observe public mobility, especially to green spaces[45]. To our knowledge, this is one of the first studies to combine public mobility data with a 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 (for example, someone with quarantine orders), we have reason to believe that providing a place with a view of green spaces[50], incorporating vertical greenery (that is, the integration of vegetation onto the vertical structures of buildings)[51], or even a plasma display of nature[52], could be beneficial for the mental wellbeing of such individuals.

Overall, our findings echo recent research on how local green spaces can help to promote citizen mobilities during COVID-19 (ref. [53]), and demonstrate a higher level of aggravating psychological distress for those who cannot access green space easily (that is, 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[54,55]. 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 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 (that is, mobility analysis in London and mental distress analysis in the UK). Ideally,

Table 4 | Empirical estimation of impact of living closer to green spaces on psychological distress

	Cross-sectional			DID (all UK respondents)			DID (London respondents)		
	Coef.	s.e.m.	*P*	Coef.	s.e.m.	*P*	Coef.	s.e.m.	*P*
Living within 800 m 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 m of the nearest green space and lockdown				−0.106	0.050	0.035	−0.378	0.163	0.021
Observations	31,259			31,259			3,314		
R^2	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		

Standard errors (s.e.m.) are clustered at the LSOA level. The analysis uses two-sided statistical tests. The specification includes the wave fixed effects to make adjustment for multiple companions across different survey waves.

we would have wanted to obtain the travel information of individual survey respondents so that we could directly associate their travel patterns to green spaces with their mental wellbeing. Next, although we believe that we have done our best to identify individual mobility and associate that with green space location, there could still 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 to the built environment such as walkability, bike-ability, and the level of noise, which could be important for the mental health of residents, especially when they stay longer in their residences after COVID-19 and during the lockdown. Future research would benefit from further investigating clearer underlying mechanisms through which green spaces mitigate the negative impacts of COVID-19 on mental health. Also, as lockdown measures vary significantly by country and by region, more comparative analyses would be useful to generalize empirical results.

Methods

Ethical regulations

The study was conducted in compliance with the EU General Data Protection Regulation and the internal privacy policies of Telefónica. Ethics approval for the COVID-19 web and telephone surveys (ETH1920-1271) in UKHLS, a major data source for this study, was granted by the University of Essex Ethics Committee, which also approved out use of this data.

Data sources

Our data come from several sources (Extended Data Fig. 3). The first is a dataset on the weekly bilateral flow information of 2 million mobile phone users from their residence (origin) to destinations within London over the period January 2019 to December 2020. We were granted access to anonymized mobility data from Telefónica that contain aggregated counts of travel between antenna points and do not include any personally identifiable information. The data consist of travel counts and travel frequency between antenna points within London as well as the time spent in the destination; stays were longer than 1 hour to exclude temporary movements by car and/or public transport. Existing research using mobile phone data suggests 1–1.5 hours as the threshold for stable detection of location changes[56,57]. Additionally, as the difference in the travel counts between 30 min and 1 h was not significant in our data, we believe that the 1-hour threshold is a reasonable choice and safer from possible noise. In our analysis, we define 'travel' as an event where a mobile phone user connects to a non-home antenna for over 1 hour, using pre-identified information about the home antenna. This means that we do not account for the antennas connected on the way to the 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 LSOAs and green/non-green space destinations. A more detailed explanation of the mobility data processing is presented in Supplementary Discussion 1.

Second, we marked 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 (ref. [58]). 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 (for example, community gardens and golf courses). More detailed explanations for our choice of green spaces are provided in Supplementary Discussion 2. By identifying whether the destination locations belong to these green spaces based on the interpolated mobility flows, we obtained 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 travel to green spaces is a recreational activity that does not occur frequently during work hours. We demonstrate that results using the ratio of green-space travel out of total travel counts are consistent with those using this main measure. To account for demographic and socioeconomic characteristics at the LSOA level, we use the LSOA-level data on population characteristics for 2019 and 2020 provided by the Office for National Statistics[59], as well as 2020 data on ethnic composition from the Consumer Data Research Centre, which was obtained with special permission[60]. 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[61]. The data include diverse neighbourhood indicators on income, employment, education, health, crime, barriers to housing affordability and local services, living environment, and income deprivation affecting children and older people.

