

HEDG

HEALTH, ECONOMETRICS AND DATA GROUP

THE UNIVERSITY of York

WP 21/03

Weather, psychological wellbeing and mobility during the first wave of the Covid-19 pandemic

Ashley Burdett; Apostolos Davillas and Ben Etheridge

February 2021

http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

Weather, psychological wellbeing and mobility during the first wave of the Covid-19 pandemic

Ashley Burdett

Department of Economics, University of Essex, U.K.

Apostolos Davillas

Health Economics Group, Norwich Medical School, University of East Anglia, U.K.; IZA, Bonn; and GLO.

Ben Etheridge

Department of Economics, University of Essex, U.K.

15 February 2021

Abstract

To reduce infection rates during the first UK wave of the COVID-19 outbreak, a 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 (UKHLS) 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 psychological wellbeing. Linkage with weather data shows that contrary to popular belief, weather conditions do not exacerbate the mental health consequences of the pandemic, while we find systematic links between park mobility and weather over the same period. Our results highlight the importance of promoting the existing guidelines on regular exercise during winter lockdowns.

Keywords: COVID-19; mental health; mobility; weather conditions

JEL codes: I10, I12, C23

Corresponding author: Apostolos Davillas. Health Economics Group, Norwich Medical School, University of East Anglia, U.K.; IZA, Bonn; and GLO. email: a.davillas@uea.ac.uk.

Acknowledgment: We thank Lisa Spantig for helpful discussions. Understanding Society is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. The research data are distributed by the UK Data Service. The funders, data creators and UK Data Service have no responsibility for the contents of this paper.

1. Introduction

COVID-19 originated in the city of Wuhan, China, in December 2019 and spread rapidly to become a global pandemic. As part of the UK response to the pandemic's first wave, 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 eased, with two subsequent lockdown easings 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 driven by the alarming projected spread of the disease, the accompanying implications for public health, and additional pressure on the health care system. This motivated a shift of focus in government policy from "mitigation", aiming to reduce the health impact of the epidemic but not to stop transmission completely, to "suppression", where lockdown is required to reduce 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., 2020); the adverse impact of COVID-19 and lockdown restrictions on mental health has also recently been documented (e.g., Banks and Xu, 2020; Davillas and Jones, 2021). Given pre-COVID studies on the link between weather conditions and wellbeing outcomes (e.g., Frijters et al., 2020), it is of particular interest to assess if adverse weather conditions during the first lockdown in the UK 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 wellbeing costs of additional lockdowns will be heightened during winter and spring 2021.

⁻

 $^{{}^{1}\}text{ COVID-19 policy tracker. The Heath Foundation.} \underline{\text{https://www.health.org.uk/news-and-comment/charts-and-infographics/covid-19-policy-tracker.}}$

In this study we use data from the UK Household Longitudinal Study (UKHLS) on psychological wellbeing, collected before and during the first wave of the COVID-19 outbreak. Similarly, 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, contrary to popular belief, weather conditions do not exacerbate the mental health consequences of the pandemic, while we find a stronger link with park mobility.²

2. Data

UK Household Longitudinal Study (UKHLS)

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 focussing 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 UK. Prepandemic data is taken from an interim release of the UKHLS main survey, containing responses from households interviewed in 2019.³

Psychological wellbeing 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 zero and standard deviation of one, with higher values implying better mental health.

Google Covid-19 mobility data

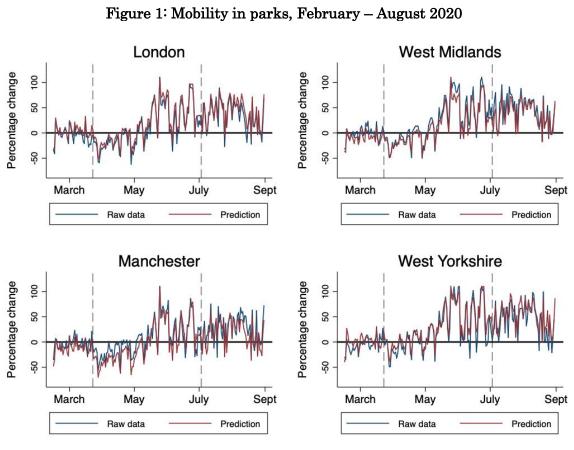
Park mobility, our proxy for outdoor recreational activity, is taken from Google COVID-19 Mobility Reports, which provide a daily measure of mobility from cell-phone locations aggregated at the mobility zone level. Mobility zones roughly correspond to major cities and counties. Mobility is measured by the percentage change in a combined index of park mobility (capturing number of visits and duration of stay in parks) relative to the baseline

² It has been claimed by columnists that the negative effect on mental health due to the COVID-19 pandemic will be exaggerated by experiences of colder and darker days (for example, The Economist, https://www.economist.com/business/2020/11/26/why-office-morale-will-be-hard-to-maintain-this-year).

