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# Weather, mental health, and mobility during the first wave of the COVID-19 pandemic

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**Abstract**

During the first United Kingdom wave of the COVID-19 outbreak, the first lockdown was announced on March 23, 2020, with a final easing of the restrictions on July 4, 2020. Among the most important public health costs of lockdown restrictions are the potential adverse effects on mental health and physical activity. Using data from the UK Household Longitudinal Study and Google COVID-19 Mobility Reports we find evidence of reduced park mobility during the initial period of the first UK lockdown and confirm existing evidence of worsening mental health. Linkage with weather data shows that contrary to popular belief, daily or weekly weather conditions do not exacerbate the mental health consequences of the pandemic, as we found no systematic associations during the first lockdown period; on the other hand, we find systematic links between park mobility and weather over the same period.

**KEYWORDS**
COVID-19, mental health, mobility, weather conditions

**JEL CLASSIFICATION**
I10, I12, C23

## 1 | INTRODUCTION

COVID-19 originated in the city of Wuhan, China, in December 2019 and spread rapidly to become a global pandemic. The closure of pubs, restaurants, gyms, and other social venues was announced on March 20, 2020, followed by the first national lockdown on March 23. It was not until May 13 that the lockdown began to be relaxed, with two subsequent lockdown easing on June 1 and 15; the final widespread easing occurred on July 4.[1]

The imposition of a national lockdown during the first wave of the COVID-19 outbreak was announced following the alarming projected spread of the disease and additional pressure on the healthcare system. The government announced that they shifted focus from "mitigation," aiming to reduce the health impact of the epidemic but not to stop transmission completely, to "suppression," where lockdown is imposed with the aim of reducing disease spread (Ferguson et al., 2020; Iacobucci, 2020). These lockdown restrictions, and the resulting impact on social life and the economy, are however linked to at least two major negative public health consequences: reduction in physical exercise (both indoors, due to the closure of gyms, and outdoors, due to mobility restrictions) and deterioration of mental health.

A growing body of international studies show that lockdown policies have a negative impact on mobility and outdoor recreational activity (e.g., Askitas et al., 2021); the adverse impact of COVID-19 and lockdown restrictions on mental health has also recently been documented (e.g., Banks & Xu, 2020; Davillas & Jones, 2021). Given pre-COVID studies on the link between weather conditions and well-being outcomes (e.g., Frijters et al., 2020), it is of particular interest to assess if adverse weather conditions during the first lockdown in the United Kingdom exacerbated the consequences of the COVID-19 outbreak and lockdown on mental health and outdoor recreational activity. This evidence is also of interest because lockdown restrictions have been designed to permit (limited) outdoor activity to alleviate concerns about mental health. Finally, such evidence allows us to better understand if the well-being costs of additional lockdowns will be heightened during winter and spring 2021.

In this study we use data from the UK Household Longitudinal Study (UKHLS) on mental health, collected before and during the first wave of the COVID-19 outbreak. Separately, Google COVID-19 Mobility Reports are employed to explore outdoor recreational activity before and during different stages of the first national lockdown. Linkage with date- and location-specific weather conditions shows that, daily or weekly weather conditions do not exacerbate the mental health consequences of the pandemic during the first wave of the COVID-19 pandemic in the United Kingdom, while we find a stronger link with park mobility.[2]

## 2 | DATA

We use two main data sources: individual-level data from UKHLS to explore mental health before and during the first wave of the COVID-19 pandemic in the United Kingdom and Google COVID-19 Mobility Reports for mobility-zone level park mobility data. Both datasets are separately linked to weather data, creating two datasets, one allowing us to explore the association of weather conditions with mobility and the other to examine the relationship between weather and mental health.

### 2.1 | UK Household Longitudinal Study

The UKHLS is a longitudinal, nationally representative UK study. From April 2020, participants of the UKHLS were repeatedly approached to complete a short web survey focusing on the impact of the COVID-19 pandemic. We utilize the April to July monthly waves of this survey, covering the first wave of the pandemic in the United Kingdom. Prepandemic data is taken from an interim release of the UKHLS main survey, containing responses from households interviewed in 2019.[3] We allow for an unbalanced panel to maximize our sample size by utilizing as much information as possible from each of the five UKHLS waves (Interim 2019 wave and all four COVID-19 waves) employed in our analysis. This ensures that we do not exclude observations from our analysis depending on whether (or not) each individual responds to all five UKHLS waves.[4] To account for nonresponse, unequal selection and attrition, particularly at the COVID-19 waves of UKHLS, sample weights are used in our analysis. Existing research has shown that sample weights typically ensure that results are not contaminated by unequal selection and nonresponse in the UKHLS, despite the concerns that may arise regarding web-based surveys during the COVID-19 outbreak (Davillas & Jones, 2021).[5]

Mental health is measured by the Likert GHQ-12 score, collected using identical questions in the interim UKHLS wave (2019) and the April–July UKHLS COVID-19 survey waves. For our analysis, scores are inverted and standardized to have a mean of 0 and standard deviation of 1, with higher values implying better mental health.