Our final dataset was generated from the UKHLS in 2020 and 2021, provided by the University of Essex, to assess individuals' psychological distress levels[62,63]. The data contain various information on respondents such as age, gender, race, family composition, income

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and physical health conditions across eight different waves of COVID-19. After cleaning up the data with no or missing responses, we have unique responses of 19,020 residents 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 approximate 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[62].

Identification strategies

Figure 1 shows how lockdown periods overlap with our datasets of mobile-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'[64]. During these lockdowns, non-essential street businesses (for example, 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 mobility analysis 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 (versus before) and during the lockdown (versus non-lockdown). We utilize straight-line distances between the edges of green spaces and residence LSOAs using a Geographic Information System. 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 m radius suggests that people residing within 800 m of green spaces show different changes in travel patterns to green spaces compared to those who live farther away. The 800 m cut-off coincides with a walkable distance in the existing literature[65]. 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 m 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 a distance limit of 800 m for each survey respondent. Our potential treatment group comprises all UKHLS respondents residing in LSOAs within 800 m 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 m of the nearest green space by using a propensity score matching (PSM) procedure. 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 Supplementary Discussion 3 for the detailed matching process and the quality of the matched sample).

Finally, we pay attention to UKHLS data where psychological distress was measured using 12 questions from the General Health Questionnaire, 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 given 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])[66].

Empirical models

We adopted a DID approach using variations in the distance from green spaces and in pre/post periods of the COVID-19 outbreak or lockdown event. We employed the DID model as follows:

$$V_{jt} = \beta D^{800}_{jt} + \theta D^{800}_{jt} \times \mathrm{Post}_{jt} + \delta \mathrm{Post}_{jt} + X'_j \gamma + \varphi_m + \alpha_l + \varepsilon_{jt}. \quad (1)$$

where V_{jt} is the proportion of travellers to green spaces out of all travellers in LSAO j in week t, D^{800}_{jt} is a binary indicator of whether there is a green space within an 800 m 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 m of the nearest green space changes after COVID-19 or during lockdown periods compared wth the pre-pandemic or non-lockdown periods. X is a control vector of LSOA-specific characteristics such as population size, gender (men versus women), racial group (White, Asian, Black, others), age group (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 monthly 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. Results of this model are presented in Table 2.

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

$$M_{iw} = \beta D^{800}_{iw} + \theta D^{800}_{iw} \times \mathrm{LD}_{iw} + \delta \mathrm{LD}_{iw} + X'_i \gamma + \varphi_w + \alpha_c + \varepsilon_{iw}. \quad (2)$$

where M_{iw} is the mental distress score of individual respondent i from the matched sample in wave w, D^{800}_{iw} is a binary indicator of whether there is a green space within an 800 m 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 m of the nearest green space during lockdown periods. X is a control vector of demographic and economic variables such as age, gender (men versus women), racial group (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. Results of this model are presented in Table 4.

Statistics and reproducibility

No statistical method was used to predetermine the sample size for the mobility data; the sample size was based on the availability of network access logs from Telefónica. Similarly, the original sample size for the individual survey data was based on UKHLS that represents the UK population (for more details of the UKHLS sampling strategy, refer to User Guide[62]). As mentioned above, we use the PSM procedures to derive treatment and comparison groups from this original sample so that these groups share similar attributes. Data preparation was carried out using Python, R package (version 4.1.0) and ArcGIS Online. Regressions were performed with the STATA statistical package (version 14.0). Heat map representation was performed in ArcGIS Online.