 $^{^3}$ 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 UK).

period, January 3 – February 6, 2020, before COVID-19 risks were fully realised. 4 We use data from February 15 to August 31, 2020, covering all stages of the first national lockdown in the UK.

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.



Note: Prediction from regression models of park mobility on location and date fixed effects, lockdown indicators and their interactions. Population weights are accounted for.

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).

⁴ It was not until February 11, 2020 that the Health Secretary made his first official parliamentary statement

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. This allows us to explore the association between weather conditions and psychological wellbeing before and during different stages of the first COVID-19 outbreak.

Weather data are also linked with our Google mobility data, again using the nearest weather station at the day and mobility zone level.⁷ 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.

⁻

⁵ The LSOAs are lower layer geographies, defined to account for population size, mutual proximity and social homogeneity; they contain on average 1,500 residents/650 households.

⁶ 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 40km away from the LSOA.

⁷ As in the case of linkage with the UKHLS data, we employ the mapping iteratively to mitigate the impact of missing weather information.

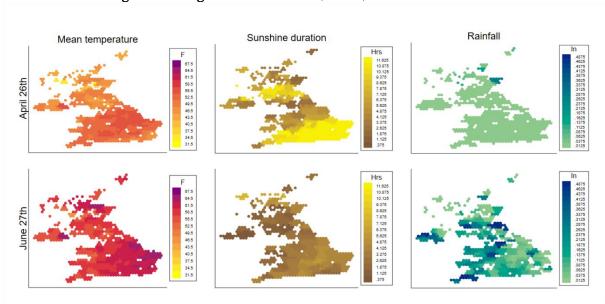


Figure 2: Neighbourhood-level (LSOA) weather variations

Control variables

Our psychological wellbeing regressions also account for a set of control variables, which may affect mental health during the COVID-19 outbreak. 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).8

3. Methods

We estimate the following model for both our outcomes, psychological wellbeing and park mobility, captured at time t by y_{it} :

$$y_{it} = a + \sum_{\theta} D_{\theta(t)} \times (\beta_{1\theta} temp_{it} + \beta_{2\theta} sun_{it} + \beta_{3\theta} rain_{it}) + \gamma X_{it} + \phi_i + \xi_t + \epsilon_{it}$$
 (1)

where, $temp_{it}$ is the mean daily temperature, sun_{lt} the daily sunshine duration and $rain_{it}$ is total daily precipitation. For the park mobility regressions, i stands for mobility zone; for the psychological wellbeing regressions, i indexes individuals.

⁸ Summary statistics of all other variables used in the analysis are available in Table A1 (Appendix).

We use a trichotomous lockdown indicator $\theta(t)$ which partitions the survey period into "pre-lockdown" (up to March 22), "lockdown" (March 23 - July 3) and "eased restrictions" (July 4 onwards)⁹. Estimates of $\beta_{1\theta}$, $\beta_{2\theta}$, $\beta_{3\theta}$ capture effects of the interaction of the weather variables with each lockdown sub-period (binary dummies, D_{θ}). All our models include fixed effects, ϕ_i , to absorb time-invariant individual (for the psychological wellbeing equation) or mobility zone (for the mobility equation) characteristics, and day effects, ξ_t , to account for seasonal and common time components, such as changes in park mobility or wellbeing around bank holidays.

A set of additional covariates, X_{it} , is also included in each equation. For the park mobility equation, this vector most importantly includes interactions between the lockdown indicator and mobility zones, 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.¹⁰

For our psychological wellbeing model, X_{it} controls for individual-level factors that may vary over time (see Section 2). We allow for arbitrary correlation of the error terms ϵ_{it} within individuals/mobility zones and across time, by clustering standard errors at the location level.¹¹

4. Results

Table 1 presents the estimates of our psychological wellbeing regression model. Compared to baseline (2019), psychological wellbeing 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 psychological wellbeing are small and not statistically significant. The interactions between weather

_

⁹ Due to the different data sources used in our analysis (UKHLS data and Google mobility data), pre-lockdown period in our mobility equation model covers February 15 – March 22, while the pre-lockdown period for our psychological wellbeing model covers the whole of 2019 up to February 2020 (Interim 2019 UKHLS wave).

¹⁰ We also include an interaction between mobility zones and day of the week indicators, primarily to account for the structure of the data, which is normalized at the location day-of-the-week level.

¹¹ Specifically, standard errors for the mobility regressions are clustered at the mobility zone level, while for the psychological wellbeing regressions the standard errors are clustered at the primary sample unit level (corresponding to postal sectors of UKHLS sample collection).

conditions and lockdown indicators show no systematic associations during any subperiod, suggesting, in particular, that weather conditions do not exacerbate the psychological wellbeing consequences of lockdown¹². In Table A2 (appendix) we show similarly small and insignificant coefficients when we estimate the effect of weather without interactions.

Table 1: Psychological wellbeing regression model

Coeff.		
	(std. error)	
M (4 C.E.)	0.025	
Mean temp. (tens of F)	(0.019)	
Sunshine duration (4 hours)	-0.013	
	(0.009)	
Rainfall (tenths of an inch)	-0.008	
	(0.011)	
Pre-lockdown x Mean temp.	-0.024	
	(0.024)	
Pre-lockdown x Sunshine duration	0.010	
	(0.021)	
Pre-lockdown x Rainfall	0.0087	
Fre-lockdown x Naiman	(0.013)	
Forced restrictions v. Moon town	0.018	
Eased restrictions x Mean temp.	(0.043)	
Eased restrictions x Sunshine duration	0.020	
Eased restrictions x Sunstine duration	(0.017)	
Eased restrictions x Rainfall	0.013	
Eased restrictions x Italinan	(0.013)	
April 2020	-0.150***	
	(0.033)	
May 2020	-0.159***	
May 2020	(0.029)	
June 2020	-0.189***	
June 2020	(0.033)	
July 2020	-0.085^{*}	
	(-0.048)	
Sample size	50,062	

Note: Analysis accounts for sample weights.

_

^{*}p<0.10, **p<0.05, ***p<0.01

¹² One may argue that psychological wellbeing may be less affected by daily fluctuations in weather but to a larger extent impacted by longer term weather conditions. Table A3 (appendix) shows the association between psychological wellbeing and local weather variations over the preceding week (7-days). These results further confirm the presence of a limited impact of weather conditions on psychological wellbeing during the first wave of the pandemic.

Detailed results of the park mobility regression model are presented in Table 2. The first column presents results from a simplified version of eq. 1, without the interaction effects between the lockdown stages and weather. The second column presents our estimates of the full specification. To ease interpretation of the later, Figure 3 offers a graphical visualization of the estimated marginal effects of weather at each lockdown stage.

Table 2: Mobility (expressed as percentage changes from pre-

lockdown baseline) regression models

	(1)	(2)	
	Coeff.	Coeff.	
	(std. error)	(std. error)	
Mean temp. (tens of F)	3.704^{**}	7.554^{***}	
	(1.697)	(1.846)	
Sunshine duration (4 hours)	11.910^{***}	10.700^{***}	
Sunshine duration (4 nours)	(0.625)	(0.698)	
Rainfall (tenths of an inch)	-0.877***	-1.410***	
	(0.177)	(0.220)	
Durada aladarum er Maara tarran		-2.832	
Pre-lockdown x Mean temp.		(2.429)	
Pre-lockdown x Sunshine duration		-1.265	
		(1.871)	
D 1 1. 1		1.253^{***}	
Pre-lockdown x Rainfall		(0.348)	
Danilandaidina - Marakana		-17.49***	
Eased restrictions x Mean temp.		(3.863)	
Eased restrictions x Sunshine duration		5.290^{***}	
		(1.272)	
Eased restrictions x Rainfall		0.454	
		(0.549)	
Sample size	12,831		