### 2.2 | Google COVID-19 mobility data

Park mobility, our proxy for outdoor recreational activity, is taken from Google COVID-19 Mobility Reports, which provide a daily measure of mobility from cell phone locations aggregated at the mobility zone level. Mobility zones roughly correspond to major cities and counties. Mobility is measured by the percentage change in a combined index of park mobility (capturing number of visits and duration of stay in parks) relative to the baseline period, January 3–February 6, 2020, before COVID-19 risks were fully realized.[6] We use data from February 15 to August 31, 2020, covering all stages of the first national lockdown in the United Kingdom.

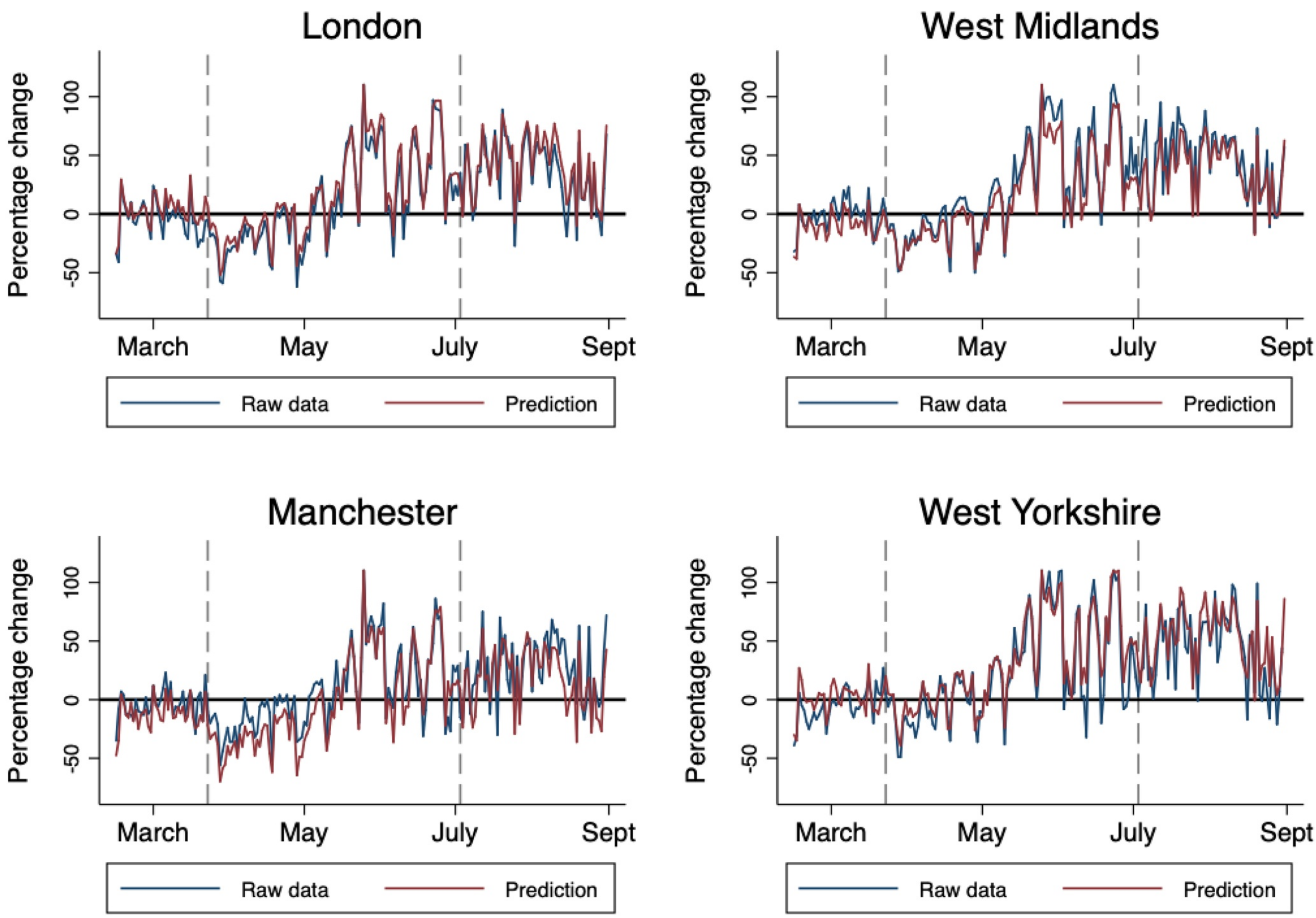


FIGURE 1 Mobility in parks, February–August 2020. Prediction from regression models of park mobility on location and date fixed effects, lockdown indicators and their interactions. Population weights are accounted for

Figure 1 plots park mobility for the four most populous mobility zones. The vertical lines demarcate the start and end of the first lockdown period. Compared to baseline (January 3–February 6, 2020), there is a drop in mobility in the initial period after the announcement of the first lockdown (as shown by the negative percentage changes in mobility from baseline) followed by a sizeable increase in our relative outdoor recreational activity measure (positive percentage changes from baseline) in the middle of May and beyond, a period that coincides with the relaxation of the lockdown restrictions on the duration of outdoor exercise and seasonal variation.