Consent
We do not use any personally identifiable data, so informed consent is not needed.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
The mobility dataset is proprietary to Telefónica and the dataset is subject to strict privacy regulations. The mobility dataset was anonymized and aggregated before being shared with the authors. The dataset could be available on request after a non-disclosure agreement is signed and discussed. Contact details for accessing the data are on https://www.telefonica.com/en/sustainability-innovation/innovation/telefonica-research/. The UKHLS is a study by Understanding Society, an initiative funded by the Economic and Social Research Council and various UK government departments. To access the UKHLS data[63] with residential LSOA information of survey respondents, one needs to receive permission from the data owner, the University of Essex, through the special licence application process with the UK Data Service. The 2020 data on ethnic composition was obtained with special permission from the Consumer Data Research Centre. Other datasets, including the location of green spaces and LSOA-level neighbourhood attributes, are publicly accessible[58,59,61].

Code availability
The custom code that supports the findings of this study is available from the corresponding author upon request.

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Author contributions
K.O.L., K.M.M. and S.P. co-designed the study. K.O.L. and S.P. collected the necessary datasets while S.P. was responsible for processing the mobility and UKHLS data. K.O.L. undertook data analyses and interpretation of the results. K.O.L. and K.M.M. wrote the report, and all authors critically reviewed the manuscript.

Competing interests
The authors declare no competing interests.

Additional information
Extended data is available for this paper at https://doi.org/10.1038/s44220-023-00018-y.

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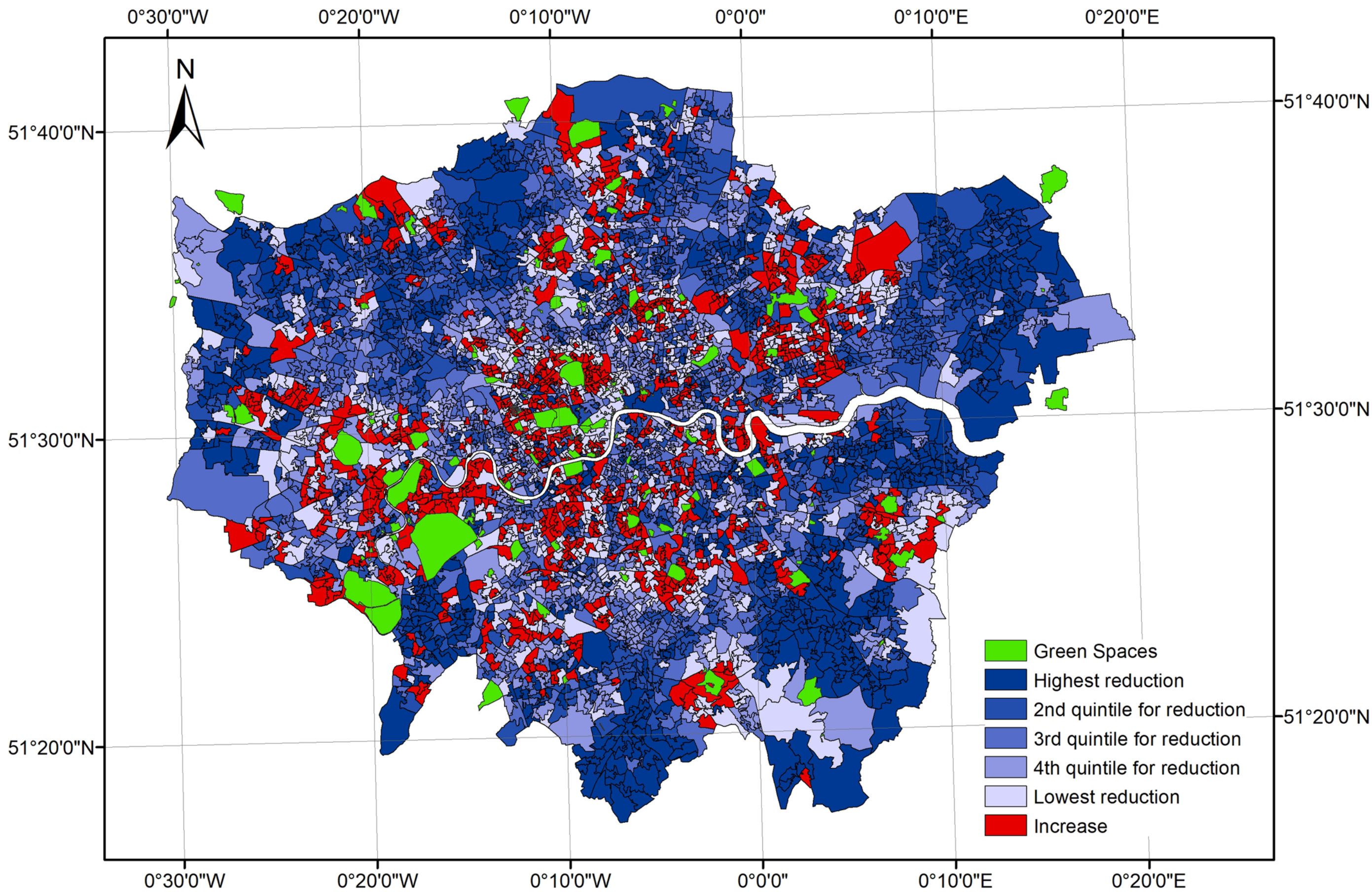