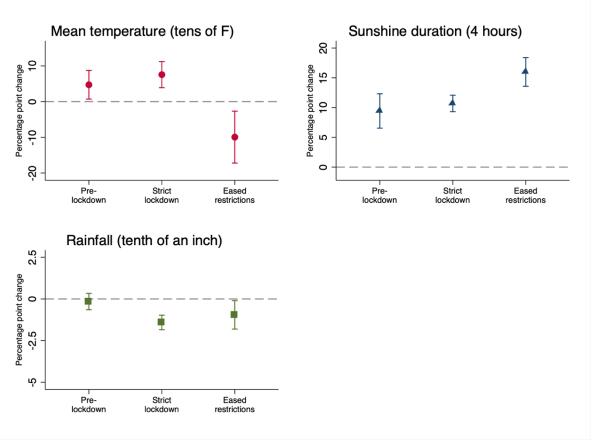
Note: Population weights are accounted for. * p<0.10, **p<0.05, ***p<0.01

In our full model specification (Column 2), given the lockdown period (March 23 - July 3) is the reference category, the first three rows are interpreted as the effect of weather on park mobility during this period. During lockdown a temperature increase of 10°F (one unit of our temperature variable) leads to a 7.6 percentage point increase in mobility; an increase in sunshine of 4 hours implies a 10.7 percentage point increase in mobility, while an increase in rainfall by 0.1 inches leads to a 1.4 percentage point mobility decline. 13

¹³ It should be explicitly mentioned that we define weather units in a way (10°F for temperature, 4 hours for sunshine, and 0.1 inches for rainfall) that they roughly correspond to one standard deviation change in each variable.

Turning to the pre-lockdown 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).

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)



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 psychological wellbeing. Weather conditions

(temperature, sunshine and rainfall) affect park mobility, while we find no systematic associations between weather conditions and psychological wellbeing 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. Promotion of the existing guidelines from public health authorities on regular indoor exercise should be further intensified during winter lockdowns as weather conditions affects people's outdoor physical activity.

References

Askitas, N., Tatsiramos, K., Verheyden, B. (2020). Lockdown strategies, mobility patterns and COVID-19. In *Covid Economics-Vetted and Real-Time Papers*.

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. IZA, Bonn, Germany. DP No. 14057.

Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., .., 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 and Organization*, 176, 747-762.

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

Appendix

Table A1: Summary statistics of selected variables used in our analysis.

Table A1: Summary statistics of selected variables used in our analysis.					
Variable	Mean	Standard deviation			
Park mobility [†]	20.905	43.662			
Mean temperature (tens of F)	57.567	8.514			
Sunshine duration (4 hours)	7.721	5.189			
Rainfall (tenth of an inch)	0.055	0.137			
GHQ-12 Likert Score ^{††}	12.270	6.019			
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			
Non-degree (reference)	0.702	0.457			
Cohabitation/married	0.637	0.481			
Non-cohabitation/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			

[†] Based on our working sample for analysis of our mobility outcome (12,831 observations). Summary statistics for all other variables are based on our full sample of 50,062 observations (sample size used in the analysis for our mental health outcome).

Note: Sample weights are accounted for.

 $^{^{\}dagger\dagger}$ 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: Psychological wellbeing regression model -Without weather-lockdown interactions

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

Note: Analysis accounts for sample weights. *p<0.10, **p<0.05, ***p<0.01

Table A3: Psychological wellbeing regression model -7-day average weather conditions

1 day average wee	7-day average weather conditions			
	(1)	(2)		
	Coeff.	Coeff.		
	(std. error)	(std. error)		
Mean temperature (tens of F)	-0.001	0.018		
	(0.018)	(0.040)		
Sunshine duration (4 hours)	0.014	0.007		
	(0.016)	(0.017)		
Rainfall (tenths of an inch)	-0.014	-0.023*		
	(0.011)	(0.012)		
Pre-lockdown x Mean temp.		-0.030		
		(0.042)		
Pre-lockdown x Sunshine duration		0.029		
		(0.035)		
Pre-lockdown x Rainfall		0.019		
		(0.019)		
Eased restrictions x Mean temp.		0.033		
		(0.046)		
Eased restrictions x Sunshine duration		-0.023		
		(0.035)		
Eased restrictions x Rainfall		0.012		
		(0.033)		
Sample size	4	8,839		

Note: Sample weights are accounted for. *p<0.10, **p<0.05, ***p<0.01