## 2.3 | Linkage of UKHLS and Google COVID-19 Mobility Records to weather data

Daily measures of mean temperature, sunshine duration and total precipitation are extracted from weather station data available from the National Centers of Environmental Information and the Meteorological Office Integrated Data Archive System. By mapping each Lower layer Super Output Area (LSOA) available in our UKHLS panel to its nearest weather station, we are able to link date- and location-specific weather data with the UKHLS.[7] Using each respondent's LSOA of residence and the date of their response at each UKHLS wave used in our analysis, date, and location-specific weather data are linked to UKHLS for each respondent and for all the five UKHLS waves employed here. As a sensitivity analysis we also constructed 7-day average weather conditions (preceding week). This allows us to explore the association between daily or weekly weather conditions and mental health before and during different stages of the first COVID-19 outbreak.[8]

Separately, weather data are also linked with our Google mobility data, again using the nearest weather station at the day and mobility zone level.[9] This dataset allows us to consider the impact of weather on park activity.

Figure 2 plots weather conditions for a day in April and a day in June 2020. These graphs show the presence of systematic variations in weather conditions across locations and over time.

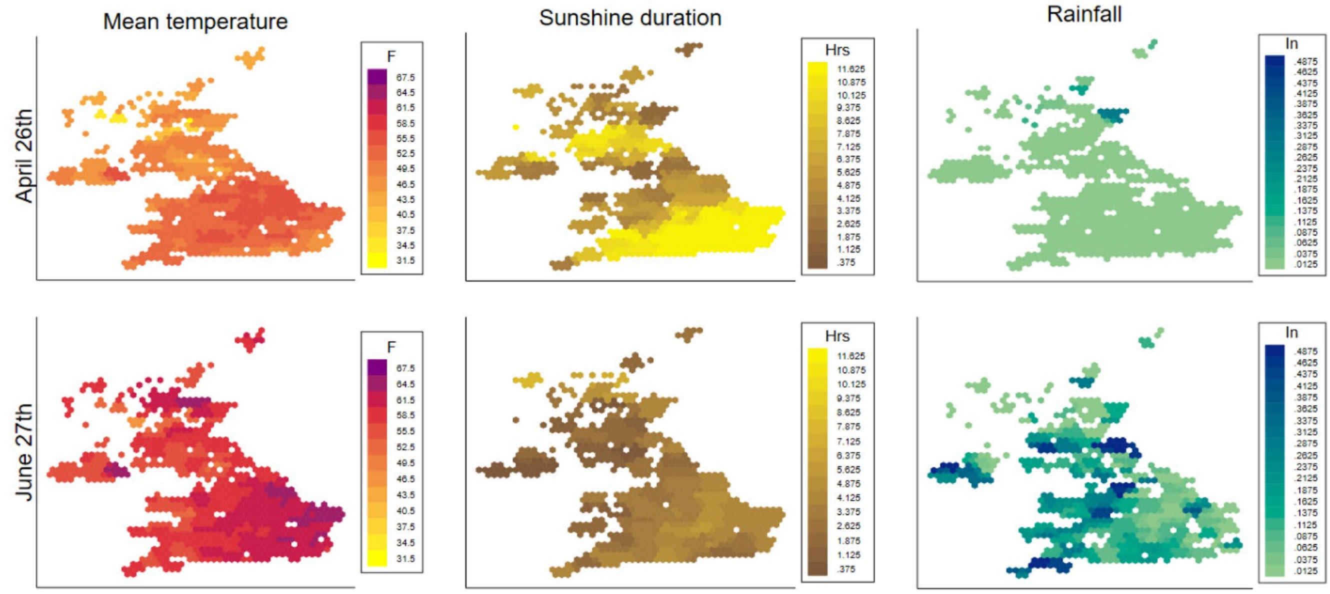


FIGURE 2 Neighborhood-level (LSOA) weather variations. LSOA, Lower layer Super Output Area

## 2.4 | Control variables

Our mental health regressions also account for a set of individual-level control variables that are extracted from UKHLS, which may affect mental health during the COVID-19 outbreak.[10] Specifically, we account for age polynomials, gender, holding a university degree, employment, presence of children in the household, living with a partner and region of residence (dummies for the nine government office regions of England, Scotland, Wales, and Northern Ireland). Excluding missing data from all variables used in mental health regression models resulted in a working sample of 50,062 person-year observations (12,325 respondents).

For the mobility regressions, no additional control variables are used beyond a set of indicators capturing mobility zones, date, and day of the week effects. Our working sample for mobility regressions is 12,831 mobility zone-date observations.

# 3 | METHODS

We estimate similar linear fixed-effects panel-data models for both our outcomes: mental health (GHQ-12) and park mobility. For mental health we estimate:

$$\begin{aligned} \mathrm{GHQ}_{\mathrm{it}} = {} & a + \delta_1 \mathrm{temp}_{\mathrm{it}} + \delta_2 \mathrm{sun}_{\mathrm{it}} + \delta_3 \mathrm{rain}_{\mathrm{it}} + \sum_{\theta} D_{\theta(\mathrm{s}(\mathrm{t}))} \left( \beta_{1\theta} \mathrm{temp}_{\mathrm{it}} + \beta_{2\theta} \mathrm{sun}_{\mathrm{it}} + \beta_{3\theta} \mathrm{rain}_{\mathrm{it}} \right) \\ & + \sum_{\mathrm{s}} \gamma_{\mathrm{s}} I_{\mathrm{s}(\mathrm{t})} + \lambda X_{\mathrm{it}} + \phi_{\mathrm{i}} + \epsilon_{\mathrm{it}} \end{aligned} \tag{1}$$

where $\mathrm{temp}_{\mathrm{it}}$ is the mean daily temperature for individual i on day t, $\mathrm{sun}_{\mathrm{It}}$ the daily sunshine duration and $\mathrm{rain}_{\mathrm{it}}$ is total daily precipitation. We capture period effects with dummies for the UKHLS survey waves, $I_{\mathrm{s(t)}}$, where s(t) indexes each of the April, May, June, and July COVID-19 waves, and the $\gamma_{\mathrm{s}}$ terms capture mean changes in our mental health measure with respect to the pre-COVID baseline period (Interim 2019 wave).

We use a trichotomous lockdown indicator $\theta(\mathrm{s}(\mathrm{t}))$, which partitions the survey period into “pre-lockdown” (i.e., the Interim 2019 wave), “strict lockdown” (April, May, and June COVID-19 waves covering the period between March 23 and the end of June), and “eased restrictions,” which includes the COVID-19 July UKHLS wave only. Estimates of $\beta_{1\theta}$, $\beta_{2\theta}$, and $\beta_{3\theta}$ capture effects of the interaction of the weather variables with each lockdown subperiod (given by the binary dummies, $D_{\theta}$), with the “strict lockdown” being the omitted category here. The main effect of weather variables

**TABLE 1** Fixed effects regression model: Mental healthOrcid

| | Coeff. (Std. error) |
|---|---|
| Heterogenous effects of weather by lockdown periods (omitted category: lockdown) | |
| Mean temp. (tens of F) [$\delta_1$] | 0.025 (0.019) |
| Sunshine duration (4 h) [$\delta_2$] | −0.013 (0.009) |
| Rainfall (tenths of an inch) [$\delta_3$] | −0.008 (0.011) |
| Prelockdown × mean temp. [$\beta_{11}$] | −0.024 (0.024) |
| Prelockdown × sunshine duration [$\beta_{21}$] | 0.010 (0.021) |
| Prelockdown × rainfall [$\beta_{31}$] | 0.0087 (0.013) |
| Eased restrictions × mean temp. [$\beta_{13}$] | 0.018 (0.043) |
| Eased restrictions × sunshine duration [$\beta_{23}$] | 0.020 (0.017) |
| Eased restrictions × rainfall [$\beta_{33}$] | 0.013 (0.013) |
| UKHLS wave dummies (period effects) (omitted category: Interim 2019 wave) | |
| April 2020 [$\gamma_2$] | −0.150*** (0.033) |
| May 2020 [$\gamma_3$] | −0.159*** (0.029) |
| June 2020 [$\gamma_4$] | −0.189*** (0.033) |
| July 2020 [$\gamma_5$] | −0.085* (−0.048) |
| Individual fixed effects | X |
| Individual-level control variables | X |
| Adjusted $R^2$ | 0.183 |
| Person-year observations | 50,062 |
| Number of respondents | 12,325 |

*Note:* Model is a linear fixed effects regression of the standardized and inverted GHQ-Likert score. Apart from the UKHLS wave dummies [2019 interim wave (omitted category) and the April, May, June, July 2020 COVID-19 waves], weather variables (mean temperature, sunshine duration, and rainfall), and the interaction of weather variables with dummies for the lockdown period [prelockdown, strict lockdown (omitted category), and eased restrictions] there is a set of additional explanatory variables included in the model but omitted from this table. These controls are: age polynomials (age and age squared), gender, education, marital status, number of children in the household, employment status, and regional dummies. The constant term is also omitted from the table. Standard errors clustered at the primary sampling unit level (capturing postal address of residence) and presented in parenthesis. The Greek letters in the table reflect coefficients presented in Equation (1) (Section 3). Analysis accounts for sample weights.

Abbreviation: UKHLS, UK Household Longitudinal Study.

*$p < 0.10$.

**$p < 0.05$.

***$p < 0.01$.

is captured by estimates of $\delta_1$, $\delta_2$, and $\delta_3$.[11] We also account for fixed effects, $\phi_i$, to absorb time-invariant individual unobserved heterogeneity, making a full use of our panel data structure.

Equation (1) also includes controls, $X_{it}$, for individual-level factors that may vary over time and are associated with people's mental health (Section 2). We allow for broad and arbitrary correlation of the error terms $\epsilon_{it}$ by clustering standard errors at the local neighborhood level using the primary sample units.[12]

For mobility we estimate:

$$\begin{aligned}\mathrm{Mob}_{\mathrm{lt}} &= a+\delta_1\mathrm{temp}_{\mathrm{it}}+\delta_2\mathrm{sun}_{\mathrm{it}}+\delta_3\mathrm{rain}_{\mathrm{it}}+\sum_{\theta}D_{\theta(\mathrm{t})}\left(\beta_{1\theta}\mathrm{temp}_{\mathrm{lt}}+\beta_{2\theta}\mathrm{sun}_{\mathrm{lt}}+\beta_{3\theta}\mathrm{rain}_{\mathrm{lt}}\right)\\ &+\ \xi_{\mathrm{t}}+\varphi_{\mathrm{l}}+\zeta_{1\theta(\mathrm{t})}+\Psi_{\mathrm{ld(t)}}+\epsilon_{\mathrm{lt}}\end{aligned} \tag{2}$$

where, the panel data structure here is mobility zone, l, by day, t. The weather variables and lockdown variable $\theta(t)$ are defined as in Equation (1). The richness of the Google mobility data allows for a full set of date effects $(\xi_t)$.[13] These account for seasonal and common time components, such as changes in park mobility around bank holidays. We also include mobility-zones fixed effects, $\phi_l$, to absorb time-invariant differences in mobility across zones.

Additionally our mobility equation model includes interactions between the lockdown indicator and mobility zones ($\zeta_{l\theta(t)}$), capturing potential effects of "local lockdowns" after the full lockdown ended in July, as well as differential location-specific compliance during the lockdown period itself. Finally, we include $\Psi_{ld(t)}$, an interaction of mobility zones

TABLE 2 Fixed effects regression models: Park mobility

| | (1) Coeff. (Std. error) | (2) Coeff. (Std. error) |
|---|---|---|
| Heterogenous effects of weather by lockdown periods (omitted category: lockdown) | | |
| Mean temp. (tens of F) [$\delta_1$] | 3.704** (1.697) | 7.554*** (1.846) |
| Sunshine duration (4 h) [$\delta_2$] | 11.910*** (0.625) | 10.700*** (0.698) |
| Rainfall (tenths of an inch) [$\delta_3$] | −0.877*** (0.177) | −1.410*** (0.220) |
| Prelockdown × mean temp. [$\beta_{11}$] | | −2.832 (2.429) |
| Prelockdown × sunshine duration [$\beta_{21}$] | | −1.265 (1.871) |
| Prelockdown × rainfall [$\beta_{31}$] | | 1.253*** (0.348) |
| Eased restrictions × mean temp. [$\beta_{13}$] | | −17.49*** (3.863) |
| Eased restrictions × sunshine duration [$\beta_{23}$] | | 5.290*** (1.272) |
| Eased restrictions × rainfall [$\beta_{33}$] | | 0.454 (0.549) |
| Date fixed effects | X | X |
| Mobility zones fixed effects | X | X |
| Mobility zone-lockdown interactions | X | X |
| Mobility zone-day of week interactions | X | X |
| Weather-lockdown interactions | | X |
| Adjusted $R^2$ | 0.927 | 0.928 |
| Mobility zones-date observations | 12,831 | |
| Number of mobility zones | 132 | |

*Note:* Column 1 presents results from a linear fixed effects regression of park mobility model on weather variables (mean temperature, sunshine duration, and rainfall) along with a set of additional variables that are not presented in the table with details: date fixed effects, mobility zones fixed effects, interactions of mobility zones, and lockdown periods [prelockdown, lockdown (omitted category), eased restrictions], an interaction of mobility zones with day of the week. Column 2 further augment the model specification by including weather-lockdown indicators interactions (Equation 2 in Section 3). The constant terms for both model specifications are omitted from the table. Standard errors clustered at mobility zone level and presented in parenthesis. The Greek letters in the table reflect coefficients presented in Equation (2) (Section 3). Analysis accounts for mobility zone population weights.

*$p < 0.10$.

**$p < 0.05$.

***$p < 0.01$.

and day of the week $d(t)$. This is primarily included to take account of the structure of the Google mobility data, which is normalized at the mobility zone × day-of-the-week level. We also allow for arbitrary correlation of the error terms $\epsilon_{lt}$ by clustering standard errors at the mobility zone level.

## 4 | RESULTS

Table 1 presents the estimates of our mental health regression model. Compared to baseline (2019), mental health declined during lockdown as shown by the negative April–July 2020 wave coefficients. This decline is strongest over April–June and less pronounced in July, in line with the easing of lockdown restrictions.

Concerning weather, we find that the estimated associations with mental health are small and not statistically significant.[14] The interactions between weather conditions and lockdown indicators show no systematic associations during any subperiod, suggesting, in particular, that weather conditions do not exacerbate the mental health consequences of lockdown.[15] However, one may argue that, in any case, mental health may be less affected by daily fluctuations in weather. Sensitivity analysis shows the presence of limited associations between weather variations from a longer time period (the preceding week, 7-day average) and mental health (Table A3), further confirming our conclusions.[16]

Detailed results of the park mobility regression model are presented in Table 2. The first column presents results from a simplified version of Equation (2), without the interaction effects between the lockdown stages and weather. The second column presents our estimates of the full specification.[17] To illustrate the heterogeneous association of weather conditions with mobility by lockdown stages, Figure 3 presents the estimated marginal effects from our full model specification.[18]

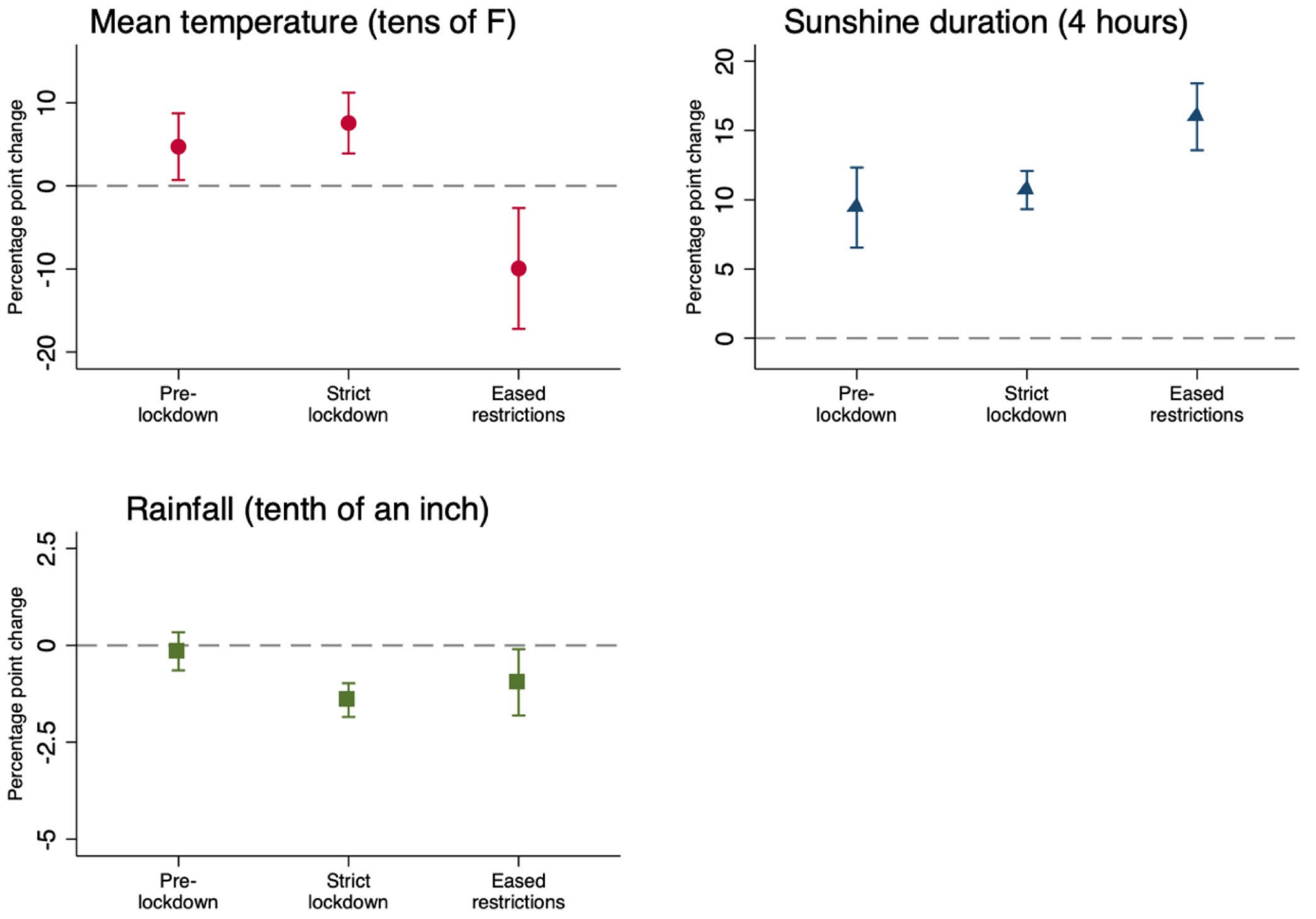


**FIGURE 3** Marginal effects (with 95% confidence interval bars) of weather on mobility in parks by stages of the first UK lockdown (Specification 2, Table 2)

In our full model specification (Column 2), given the strict lockdown period is the omitted category in the interactions, the first three rows are interpreted as the effect of daily weather on park mobility during this period (also confirmed by the relevant marginal effects, Figure 3). During lockdown a temperature increase of 10°F (one unit of our temperature variable) leads to a 7.6% increase in mobility; an increase in sunshine of 4 h implies a 10.7% increase in mobility, while an increase in rainfall by 0.1 inches leads to a 1.4% mobility decline.[19]

Turning to the prelockdown period, there is limited evidence that temperature and sunshine conditions exert systematically different effects compared to the lockdown period itself (fourth and fifth rows of Table 2). However, in the period after lockdown ("eased restrictions"), there is evidence of differential effects of these variables: while the effect of sunshine on mobility is heightened, temperature has a negative effect on mobility (Figure 3). Although initially surprising, the later seems plausible; during the summer months, cooler weather is more amenable to outdoor activity. We also find a systematic negative association between mobility and rainfall during the same period (Figure 3).

## 5 | CONCLUSION

Using survey and Google mobility data we find evidence for reduced outdoor recreational activity (proxied by park mobility) during the initial period of the first UK lockdown and confirm existing evidence of worsening mental health. Daily weather conditions (temperature, sunshine, and rainfall) affect park mobility, while we find no systematic associations between weather variations and mental health either before, during, or after the first national lockdown. Overall, our evidence suggests that weather conditions do not exacerbate the mental health costs of the pandemic.

## ACKNOWLEDGMENTS

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## CONFLICT OF INTEREST

The authors declare that there are no conflict of interests.

## DATA AVAILABILITY STATEMENT

The data used in our study are available via the UK Data Service (UKDS) as well as via the web.


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## ENDNOTES

[1] COVID-19 policy tracker. The Heath Foundation. https://www.health.org.uk/news-and-comment/charts-and-infographics/covid-19-policy-tracker.

[2] It should be mentioned that we do not aim to explore the effect of park mobility on mental health or the opposite during the first wave of the pandemic in the United Kingdom. Of course, establishing causality with absolute certainty using survey data is difficult in general but, in this particular case, the structure of our available datasets creates further complications as it is difficult to overcome endogeneity and simultaneity biases; for example, we are not able to assess whether people experience mental health problems and as a result limit their outdoors recreational activities or vice versa.

[3] Due to delays in data collection, the dataset also contains a very small number of responses from January and February 2020 (before the COVID-19 outbreak in the United Kingdom).

[4] It should be noted here that estimating our mental health regressions using a balanced sample resulted into similar results to those presented in Table 1; all weather variables and the weather-lockdown interactions are not statistically significant at the 10% level. This indicates that attrition due to non-response it at least two out of the five UKHLS waves used in our analysis may not change the conclusions of our study.

[5] Weighted summary statistics on age and gender reveals similar results when focusing on the unrestricted sample of previous UKHLS waves as opposed to when this sample is restricted to those who responded at least once during the COVID-19 waves (available upon request). This suggests that our longitudinal sample weights account for non-response and attrition during COVID-19 waves (where selective attrition is more likely as a result of COVID itself and the online mode of interview) and balance the age and gender mean values for the COVID-19 waves (age and gender composition of the sample) to those from the pre-COVID waves. As age is a risk factor for COVID-19 severity and mortality, these may suggest that our sample weights are adequate for accounting for nonresponse at the COVID-19 waves.

[6] It was not until February 11, 2020 that the Health Secretary made his first official parliamentary statement regarding the potential risks of COVID-19 for the UK population. The UK government set out the first COVID-19 "battle plan" much later (March 1, 2020).

[7] The LSOAs are lower layer geographies, defined to account for population size, mutual proximity and social homogeneity; they contain on average 1500 residents/650 households.

[8] Some weather observations are missing at both the daily and within day level because stations intermittently go offline. To alleviate this problem, we apply the mapping iteratively to find the closest weather stations to each LSOA. We then assume weather information is missing if the nearest weather station with data is more than 40 km away from the LSOA.

[9] As in the case of linkage with the UKHLS data, we employ the mapping iteratively to mitigate the impact of missing weather information.

[10] Summary statistics of selected variables used in the analysis are available in Table A1.

[11] It should be noted that the trichotomous lockdown main effects are co-linear with the period effects $I_{s(t)}$ and, thus, not included in Equation (1). However, the main effect of the lockdown variable can be inferred by averaging the period effect coefficient $\gamma_s$ for the April, May, and June 2020 survey wave dummies (for the strict lockdown effect), while the easing restrictions main variable "effect" is captured by the July 2020 dummy. If we change the specification replacing the period effects with a pure "lockdown" main effect variable, our results are identical (results available upon request). We believe, however, that having a set of UKHLS wave dummies/period effects instead is more informative as they provide an estimate of the worsening mental health for each month during the first wave of the pandemic in the United Kingdom (rather than, e.g., an aggregate measure for the "strict lockdown" that summarized across a number of waves).

[12] Primary sample units correspond to postal sectors, the level at which UKHLS sampling is conducted.

[13] Due to the different data sources used in our analysis (UKHLS data for mental health and Google mobility data for the GHQ-12 models), prelockdown period in our mobility equation model covers February 15–March 22, while the prelockdown period for our mental health regression model covers the whole of 2019 up to February 2020 (Interim 2019 UKHLS wave).

[14] Given that our aim here is to explore the potential heterogenous association of weather conditions with mental health by lockdown period, the main effects of the weather conditions and their interactions with lockdown indicators (with their linear combination typically used to estimate the effect of weather on mental health at each of the three stages of the lockdown) are presented in Table 1. For clarity, as also mentioned in Section 3, the main effect of the lockdown trichotomous variable could be inferred by averaging the coefficients on the April, May, and June 2020 month dummies (for the strict lockdown effect), while the easing restrictions main variable "effect" is captured by the July 2020 dummy.

[15] In Table A2 we show similarly small and insignificant coefficients when we estimate the effect of weather without interactions.

[16] It should be explicitly mentioned that the scope of our analysis is not to explore the long-run effects of weather for people's mental health. Our study is limited to explore the effect of daily or weekly weather variations on mental health before and during the first wave of the UK response to the pandemic.

[17] The date fixed effects (which are not presented in Table 2 with details) account for the main "effect" of the lockdown periods.

[18] Given that we are interested in exploring the heterogeneous effect of weather by lockdown, marginal effects typically take into account the linear combinations of the main weather coefficients and their interactions with the trichotomous lockdown variable. Figure 3 presents these results.

[19] It should be explicitly mentioned that we define weather units in a way (10°F for temperature, 4 h for sunshine, and 0.1 inches for rainfall) that they roughly correspond to one standard deviation change in each variable.

## REFERENCES

Askitas, N., Tatsiramos, K., & Verheyden, B. (2021). Estimating worldwide effects of non-pharmaceutical interventions on COVID-19 incidence and population mobility patterns using a multiple-event study. *Scientific Reports*, *11*(1), 1972.

Banks, J., & Xu, X. (2020). The mental health effects of the first two months of lockdown during the COVID-19 pandemic in the UK. *Fiscal Studies*, *41*(3), 685–708.

Davillas, A., Jones, A. M. (2021). The first wave of the COVID-19 pandemic and its impact on socioeconomic inequality in psychological distress in the UK. *Health Economics*, http://dx.doi.org/10.1002/hec.4275

Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunubá, Z., Cuomo-Dannenburg, G., Dighe, A., Dorigatti, I., Fu, H., Gaythorpe, K., Green, W., Hamlet, A., Hinsley, W., Okell, L. C., van Elsland, S., … Ghani, A. (2020). Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. *Imperial College London*, *10*(77482), 491–497.

Frijters, P., Chitwan, L., & Debayan, P. (2020). Daily weather only has small effects on wellbeing in the US. *Journal of Economic Behavior & Organization, 176*, 747–762.

Iacobucci, G. (2020). Covid-19: UK lockdown is "crucial" to saving lives, say doctors and scientists. *BMJ*, *368*, m1204. https://doi.org/10.1136/bmj.m1204

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# APPENDIX

TABLE A1 Summary statistics of selected variables used in our analysis

| Variable | Mean | Standard deviation |
|---|---|---|
| Park mobility[a] | 20.905 | 43.662 |
| Mean temperature (tens of F) | 57.567 | 8.514 |
| Sunshine duration (4 h) | 7.721 | 5.189 |
| Rainfall (tenth of an inch) | 0.055 | 0.137 |
| GHQ-12 Likert score[b] | 12.270 | 6.019 |

*(Continues)*

TABLE A1 (Continued)

| Variable | Mean | Standard deviation |
|---|---|---|
| Control variables at the GHQ-12 models | | |
| Age (in years) | 51.406 | 17.661 |
| Female | 0.526 | 0.499 |
| Male (reference) | 0.474 | 0.499 |
| Degree | 0.298 | 0.457 |
| Nondegree (reference) | 0.702 | 0.457 |
| Cohabitation/married | 0.637 | 0.481 |
| Noncohabitation/married (reference) | 0.363 | 0.481 |
| Children in hh | 0.178 | 0.383 |
| No children in hh (reference) | 0.822 | 0.383 |
| Employed | 0.589 | 0.492 |
| Non-employed (reference) | 0.411 | 0.492 |
| North West | 0.091 | 0.287 |
| Yorkshire and the Humber | 0.064 | 0.245 |
| East Midlands | 0.087 | 0.283 |
| West Midlands | 0.097 | 0.296 |
| East of England | 0.100 | 0.299 |
| London | 0.122 | 0.328 |
| South East | 0.167 | 0.368 |
| South West | 0.089 | 0.284 |
| Wales | 0.038 | 0.190 |
| Scotland | 0.084 | 0.277 |
| Northern Ireland | 0.021 | 0.144 |
| North East (reference) | 0.044 | 0.206 |

*Note:* Sample weights are accounted for.

Abbreviation: UKLHS, UK Household Longitudinal Study.

[a]Based on our working sample (Google mobility data) employed for the analysis of our mobility outcome (12,831 mobility zones-date observations). Summary statistics for all other variables are based on our working UKHLS sample that used to estimate our mental health regression models (50,062 person-year observations). [b]Summary statistics of the raw GHQ-12 Likert score are presented here. For the needs of our analysis, the GHQ-12 Likert score is inverted and standardized so that higher values imply better mental health.

TABLE A2 Mental health regression model—without weather-lockdown interactions

| | Coeff. (Std. error) |
|---|---|
| Mean temp. (tens of F) | 0.010 (0.013) |
| Sunshine duration (4 h) | −0.006 (0.007) |
| Rainfall (tenths of an inch) | −0.002 (0.005) |
| Sample size | 50,062 |

*Note:* Analysis accounts for sample weights. The full set of covariates used in our mental health regression models are described in Table 1.

*$p < 0.10$.

**$p < 0.05$.

***$p < 0.01$.

TABLE A3 Mental health regression model—7-day average weather conditions

| | (1) Coeff. (Std. error) | (2) Coeff. (Std. error) |
|---|---|---|
| Mean temperature (tens of F) | −0.001 (0.018) | 0.018 (0.040) |
| Sunshine duration (4 h) | 0.014 (0.016) | 0.007 (0.017) |
| Rainfall (tenths of an inch) | −0.014 (0.011) | −0.023* (0.012) |
| Prelockdown × mean temp. | | −0.030 (0.042) |
| Prelockdown × sunshine duration | | 0.029 (0.035) |
| Prelockdown × rainfall | | 0.019 (0.019) |
| Eased restrictions × mean temp. | | 0.033 (0.046) |
| Eased restrictions × sunshine duration | | −0.023 (0.035) |
| Eased restrictions × rainfall | | 0.012 (0.033) |

*Note:* Sample weights are accounted for. The full set of covariates used in our regression models are described in Table 1.

*$p < 0.10$.

**$p < 0.05$.

***$p < 0.01$.