Extended Data Fig. 1 | Changes in share of number of travellers to green spaces during lockdowns compared to share of green-space travellers during pre-COVID-19 periods. The blue colours represent LSOAs that experienced the reduction in the share of the number of travellers to green spaces out of total travellers during the lockdowns when compared to pre-COVID-19 periods. Darker blue areas experienced a higher reduction. On the other hand, the red colour represents LSOAs that experienced the increase in the share of green-space travellers during the lockdowns when compared to pre-COVID-19 periods. Each of the six categories with different colours have approximately the same number of LSOAs.

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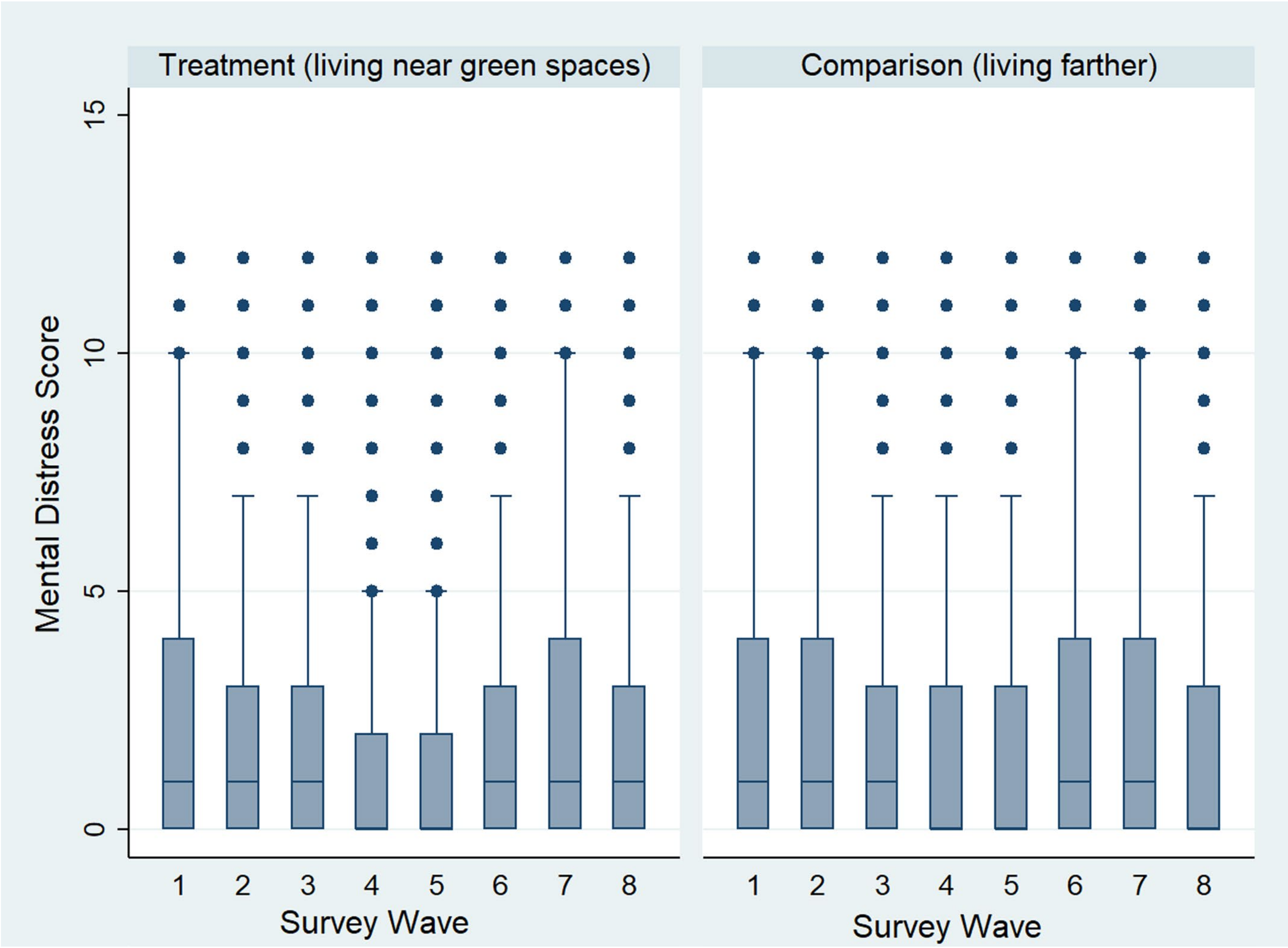
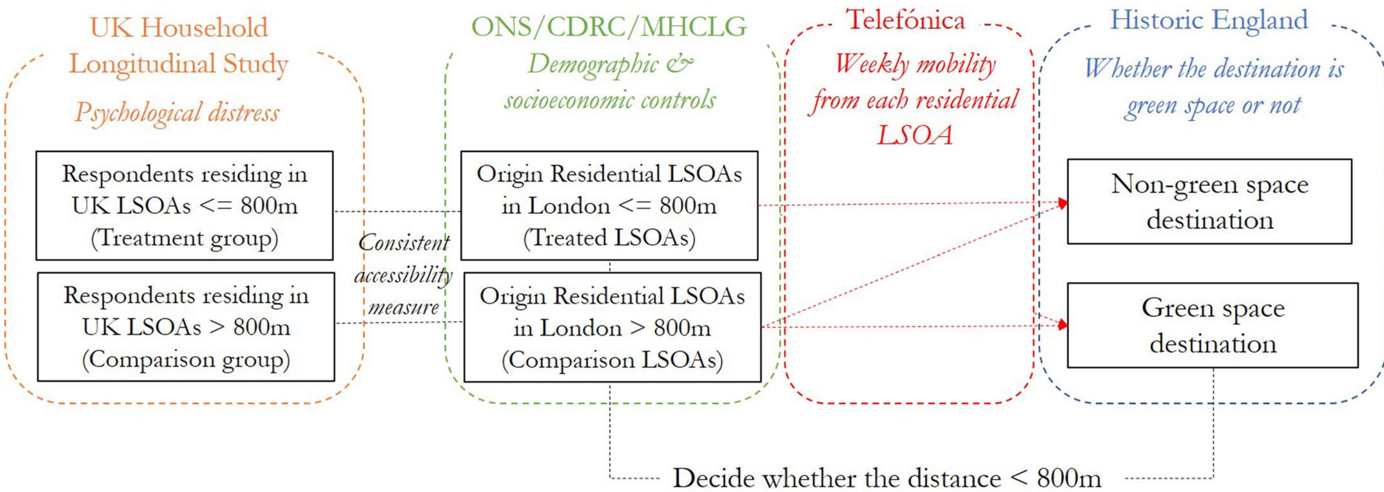


Extended Data Fig. 2 | Boxplot of mental distress score by different waves for treatment versus comparison groups. Note that Waves 1, 2, 6, 7, and 8 fall into the lockdown periods in the UK. Here, we did not derive results from technical replicates because each wave belongs to the different time periods (lockdown versus non-lockdown) and this temporal variation is a key for our analysis. N (Treatment) = 2,496 individuals observed over 8 independent waves; N (Comparison) = 2,496 individuals observed over 8 independent waves. Boxplot minimum is the smallest value within 1.5 times interquartile range below 25th percentile, maximum is the largest value within 1.5 times interquartile range above 75th percentile. Centre is the 50th percentile (median), box bounds 25th and 75th percentile.

https://doi.org/10.1038/s44220-023-00018-y



Extended Data Fig. 3 | Summary of data and sources. This summarizes the data sources, key indicators, and their links. ONS: Office for National Statistics; CDRC: Consumer Data Research Centre; MHCLG: Ministry of Housing, Communities and Local Government.

Extended Data Table 1 | Robustness test for Table 2 with the travel frequency measure (rather than number of travellers). Standard errors (s.e.m.) are clustered atthe LSOA level. The analysis uses twosidedstatistical tests.

	(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		

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Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. F, t, r) with confidence intervals, effect sizes, degrees of freedom and P value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection
Data analysis	STATA statistical package (version 14.0), ArcGIS Online, Python, R (4.1.0)

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

First, the mobility dataset is proprietary to Telefónica and the dataset is subject to strict privacy regulations. The mobility dataset was anonymised and aggregated before being shared with the authors. The dataset could be available on request after a Non-Disclosure Agreement is signed and discussed. Contact details for accessing the data are on https://www.telefonica.com/en/sustainability-innovation/innovation/telefonica-research/. Next, to access the UKHLS data63 with residential LSOA information of survey respondents, one needs to receive permission from the data owner, the University of Essex, through the special license application process with the UK Data Service. Also, the 2020 data on ethnic composition was obtained with special permission from the Consumer Data Research Centre. Other datasets including the location of green spaces and LSOA-level neighbourhood attributes are publicly accessible.

Human research participants

Policy information about studies involving human research participants and Sex and Gender in Research.

Reporting on sex and gender	N/A
Population characteristics	N/A
Recruitment	N/A
Ethics oversight	N/A

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Our study examines the association between green space accessibility and mental health outcomes during the COVID-19 pandemic.
Research sample	We used several existing datasets to conduct our research. First, we used the UK Household Longitudinal Study that represents the population of the UK (https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=8644). We received permission to use this data with residential LSOA information of survey respondents through the special license (Project No. 212669). Next, the mobility dataset is proprietary to Telefónica and the dataset is subject to strict privacy regulations. The mobility dataset was anonymised and aggregated before being shared with the authors. The dataset could be available on request after an NDA is signed and discussed. Finally, other data that we used are all aggregate data. We use the LSOA-level data on population characteristics for the years of 2019 and 2020 provided by the Office for National Statistics (source: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates), as well as the 2020 data on ethnic composition from the Consumer Data Research Centre (https://data.cdrc.ac.uk/dataset/cdrc-modelled-ethnicity-proportions-la-geography), which was obtained with special permission. 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 (source: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019).
Sampling strategy	For the UK Household Longitudinal Study, we copy the sample description from User Guide: "These samples are probability samples of postal addresses. In England, Wales and Scotland they are clustered and stratified, in Northern Ireland unclustered systematic random samples. Northern Ireland and areas in Great Britain with high immigrant and ethnic minority populations were oversampled." For more details please refer to User Guide available at https://doc.ukdataservice.ac.uk/doc/8644/mrdoc/pdf/8644_ukhls_covid19_user_guide_v10.0.pdf. For the mobility data, the sample size was based on the availability of network access logs from Telefónica.
Data collection	For the UK Household Longitudinal Study, according to User Guide, the survey was conducted either by phone or the web. The survey data was collected irrelevantly from our study hypotheses. This is same for the mobility dataset provided by Telefónica.
Timing	The survey was conducted from Apr. 2020 to Sep. 2021.
Data exclusions	No data from the original survey sample were excluded.
Non-participation	No participant dropped out.
Randomization	Randomization is not relevant to our study as we did not perform any experiment.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging