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Weather Affects Mobility but not Mental Well-being During Lockdown

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Non-Technical Summary

A noticeable feature of the Covid-19 pandemic has been a decline in mental well-being. This decline has several causes, including the direct effects of lockdown policies themselves. Many countries in the northern hemisphere now head into winter facing a resurgence of the disease. When weighing up the costs and benefits of lockdown policies, a key question, therefore, is the extent to which winter weather would make the negative effects of lockdown on well-being even worse.

This study provides evidence in this direction by examining the effects of local variation in weather during the spring lockdown in the UK. We not only assess the effects on well-being, but also examine one of the major channels through which weather affects behaviour and subsequent outcomes: physical mobility. Mobility itself is especially relevant because UK government policy during the spring was explicitly designed to maintain well-being by encouraging exercise. Even at its strictest, the lockdown policy allowed for one hour of outdoor activity per day.

For our analysis we combine data from both the UKHLS main survey and covid module, with data from Google mobility reports, and with data from the UK MET office weather stations.

The established literature has typically found little effect of weather on mental well-being on average. We similarly find no noticeable effect during lockdown. To the best of our knowledge we are the first to examine this relationship under lockdown restrictions. Conversely we find that, during lockdown, weather has increased effects on mobility, specifically in parks. Ours is the first study to assess the relationship between mobility and weather in the UK. We estimate effect sizes similar to those found for the U.S.

In terms of implications for policy, our results indicate that the direct well-being costs of lockdown would not be accentuated by winter weather. Our results also suggest a modest effect on well-being of recreational activity in this context. In this sense, our results imply that policy may be better targeted at other factors that affect well-being during lockdowns; for example finding ways to encourage social interaction while maintaining physical distancing.

Weather affects mobility but not mental well-being during lockdown*

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Abstract

Mental well-being has declined during the Covid-19 pandemic in several developed countries, and particularly in the UK. Given the resurgence of the disease in western Europe during autumn 2020 and concurrently increasing restrictions, we investigate the possible effect on well-being of a winter lockdown. Using local variation during the spring lockdown in the UK, we find little effect of weather (temperature and rainfall) on well-being. This finding is despite a strong effect of weather on mobility in parks during the same period. Together, our results suggest a limited role for recreational mobility in maintaining well-being during this period. Our evidence suggests that winter weather will not exacerbate the well-being costs of lockdowns.

JEL Classification:

Keywords: Mental well-being, Mental health, Weather, Mobility, Covid-19

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1 Introduction

A salient feature of the Covid-19 pandemic across many countries has been a decline in mental well-being (Brooks et al. 2020).[1] This decline likely has several causes, including anxiety about infection, the effects of economic recession, and more direct effects of lockdown policies themselves. Many countries in the northern hemisphere now head into winter facing a resurgence of the disease. When weighing up the costs and benefits of lockdown policies, a key question is the extent to which winter weather would make the negative effects of lockdown on well-being even worse.

This study provides evidence in this direction, by examining the effects of local variation in weather during the spring lockdown in the UK. We not only assess the effects on well-being, but also examine one of the major channels through which weather affects behaviour and subsequent outcomes: physical mobility (Wilson 2020). Mobility itself is especially relevant because UK government policy during the spring was explicitly designed to maintain well-being by encouraging exercise, such as in parks. Even at its strictest, the lockdown policy allowed for one hour of outdoor activity per day.[2] We therefore examine the impact of weather both on well-being and on mobility, exploring differential effects during the spring lockdown period compared to the periods before and after.

The established literature has typically found little effect of weather variation on mental well-being on average. Did the lockdown induce a different relationship? The answer we arrive at is no. To come to this conclusion, we use representative household panel survey data containing precise location identifiers. In all we match 30,000 individual well-being reports during the spring lockdown to local weather data, exploiting detailed information on daily temperatures and rainfall. Our point estimates of the effect of weather variation are all close to zero. In terms of inference, the bounds on 95% confidence intervals would imply non-negligible effects. However, even at these bounds, these effects would be over-shadowed by other factors prevalent in the spring. Therefore, while the effects of lockdown seem substantial, our evidence suggests that winter weather itself should not bring about a strongly differential impact on well-being.

To explore the effects of weather further, we examine its relationship with a key human behaviour, mobility. We find that temperature and rainfall impact movement in parks in the expected ways, and that the effects were accentuated during the lockdown compared to the prior period, February through early March. The size of the effects are similar to those seen elsewhere, such as in the US (Wilson 2020). This evidence implies that weather does impact human activity. Consequently, in combination our results suggest that reduced physical mobility *per se* was not an important determinant of well-being in this context. The negative effects on well-being, therefore, may have

[1] For extensive references on all the issues discussed in the introduction, see the dedicated literature review below.

[2] The importance of exercise on well-being was explicitly stated in Government guidance. See `https://www.gov.uk/government/publications/covid-19-guidance-for-the-public-on-mental-health-and-wellbeing/guidance-for-the-public-on-the-mental-health-and-wellbeing-aspects-of-coronavirus-covid-19` (accessed Oct 6th, 2020).

been caused by other aspects of the lockdown, such as social isolation, or consequences of the outbreak itself.

As elsewhere, the lockdown in the UK was introduced fairly swiftly in the middle of March, culminating in a stay-at-home order on March 23. Various components of the lockdown were then eased from early May onwards. This easing accelerated for most of the country through June, largely concluding with the opening of bars and restaurants on July 4. An important day within this sequence is May 11, when the one-hour restriction on outdoor exercise was lifted. In our analysis we explore different definitions of the timing of lockdown, but generally favour the broadest period, from March 23 to July 3, because even towards the end of this period, behaviour was affected by the closure of the hospitality sector.[3]

For analysis we use daily weather data from official weather stations employed by the UK MET office. We match weather observations to data on well-being from the UK Household Longitudinal Survey (UKHLS) which collected around 10,000 survey responses in each of the final weeks of April, May and June, alongside data from the most recent wave of the UKHLS main survey. By using short-term weather variation to make inference about the effect of longer-term patterns we follow the approach employed in the current literature on climate change (see, for example, Dell et al. 2014). By comparing the variation during the lockdown with that before, we assess if the relationship between weather and well-being is any different during periods of restricted activity. The data imply that it is not.

To assess mobility, we use data from Google Mobility (Google LLC 2020). These data have been widely used by researchers during the pandemic period in a variety of contexts, particularly to consider disease spread. Because it is the most plausible mediator between weather and well-being, we analyse mobility in parks most closely. We also show results for mobility in grocery shopping, in other retail and recreation, as well as in the additional available contexts: workplace, transit and residential. Consistent with the literature from the US, the effect of weather on these other categories of mobility has the expected signs, though compared to parks the effect sizes are typically small.

As discussed, our results on weather and well-being are broadly consistent with an established literature. On the other hand, while our findings also provide little evidence that mobility is a key driver of well-being, there is a large literature that argues that well-being is improved by exercise

[3] It is worth noting that this broader period coincides with declining infection rates, and hence a reproduction number of below 1. The backward-looking 7-day moving-average recorded case numbers peaked on April 13, 21 days after the start of the full lockdown and bottomed-out on July 8, four days after the full relaxation (`https://www.worldometers.info/coronavirus/country/uk/`). The ONS infection survey, which has reliable information on disease spread since May, indicates that infections bottomed out in the two-week period ending on July 16 (`https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/bulletins/coronaviruscovid19infectionsurveypilot/englandwalesandnorthernireland9october2020`). According to both reported cases and the ONS survey, infections then stayed low until the beginning of September before rising steadily.

and recreational activity (see the dedicated literature review below). Perhaps the most relevant study to ours, however, is Day (2020). He estimates the value of de-restricting access to green space in England after May 11 and up to the middle of June at around £1-1.5bn. This equates to roughly £20 per person for this five-week period. At this valuation, the value of access to parks seems modest and consistent with our results on well-being.

In terms of implications for policy, our results indicate that, contrary to intuition, the direct well-being costs of lockdown would not be accentuated by winter weather. These results, however, should be put into the context of large estimated negative effects of lockdown on well-being overall. Our findings also suggest a modest effect of recreational activity in this context. In this sense, our results imply that policy may be better targeted at other factors that affect well-being during lockdowns; for example finding ways to encourage social interaction while maintaining physical distancing.

In terms of optimal policy, our results should be put in the context of the wider effects of seasonality. It should first be remembered that many of the benefits of lockdown, such as slowing disease spread, are possibly greater in winter.[4] Second, it is possible that some of the economic costs of lockdown might vary by season, if less work can be performed outdoors. Additionally, mental well-being itself can follow a seasonal pattern (see e.g. the analysis in Banks and Xu (2020) who use the same well-being data). This pattern is related to various aspects of the changing seasons, including not only the weather metrics we analyse here, but also (and more importantly) day length (Huibers et al. 2010; Young et al. 1997). To the extent that these aspects are covered in our analysis, this paper finds no evidence that these seasonal well-being patterns would be magnified by lockdown.[5]

After a review of the literature, the paper proceeds as follows. We describe the data in Section 2 and provide a brief overview of the climate and weather patterns in the UK in Section 3. In Section 4 we present and discuss our results, before we conclude in Section 5.

Related Literature

Our paper relates to literatures on the associations between weather, well-being and mobility in general, and recreational mobility more specifically.

The pandemic has led to both voluntary and mandated reductions in mobility. Estimates from the US for late February and early March suggest that mobility started to decrease before restrictions were implemented (Engle et al. 2020). For example, a rise in the local infection rate from 0% to 0.003% was associated with a decrease of mobility by 2.3%. In contrast, an official stay-at-home

[4] There is limited evidence regarding the direct impact of winter weather on the spread of the disease (Smit et al. 2020), however, there are clear benefits, in terms of NHS capacity, from slowing the spread of the Covid-19 in the winter months.

[5] We cover three weather metrics: within-day temperature mean; within-day difference between maximum and minimum temperature ('temperature range'), and total within-day precipitation. Of these, temperature range is a proxy for total hours of sunshine (Dai et al. 1999), which in turn correlates strongly with length of day.

requirement reduced mobility by 7.9%. Brzezinski et al. (2020) estimate a very similar effect of official lockdown policies in the US on mobility reductions. Using data from 108 countries up to May and an event study design, Askitas et al. (2020) document that stay-at-home policies and workplace closures had a large negative impact on mobility, whereas international travel controls only had small effects.[6] With a similar dataset, but a different identification approach, Bharati and Fakir (2020) also estimate large reductions in mobility with stringent restrictions.

While it is not clear yet to what extent weather impacts the virus itself (see Smit et al. 2020, for a review), weather during the pandemic has been found to affect mobility. Kapoor et al. (2020) use county-level rainfall during the last weekend before lockdown (in the US) as an instrument for early social distancing. Their first stage results indicate a negative and significant relationship between mobility and "excess" rainfall.[7] Wilson (2020) uses daily (absolute) measures of maximum and minimum temperature, precipitation and snowfall at the county-level and finds that weekday temperatures have a strong positive effect on mobility in the US. For example, with a one degree increase in temperature, mobility in parks increases by 1.2 percentage points. The effects are smaller for weekend temperatures, where the same temperature rise is associated with a mobility increase by 0.7 in parks. Rain and snowfall have a negative effect on all measures of mobility, for both weekdays and the weekend.[8] This relationship of weather and mobility has been used to study how mobility affects the spread of Covid-19 (see, e.g., Kapoor et al. 2020; Wilson 2020). It should be noted that all these studies combining weather and mobility data focus exclusively on the US, whereas we will focus on the UK.

To the best of our knowledge, this literature on weather and mobility has not yet been linked to the research that investigates the mental health impact of the pandemic, even though it is conceivable that in addition to fears of infection and loneliness, the mobility restrictions also impact mental well-being.[9] The overall negative impacts of the pandemic on a variety of psychological factors, including (post-traumatic) stress symptoms and anxiety have been well-documented (see e.g. Brooks et al. (2020) and Rajkumar (2020) for reviews, Fetzer et al. (2020a) for a causal identification and e.g., Banks and Xu (2020), Chandola et al. (2020), Davillas and Jones (2020), and Pierce et al. (2020) for the impact on mental health in the UK).[10] Several subgroups of the population have been documented to have a larger deterioration in mental health, such as the young (Banks and Xu 2020; Davillas and Jones 2020), women (Banks and Xu 2020; Davillas and Jones 2020; Etheridge

[6] Mobility is reported for different locations, such as grocery and pharmacy, parks and workplaces (see also Google LLC 2020). Stay-at-home and workplace restrictions were the only types of policies that affected mobility in all measured domains.

[7] The authors measure rainfall as deviation from five-year historic averages for a given day. Similarly, Brzezinski et al. (2020) use temperature and rainfall as instruments for individuals' voluntary practice of social distancing (they do not, however, discuss or show their first stage results).

[8] The effects of all weather variables are largest for mobility in parks, but statistically significant for almost all other mobility measures as well.

[9] See e.g. Footnote 1 on how this potential relationship was taken into account in designing government policies in the UK.

[10] We refer the interested reader to those papers for a more detailed literature review.

and Spantig 2020) and BAME groups (Proto and Quintana-Domeque 2020). While these studies focus on personal characteristics, we explore the influence of individuals' environment, focussing on weather.

There exists, however, a general literature that examines the link between weather and health, and in particular mental well-being, with mixed empirical results.[11] Regarding temperature, Brereton et al. (2008), Feddersen et al. (2016), and Frijters and Van Praag (1998) use cross-sectional or panel data for Ireland, Russia and Australia, respectively, and find that relatively warm or sunny days are related to higher subjective well-being. However, there is also evidence of a more complicated relationship as, in hotter weather, an additional increase in temperature has been documented to decrease well-being in two different studies in the US (Connolly 2013; Levinson 2012). Lastly, the results of Frijters et al. (2020) and Lucas and Lawless (2013) show no clear or robust relationship between temperature and well-being in the US. The same mixed picture emerges for the effects of precipitation. Frijters and Van Praag (1998) report a negative relationship of humidity, but only in warmer places. In contrast, Barrington-Leigh and Behzadnejad (2017) find a negative effect of increased precipitation levels in Canada, which does not survive robustness checks such as the inclusion of fixed effects. Frijters et al. (2020) present similarly non-robust findings, and Levinson (2012) find no relationship at all.[12] These mixed findings can potentially be explained by Feddersen et al. (2016) who show that experience with the employed measure attenuates the effect of weather on well-being.

Apart from weather, measures of well-being have been shown to be subject to seasonality, but this relationship varies with measures of well-being and study location (see e.g. Ayers et al. 2013; Blacker et al. 1997). Most reliably, effects of seasonality have been linked to length of the day, especially for the clinically defined form of depression, seasonal affective disorder (Kamstra et al. 2003; Young et al. 1997). For the GHQ, our measure of well-being, seasonality has been documented in recent studies such as Banks and Xu (2020), but not older ones such as (Blacker et al. 1997).

A large literature discusses the general relationship between physical activity and mental well-being. Meta-analyses and systematic reviews suggest a link between physical activity and reduced levels of anxiety (e.g. McDowell et al. 2019) and depression (e.g. Kandola et al. 2019), not only for adults, but also for children and adolescents (e.g. Biddle et al. 2019; Dale et al. 2019). This correlation has been found to persist during Covid-19 in the UK (Jacob et al. 2020), in Canada and the US (for adults older than 49; Callow et al. 2020), in Spain (for adults older than 59; Carriedo et al. 2020) and in Austria (Pieh et al. 2020). However, as discussed in the reviews, all studies suffer

[11]More generally, our study is related to the effects of weather that have received increasing attention in economics. Research studies the effects of temperature, precipitation and extreme weather events on, inter alia, economic growth, industrial output, labor productivity, political stability and health (for an overview of the recent literature that uses panel estimation see Dell et al. 2014). Regarding health, outcomes that have been studied include death (e.g., Barreca 2012; Deschênes and Greenstone 2011), infant health (e.g., Maccini and Yang 2009) and mental well-being.

[12]Keller et al. (2005) and Klimstra et al. (2011) discuss substantial heterogeneity in the relationship of weather and mood (which is part of subjective well-being) with respect to seasonality and individual preferences, respectively. Coviello et al. (2014) find a quantitatively small, but statistically significant, negative relationship between rainfall and emotional expression.

from identification problems and cannot establish causal effects of physical activity on well-being. Similar identification issues exist in the literature discussing the positive relationship of greenspace and mental health (see e.g. Collins et al. (2020) for a review and Dzhambov et al. (2020) for a methodological critique). During Covid-19, studies indicate an increased use of urban green space during the pandemic (Day 2020; Rice and Pan 2020; Venter et al. 2020) and a negative association of living in poorer housing conditions and mental health (Amerio et al. 2020). Lades et al. (2020) find within-person positive correlations of outdoor activities and emotional well-being in Ireland on March 25.

Any effects of weather on mental well-being during lockdown can operate through an array of channels. Most relevant here are direct effects and the indirect effect through mobility restrictions.

2 Data

We combine data from three different sources: the main survey and Covid-19 module from the UK Household Longitudinal Survey (UKHLS); Google Covid-19 Mobility Reports (Google LLC 2020), and daily weather data from NOAA's National Centers for Environmental Information (NCEI).

Individual Panel Survey Data

We use the first three waves of the Covid-19 module from the UKHLS (University of Essex and Research 2020), administered via online questionnaires in April, May and June 2020. Building upon the UKHLS (also known as 'Understanding Society'), a large-scale national survey, this module covers the experience and behaviour of individuals during the Covid-19 pandemic. The underlying sampling frame consists of all those who were aged sixteen years or older and participated in at least one of the UKHLS main survey's last two waves. We merge these data with wave 9 of the UKHLS main survey that was administered between 2017-2019.[13] For a further discussion of the Covid-19 modules and underlying UKHLS design see Institute for Social and Economic Research (2020).

The main variable of interest is mental well-being. We use the General Health Questionnaire (GHQ-12), that asks respondents to evaluate 12 different aspects of their life and feelings on a 4-point Likert-scale. These include, for example, the ability to concentrate, loss of sleep and enjoyment of day-to-day activities. Importantly, in the questions, participants evaluate their well-being with respect to 'usual'. This induces a reference point against which respondents evaluate their current feelings, a feature that distinguishes our measure from other measures of mental well-being. For example, the WHO 5-question module (used e.g. in Adams-Prassl et al. 2020) or the PHQ9 depression questionnaire (adopted e.g. in Fetzer et al. 2020b) ask about occurrence of specific feelings

[13] It should be noted these data were collected mainly in 2017 and 2018, but also, to a lesser extent, in 2019.

or behaviours. While the latter measures have been shown to reflect the cognitive dimension of well-being, our measure captures affective well-being (see e.g. Diener et al. 1985). The GHQ-12 from this survey has been widely used, both in psychological (e.g. Bridger and Daly 2019) and other social sciences research (e.g. Clark et al. 2019; Davillas et al. 2016; Davillas and Jones 2020; Powdthavee et al. 2019). Importantly the GHQ-12 questionnaire has been administered in all waves of UKHLS, including the Covid-19 modules, in exactly the same form. For more details on the GHQ-12 questionnaire see the appendix and Etheridge and Spantig (2020).

Our measure for mental well-being is derived from the Likert score that sums the answers to the 12 questions, where each answer is scaled from 0 (least distressed) to 3 (most distressed). We standardize this score across all waves and invert it so that, in our analysis, lower scores indicate lower well-being. We do not go back before wave 9 of the UKHLS main survey because our focus is on the effect of lockdown and the immediately preceding period. The wave 9 data do, however, allow us to employ fixed effect models, which enable us to allow for interpersonal differences in reporting style of well-being.

In addition, we make use of the extensive background information collected in both the Covid-19 module and the prior UKHLS survey wave 9. In particular we use the respondent's location, measured at the very detailed Lower Layer Super Output Area (LSOA) level. Roughly speaking, LSOAs define local neighbourhoods, covering, on average 1,500 individuals. More broadly, in both the Covid module and main survey, participants were asked a battery of questions about their current experiences. In various regressions we include controls for age, sex, education, ethnicity, co-residency with a partner, the presence of own children in the household, employment status, as well as the region of residence. Of these, employment status is potentially the most important factor not controlled for by individual fixed effects. The adjusted number of interviews for which full information is available on all measures, is 55,874, coming from 16,576 individuals.

To adjust our analysis for non-response, we use the survey weights provided.[14] In addition, to account for the sample design, regressions are clustered at the 'primary sampling unit' (postcode sector) level. This accounts for the fact that many respondents are related through primary residence or local area.[15]

Weather Data

We use "Global Surface Summary of the Day" data from the US National Centers for Environmental Information (NCEI). This dataset contains daily observations from 201 weather stations in the UK. We obtain mean, maximum and minimum temperature of a given day as well as the daily

[14]This is particularly important here given response rates of 38.7%, 39.7% and 43.5% for the first three waves respectively.

[15]The sample design for Northern Ireland differs from the rest of the UK. For details see Lynn (2009).

precipitation amounts. The temperature data themselves are gathered using 24 consecutive hourly measurements. We use data from January 5 2017 until August 7 2020, covering all days with the well-being observations from the UKHLS (as well as the mobility data described below). The stations are located with precise latitude and longitude information, which can be used to merge with the UKHLS data

In more detail, we calculate weather for each LSOA neighbourhood by interpolating using the nearest weather station, with distances calculated using the Haversine formula. A problem to be overcome is that the data are incomplete both at the daily level and within a day. For example, the temperature data are sometimes given with only a few hourly measurements. We therefore mark as missing any temperature measurements based on 16 or fewer hours. Because of these missing observations we use an iterative procedure to find the nearest station to each LSOA on each day and for each weather category. Throughout our analysis we limit this search to the nearest 30km, and treat as missing any nearest weather observations that is above this limit, as is standard in the literature. Using this procedure results in obtaining satisfactorily accurate weather data for over 80% of respondents in each wave of data.

For our analysis, we use mean daily temperature and calculate 'temperature range' as the difference between the maximum and the minimum temperature of a given day. The latter can be interpreted as a rough proxy for cloudiness as the temperature range is larger with a clear sky.[16] To ease interpretation and comparison between the weather variables, we de-mean them across the sample and re-scale them as follows: we divide mean temperature and temperature range by 10 and multiply precipitation by 10. The relevant units are therefore 10°Farenheit and 1/10s of an inch.

Mobility Data

Mobility data are obtained from the Google Covid-19 Mobility Reports, which provide anonymized and aggregated measures of mobility constructed from users' cell-phone location histories activated in their Google account (the default is to have this deactivated). Data are available for 151 mobility zones in the UK between February 15 and August 7 2020. These zones are typically major cities or counties, corresponding roughly to an aggregated form of local authorities.[17] The measure of mobility provided is the change in a mobility metric, capturing the number of visits and duration of stay in six different categories of locations (retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residential homes), compared to a baseline. This baseline mobility measure is the median value of the mobility metric of the set of same days of the week between January 3 and February 6 2020.

[16] As discussed in the next section, the range also varies by season, a fact that is controlled for with time fixed effects in the regression analysis.

[17] For example, Greater London comprises 32 local authorities ('borough councils') but is aggregated to single zone here.

Table A.1 shows that, in our sample period, retail and recreation has the largest reduction in mobility. This is not surprising: a large fraction of the data covers the UK lockdown period and this category of mobility is most impacted by the lockdown rules. Even though grocery and pharmacy can be considered an essential movement category, the average mobility (as compared to the baseline period) is reduced. In contrast, mobility in parks increased compared to the baseline, likely a joint effect of changing seasons in our sample period and the lack of alternative recreational activities during the lockdown period.[18]

We match mobility zones to the station weather data using the geographic central point of each mobility zone, and then employ the same iterative procedure used for the individual panel data specified above. Of the six different categories we focus on retail and recreation, grocery and pharmacy and, most importantly, parks as likely factors influencing well-being. We present results from the main specification for the remaining categories in the appendix. We weight all regressions using zone population to make the results representative for the country as a whole.

3 Climate and Weather in the UK

This section first provides a short descriptive overview of weather patterns in our sample and in the UK in general to illustrate the variation we will be using and to facilitate interpretation of our results. We start with an overview of the UK climate in terms of temperature and rainfall patterns over the last forty years.

Climate in the UK

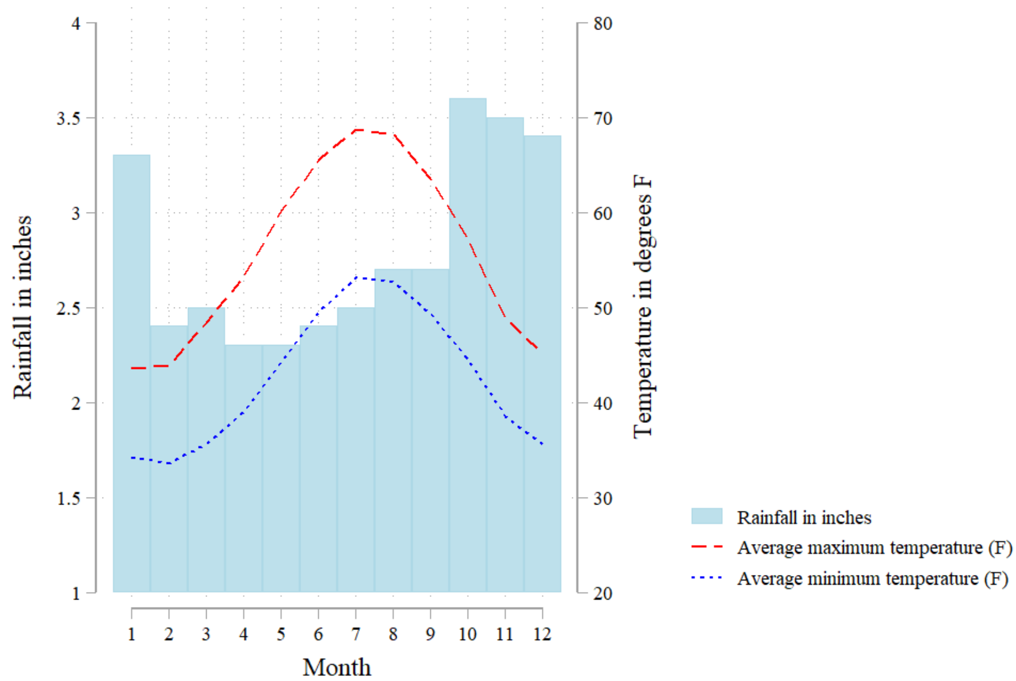
Figure 1 shows monthly averages for maximum and minimum temperatures in England averaged over the period of 1981-2010.[19] The hottest month in England is usually July with an average maximum temperature of 68.7°F and an average minimum of 53.1°F. The coldest month is usually February (43.9°F average maximum and 33.6°F average minimum temperature).

The time from October to January can be considered the 'wet' season with average monthly rainfall of 3.3-3.6 inches compared to February to September with average rainfall levels between 2.3-2.7 inches. The wet season is also the time with more rain days (defined by having at least 0.04 inches of precipitation; the average daily precipitation in our data): on average, there are 13 days per month in this season as compared to 10 days in the dry season. Both the average number of rain days and the average precipitation conceal substantial heterogeneity across regions. Figures A.1 and

[18] It should be noted that there are fewer observations for mobility in parks. This is likely related to missing data due to too few observations to retain confidence in the metric capturing meaningful change (Aktay et al. 2020).

[19] Data for this general description of patterns come from the MET office. The most recent statistics available only cover the period from 1981 up to 2010.

Figure 1: England Weather Averages 1981-2010



Notes: Data from the MET Office.

A.2 illustrate this heterogeneity by showing the geographical (in addition to seasonal) variation of average rain days and rainfall, respectively. For example, the East is comparatively dry throughout the seasons.

Table 1 builds on this by showing simple tabulations of various quantiles of daily rainfall across broad regions of the UK. These regions roughly capture the dry areas - the south east (including London), and the north east of England (including the midlands and Yorkshire) - and the wetter areas - the south west (including Wales), and the north west (including Scotland and Northern Ireland). The statistics are split by wet and dry seasons. Looking forward to our regression results in Section 4, it is worth keeping in mind the upper end of these distributions: During the wet season in the south west, there is over 0.4 inches of rain on at least one in ten days.[20]

Weather in our Sample Period

To illustrate the daily weather during the UKHLS Covid waves, Figure 2 plots the mean temperatures for one day per survey wave. With average temperatures of 51.1°F during the data collection

[20]Having said this, it should also be remembered that these distributions are equally weighted across each region's geographic extent. In each region the population is typically clustered away from the rainiest areas such as mountains and towards low lands which are dryer.

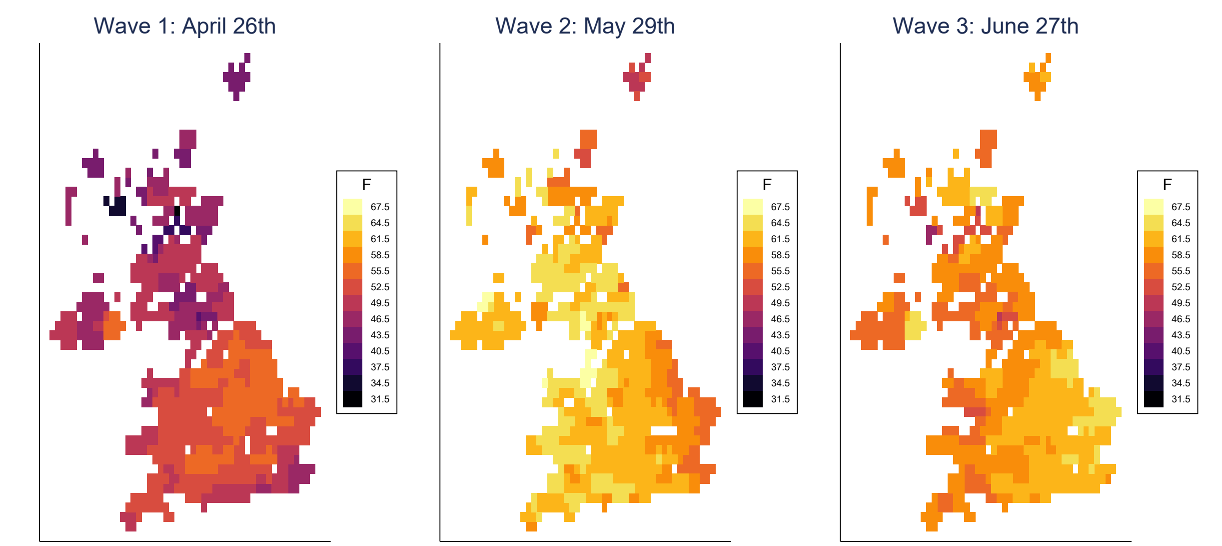
Table 1: Percentiles of Daily Rainfall Distribution (Inches)

	Feb-Sep			Oct-Jan		
	Median	70th	90th	Median	70th	90th
South East	0	0.02	0.17	0	0.04	0.24
Mid. & North East	0	0.02	0.20	0.01	0.04	0.21
SW and Wales	0.01	0.06	0.31	0.02	0.13	0.43
NW, Scot. & NI	0.01	0.07	0.29	0.02	0.10	0.35

Notes: Statistics computed using NCEI data over 2016-2020. Rows are aggregated government office regions: 'South East' comprises South East region, London and East of England. 'Mid.' comprises West and East Midland regions. 'North East' comprises the North East and Yorkshire regions. 'SW', 'NW' are the North East, South West and North West regions. 'NI' is Northern Ireland. Distributions defined by geography; i.e. they are *not* weighted by population.

in April, 61.2 ˚F in May and 65.4˚F in June, the weather was warmer during the surveys than long-run England averages for April (46.1˚F), May (52.2˚F) and June (57.5˚F).

Figure 2: Temperatures During UKHLS Covid Waves

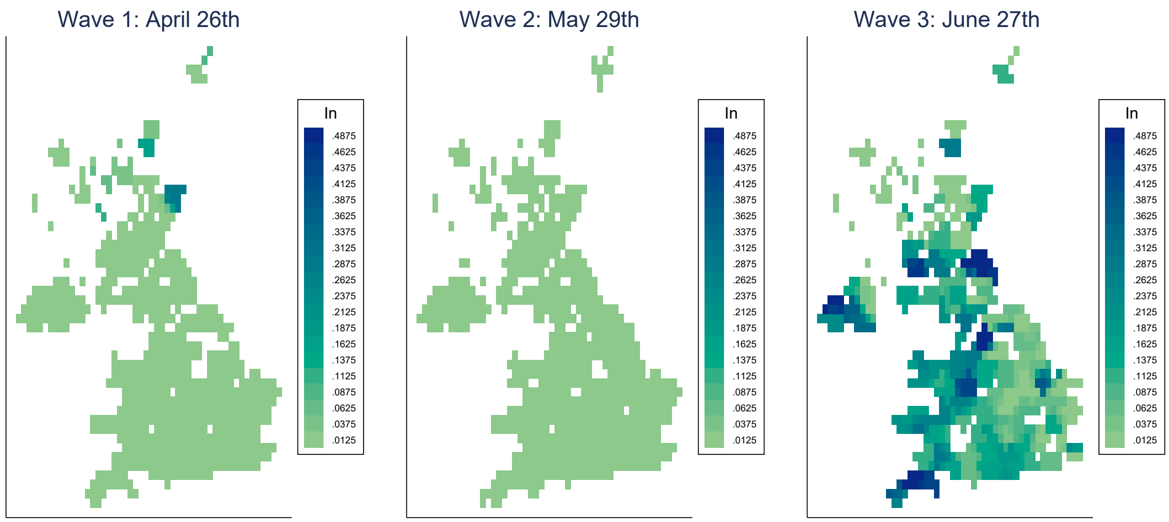


Notes: Cell mean temperature is assumed to be missing if the nearest weather station without missing information is further than 30km away. Source: NCEI.

Figure 3 plots total precipitation for the third day of the first, second and third UKHLS covid waves. The figure also clearly shows that the third wave in June has more variation in rainfall across regions than the other two waves.

Table A.1 shows descriptive statistics for all main variables. Compared to England's climate, our sample period is relatively hot, with a mean daily temperature of 57˚F (SD: 9.1) and relatively dry, with a mean daily precipitation of 0.04 inches (SD: 0.13). Temperature range stretches from approximately zero (constant temperature throughout the day and night) to 40˚F, with a mean

Figure 3: Precipitation During UKHLS Covid Waves



Notes: Cell mean temperature is assumed to be missing if the nearest weather station without missing information is further than 30km away. Observations are winsorized at 0.5 inches, this impacts Covid wave 3 only, and covers 95% of the sample. Source: NCEI.

of 18°F, slightly larger than the 1981-2010 average (16°F in June). As Figure 1 shows, the range is generally larger in warmer months. The warmer and dryer sample period than the 1981-2010 averages are consistent with global warming.

4 Results

We first present results on the relationship between weather and mobility before moving on to discuss the relationship between weather and well-being. Throughout our analysis, our main independent variables are mean temperature, temperature range as well as total precipitation (similar to e.g. Barrington-Leigh and Behzadnejad 2017). Including these variables in one model takes into account that temperature and precipitation tend to be correlated and that this correlation can differ across regions (Auffhammer et al. 2013).

Weather and Mobility

We first show how daily weather, in terms of temperature and precipitation, affects mobility patterns in the UK. To this end, we use the following base model (equation 1), that regresses changes in mobility (m; measured in percent change from the baseline) in location l on day t on our weather variables:

$$m_{lt} = \alpha + \beta_1 temp_{lt} + \beta_2 range_{lt} + \beta_3 rain_{lt} \\ + \phi_l + \xi_t + \zeta_{l\vartheta(t)} + \psi_{ld(t)} + \epsilon_{lt}, \tag{1}$$

where $temp_{lt}$ is the mean daily temperature, $range_{lt}$ the difference between maximum and minimum temperature during the day and $rain_{lt}$ is the level of total precipitation. To absorb time-invariant characteristics of local communities such as demographic composition or infrastructure, we add location fixed effects ϕ_l, as is standard in the literature. As is also standard, date fixed effects ξ_t are included to absorb seasonal factors as well as any common time components, such as increased activity around Bank Holidays. As we shall see shortly, mobility has also seen an upward trend from the strictest period of restrictions in April.

We augment the model by including $\zeta_{l\vartheta(t)}$, an interaction of location and a trichotomous lockdown variable $\vartheta(t)$. In the base model, this lockdown variable partitions the period into 'pre-lockdown' (February 15 – March 22), 'lockdown' (March 23 – July 3) and 'eased restrictions' (July 4 onwards). The interaction with location is included to capture the result of location-specific restrictions after the end of full lockdown in July and August ('local lockdowns'), as well as any differential compliance during the lockdown period itself.[21] Finally, we add $\psi_{ld(t)}$, an interaction of location and day of the week $d(t)$. This is primarily included to take account of the structure of the data, which is normalized at the location $\times$ day-of-the-week level. It also controls for, say, different patterns of mobility across the week and across rural and urban locations. We allow for arbitrary correlation of the error terms ϵ_{lt} within locations and across time, by clustering standard errors at the location level.

Given this model, the variation in weather we mostly exploit is deviations from day- and location-specific averages. By including the interaction term $\zeta_{l\vartheta(t)}$ we also control, to a large extent, for location-specific seasonal patterns. Having said this, because we only use one year of data, we also remove variation induced by unusual weather within each 'cell' which we would ideally prefer to include.[22]

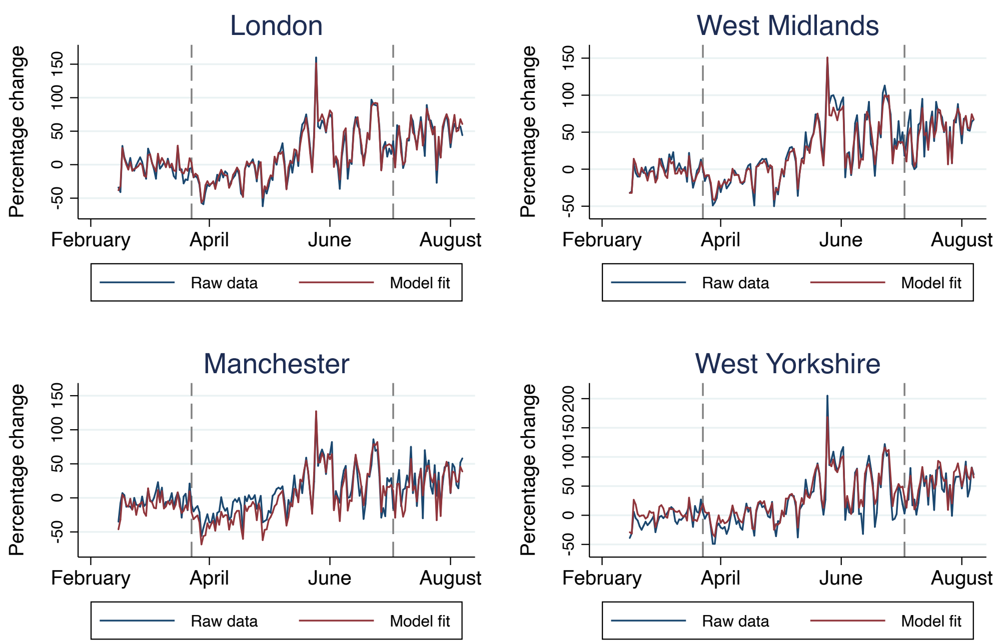
To illustrate the mobility patterns over time and across locations, Figure 4 plots the raw mobility data for parks (blue line) for the four most populous zones in the data: London; West Midlands; Manchester, and West Yorkshire. The vertical lines represent the start and the end day of the lockdown period respectively. The overall pattern is similar in all four mobility zones: before the lockdown, average mobility appeared to be no different from the baseline. The introduction of

[21] Note that locations not only varied in the *level* of restrictions after July 4, but also in the timing of transition to this eased period. For example Scotland started relaxing restrictions with the reopening of outdoor hospitality on July 6. For simplicity we ignore these slight differences in timing.

[22] A final point to note is that by including the $\zeta_{l\vartheta(t)}$ term we control for possible differences in local restrictions caused by the weather or climate directly. Although this channel is conceivable, we have not seen any evidence supporting it in the literature or media.

the strict lockdown coincided with a noticeable drop in mobility in parks, despite them generally remaining open throughout the lockdown period.[23] Following the relaxation in May of rules on time spent outdoors, mobility rose significantly above the baseline with a noticeable peak in all four areas on the Spring bank holiday (May 25). As discussed, since the google mobility data are only available for this year, we cannot separate effects of lockdown restrictions and weather from seasonality patterns. Indeed, the analysis in Rice and Pan (2020) suggests that large parts of the changes in park mobility in the US is driven by seasonality.

Figure 4: Changes in Mobility



Notes: The raw data captures the change in visits and length of stay in parks compared to the median values for the day of the week between January 3-February 6 2020. Predicted values are obtained by regressing park mobility on location fixed effects, date fixed effects, an interaction of location and the trichotomous lockdown variable and an interaction of location and day of the week. Population weights are used.

To illustrate the quality of the model, Figure 4 also includes fitted values (red lines), from a specification *without* the weather variables included. It shows that the raw fixed effects capture the bulk of variation in mobility. This fit shows that our regression results presented later are unlikely to be the result of spurious regression between weather and, say, bank holidays.

Table 2 shows our main regression results for the effects of weather and the lockdown on changes in mobility. We focus here on mobility in parks, which is the best available proxy for recreational outdoor activities. Column 1 shows results from the specification in equation 1 without the location-

[23] Over March 23 – May 10 the population was asked to stay at home except for essential trips to e.g. supermarkets or pharmacies and a daily exercise session. During this period several parks in London (e.g. Victoria Park and Brockwell Park) and in other parts of the country (e.g. Stevens Park Quarry Bank in Dudley Council) closed temporarily because distancing rules were not followed. Other parks, e.g. the Royal Parks, remained open with restrictions such as shorter opening hours, closure of cafes and the ban of picnics.

lockdown interaction, while Column 2 includes this interaction. Both columns show qualitatively similar results, with slightly stronger results (larger and more precisely estimated coefficients) in Column 2: Throughout the sample period, mobility in parks is larger when i) temperature is high, ii) the difference between the minimum and the maximum temperature is large and iii) there is no or little rainfall. Following (Frijters et al. 2020), we also present results for specifications including differences of the weather variables with respect to the previous day in Column 3. When temperature (both in terms of the mean and the range) improves as compared to the previous day, mobility in parks increases, while the positive effects of temperature mean and range as well as the negative effect of precipitation persist. We find no statistically significant effect of rainfall "shocks" on mobility in parks.

Our preferred specification is presented in Column 4 of Table 2, where each of the daily weather variables can impact mobility differently across the three time periods. Since lockdown is the omitted category, the coefficients for the weather variables can now be interpreted as the effect of weather on mobility in parks during this lockdown period. During the lockdown, a temperature increase of 10°F leads to a 8.2 percentage point increase in mobility. Evaluated at the mean mobility during the lockdown (11.9 percent above the January/mid-February baseline), this implies an increase of 7.4%. Similarly, an increase in the temperature range of 10°F implies a 9.5 percentage point or a 8.5% increase in mobility. These are large effects considering that the average temperature during the data collection for the second covid wave was around 10°F above the average temperature seen during the first wave. Conversely, an increase in rainfall by 0.1 inches (the sum of 2.5 average days) leads to a decrease in mobility of 1.3 percentage points or 1.2%. Keeping in mind the percentiles presented in Table 1, this is a small effect given that the median days in all regions in the wet season see at most 0.02 inches of rainfall, which would imply a decrease in mobility by 0.2% compared to a completely dry day. These patterns are not statistically significantly different to the period after the lockdown ('eased restrictions'). For the pre-lockdown period, in contrast, the effect of an increase in mean temperature on mobility is less pronounced. The same holds true for the effect of precipitation, with both effects being indistinguishable from zero.

We present estimates from our preferred specification for parks, grocery and pharmacy as well as retail and recreation in Table 3. Column 1 is identical to Column 4 of Table 2 and is included for ease of comparison. During lockdown, the effects of weather on mobility work in the same direction for all three types of mobility (first three rows): temperature is positively associated with mobility, whereas precipitation affects mobility negatively. However, we note stark differences with respect to effect sizes, where the impact of weather is largest on park mobility. Given that grocery and pharmacy are more likely to constitute essential trips, it is not surprising that weather affects this type of mobility much less, or – as in the case of precipitation – not at all (0.6 percentage points or 0.8% increase in mobility as compared to the lockdown mobility of 23.6 percent below the baseline for an increase in mean temperature and 1.7 percentage points (1.5%) for an increase in the temperature range). The even smaller effect sizes for retail and recreation in terms of percentage

Table 2: Mobility Regression Estimates - Parks

	(1)	(2)	(3)	(4)
Mean temp. (tens of F)	5.797	7.866***	5.643***	8.234***
	(3.531)	(1.834)	(2.144)	(1.737)
Temp. range (tens of F)	8.866***	9.212***	7.071***	9.463***
	(1.046)	(0.897)	(1.232)	(1.099)
Rainfall (tenths of an inch)	-0.475**	-0.820***	-0.775**	-1.292***
	(0.219)	(0.204)	(0.365)	(0.355)
Δ Mean temp.			4.516***	
			(0.963)	
Δ Temp. range			2.359***	
			(0.480)	
Δ Rainfall			0.0342	
			(0.214)	
Pre-lockdown × Mean temp.				-4.840**
				(2.170)
Pre-lockdown × Temp. range				-0.943
				(1.619)
Pre-lockdown × Rainfall				1.394***
				(0.438)
Eased restrictions × Mean temp.				0.920
				(5.340)
Eased restrictions × Temp. range				-1.034
				(1.868)
Eased restrictions × Rainfall				-0.458
				(0.733)
N	13,211	13,211	11,816	13,211
DV mean	20.39	20.39	19.70	20.39
Location and date fixed effects	✓	✓	✓	✓
Location-day of the week interaction	✓	✓	✓	✓
Location-lockdown interaction	.	✓	✓	✓
Adj. R^2	0.828	0.918	0.918	0.918

Notes: Sample covers February 15 2020-August 07 2020. The lockdown period is specified as March 23-July 03 2020. The measure of mobility captures the change in visits to and length of stay in parks compared to January 03-February 06 2020. Weather variables have been centered. Weights are used to account for population. Standard errors are robust and clustered at the mobility zone level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

points are likely due to a combination of reduced availability and the fact that many of the places covered in retail and recreation take place inside.[24] For completeness, Table A.3 presents results for the other three available mobility measures, workplaces, transit stations and residential areas. The effects are consistent, showing a positive effect of temperature and a negative effect of precipitation on mobility outside the house for the lockdown period.

Table 3: Mobility Regression Estimates

	Parks	Grocery and Pharmacy	Retail and Recreation
Mean temp. (tens of F)	8.234***	0.638***	0.240
	(1.737)	(0.186)	(0.263)
Temp. range (tens of F)	9.463***	1.172***	0.725***
	(1.099)	(0.150)	(0.123)
Rainfall (tenths of an inch)	-1.292***	-0.0446	-0.126**
	(0.355)	(0.0421)	(0.0545)
Pre-lockdown × Mean temp.	-4.840**	2.150***	-0.951
	(2.170)	(0.706)	(0.773)
Pre-lockdown × Temp. range	-0.943	-0.0390	0.798
	(1.619)	(0.518)	(0.759)
Pre-lockdown × Rainfall	1.394***	0.0799*	0.397**
	(0.438)	(0.0408)	(0.193)
Eased restrictions × Mean temp.	0.920	-0.645	-3.819***
	(5.340)	(0.474)	(1.233)
Eased restrictions × Temp. range	-1.034	-0.861***	-0.685**
	(1.868)	(0.209)	(0.276)
Eased restrictions × Rainfall	-0.458	0.0131	-0.000864
	(0.733)	(0.0784)	(0.121)
N	13,211	17,525	17,406
DV mean	20.39	-13.74	-45.01
Location and date fixed effects	✓	✓	✓
Location-day of the week interaction	✓	✓	✓
Location-lockdown interaction	✓	✓	✓
Adj. R^2	0.918	0.978	0.987

Notes: Sample covers February 15 2020-August 07 2020. The lockdown period is specified as March 23-July 03. The measure of mobility captures the change in visits to and length of stay in places specified in the dependent variable compared to January 03-February 06 2020. Weather variables have been centered. Weights are used to account for population. Standard errors are robust and clustered at the mobility zone level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[24] The effect of temperature range on retail mobility compared to a lockdown mobility of 67.3 percent below the baseline is a 2.2% increase and for precipitation a 0.39% decrease.

These patterns are not driven by our comprehensive definition of the lockdown period (March 23 – July 3). Table A.4 replicates Table 3 but uses a more detailed distinction between different lockdown restrictions. In particular, we now distinguish strict lockdown (March 23 – May 10) and a period in which unlimited exercise was allowed (May 11 – July 3). The last period remains the one of eased restrictions, that started on July 4 when the hospitality industry was allowed to re-open. Using this more nuanced definition of the different lockdown phases, we find the strongest effects of temperature on mobility in parks for the period in which unlimited exercise was allowed (shown in the top two rows: 9 percentage points for mean temperature and 13 percentage points increase in mobility for temperature range). Effects of mean temperature are similar in the strict lockdown and the eased restriction period and weaker and not statistically significant before the lockdown. The effect of temperature range is weaker (but still statistically significant) in all other periods but rainfall *only* reduces mobility in the lockdown periods ('strict lockdown' and 'unlimited exercise'). We conclude from these results that, although aggregate mobility patterns are very different across the two halves of lockdown, the response of mobility to weather is similar across these sub-periods.

In terms of estimated effect sizes, our results are comparable to those of Wilson (2020). For the period of February 29 – June 23, he estimates that an increase in the *maximum* daily temperature by 10°F leads to an increase in mobility at parks in the US by 12.0 percentage points on weekdays and 7.0 percentage points on weekends. We estimate the effect of a similar increase in the *mean* daily temperature to lead to a 8.2 percentage point increase in the UK for the period of March 23 – July 3. For precipitation, Wilson (2020) finds a decrease in mobility in parks by 1.13 percentage points on weekdays and 2.12 percentage points on weekends. In comparison, we estimate the decrease to be 1.3 percentage points in the UK.

Weather and Well-Being

Similar to the estimation of the effect of weather on mobility, we use variants of the following model:

$$\begin{aligned} GHQ_{it} = \alpha &+ \beta_1 temp_{rt} + \beta_2 range_{rt} + \beta_3 rain_{rt} \\ &+ \gamma_1 Wave1_t + \gamma_2 Wave2_t + \gamma_3 Wave3_t \\ &+ \lambda X_{it} + \zeta_i + \phi_{g(r)} + \epsilon_{it} \end{aligned} \tag{2}$$

that regresses mental well-being measured by the inverted GHQ score of individual i on survey date t on our weather variables, as defined above. Weather (mean and range of temperature, and rainfall) is defined at the LSOA-day level. LSOAs are denoted by r, which could more fully be expressed as a function of i and t, though we omit this dependence for ease of notation. Additionally, we include indicators for the three Covid waves, leaving UKHLS wave 9, which we refer to as 'pre-lockdown', as the reference category. ζ_i is an individual fixed effect that absorbs all time invariant characteristics such as race. The vector X_{it} includes individual-level controls that might vary over time such as age and more importantly employment status, co-residency with a partner and the day of the week the survey was completed (the table notes present an exhaustive list).

For location, we include $\phi_{g(r)}$ as government office region fixed effects. Theoretically, we therefore exploit systematic variation in weather within these regions. In practice, however, most individuals do not change residency over the survey period, and so most of this within-region variation is absorbed by the individual fixed effects. Similarly to before, we allow for broad correlation of the error terms ϵ_{it} across time by clustering standard errors at the primary sampling unit (postcode sector) level.

Table 4 presents results of the effect of weather on mental well-being. Column 1 includes government office region fixed effects and thus exploits variation within these regions, Column 2 includes individual characteristics as well as the month of the wave 9 interview to capture potential seasonality in our well-being measure, and Column 3 presents results from the model described in equation 2, where we include individual fixed effects to exploit within-individual variation. The qualitative results are the same across all three specifications: weather does not impact well-being, with all estimated coefficients being small and statistically insignificant. Column 4 follows Column 3 of Table 2 in terms of including the differences of the weather variables with respect to the previous day. Neither the weather variables nor the differences matter for well-being in this specification. Column 5 is most similar to our preferred specification for the analysis of mobility patterns by allowing differential effects of weather before and during the lockdown.[25] Consistent with the results from the previous specifications, we do not find any significant effect of weather on well-being. Lastly, Column 6 presents estimates for the 75% of the sample living in urban areas where access to greenspace is most likely limited to parks, and thus might make the sample more comparable to the one whose mobility data we use. The estimates of the effect of weather on well-being during the lockdown are somewhat larger, but remain statistically insignificant.

Interestingly, a comparison of the standard errors reveals that the effects of weather are more precisely estimated than the effects of the lockdown itself. For example, we would be able to detect an effect of mean temperature on well-being if it were at least 0.05 points large (range: 0.04 points and rainfall 0.02 points; based on Column 5). This compares to a fifth the effect size of the lockdown and is dwarfed by the effects of, for example, financial insecurity or loneliness.[26] Note that the level of precision is similar for pre-lockdown estimates. We therefore conclude that weather does not impact well-being to a large extent, either before or during the lockdown.

A final way of comparing effect sizes is to consider the difference in average temperatures between winter and summer. As shown in Figure 1, February is, on average 22°F colder than July. At the

[25] Note, however, that the pre-lockdown period in the mobility data covers February 15 – March 22, whereas the pre-lockdown period in the UKHLS data means the wave 9 interview, conducted between 2017 and 2019.

[26] For example, men who reported a "very difficult" financial situation also reported a well-being decline 0.65 points larger during April 2020 compared to wave 9 than those whose finances were "comfortable". Women who reported often feeling lonely also reported a well-being decline 0.99 points larger than those who were never lonely.(see Etheridge and Spantig 2020)

Table 4: Well-being Regression Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Mean temp. (tens of F)	-0.00635	-0.00965	-0.000671	-0.0138	0.00264	0.00387
	(0.0172)	(0.0154)	(0.0140)	(0.0171)	(0.0240)	(0.0264)
Temp. range (tens of F)	-0.0102	-0.00174	-0.00747	0.00337	-0.0167	-0.0310*
	(0.0198)	(0.0187)	(0.0165)	(0.0234)	(0.0181)	(0.0184)
Rainfall (tenths of an inch)	0.00388	0.00359	-0.00260	-0.00568	-0.00713	-0.00861
	(0.00703)	(0.00671)	(0.00512)	(0.00686)	(0.0104)	(0.00853)
Δ Mean temp.				0.0234		
				(0.0260)		
Δ Temp. range				-0.0250		
				(0.0199)		
Δ Rainfall				0.00401		
				(0.00561)		
Wave (Wave 9 UKHLS omitted)						
Covid wave 1	-0.179***	-0.241***	-0.187***	-0.197***	-0.189***	-0.133*
	(0.0236)	(0.0227)	(0.0601)	(0.0608)	(0.0650)	(0.0687)
Covid wave 2	-0.165***	-0.184***	-0.181***	-0.177***	-0.186***	-0.117*
	(0.0302)	(0.0291)	(0.0633)	(0.0648)	(0.0638)	(0.0708)
Covid wave 3	-0.175***	-0.196***	-0.195***	-0.174***	-0.203***	-0.154*
	(0.0347)	(0.0333)	(0.0639)	(0.0667)	(0.0654)	(0.0803)
Pre-lockdown × Mean temp.					-0.00683	-0.0172
					(0.0284)	(0.0327)
Pre-lockdown × Temp. range					0.0262	0.0530
					(0.0349)	(0.0432)
Pre-lockdown × Rainfall					0.00727	0.00654
					(0.0121)	(0.0107)
N	41,055	40,810	41,041	39,247	41,041	28,677
Mean of DV	0.02	0.02	0.02	0.02	0.02	0.00
Wave and region fixed effects	✓	✓	✓	✓	✓	✓
Control for month of wave 9 interview	.	✓	.	.	.	.
Controls	.	✓	✓	✓	✓	✓
Individual fixed effects	.	.	✓	✓	✓	✓
Sample	Full	Full	Full	Full	Full	Urban only
Adj. R^2	0.00812	0.0767	0.0283	0.0291	0.0284	0.0257

Notes: Controls include age, age squared, race, sex, level of education, a dummy capturing whether the individual co-resides with a partner, a dummy capturing own children in the household dummy, the season of UKHLS interview and whether the day of response was during a weekend. January is the omitted category from 'month of wave 9'. Likert score is inverted, so that a greater value implies greater wellbeing, and standardized. Cross sectional weights are used for models without individual fixed effect, and weights from the April UKHLS Covid survey are used for estimated models with individual fixed effects. Weather information is assumed to be missing if the weather station is more than 30km away from the LSOA in which the individual lives. Standard errors are robust and clustered at the primary sampling unit level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

upper bound of the 95% confidence interval, this temperature difference would generate a well-being effect of 0.11 points. This is non-negligible, but still overshadowed by the effects listed above.

We present results for the more nuanced definitions of lockdown in Table A.5. For ease of comparison, Column 1 shows Column 3 from Table 4 while Column 2 extends the specification in Column 5 of Table 4. As in the mobility analysis, 'unlimited exercise' (May 11 – July 3) is now the omitted category, so the estimates in the first three rows of Column 5 show the effect of weather on well-being during this period. We lose some precision, but the results remain similar to the ones discussed above: we find no statistically significant effect of any weather variable on well-being, either during the unlimited exercise period or during the strict lockdown. As before the absence of an effect of weather on well-being also holds true for wave 9 data (labeled as pre-lockdown in the table).

How plausible are the results? First, a negligible effect of weather on well-being is in line with the recent literature on this topic (e.g. Barrington-Leigh and Behzadnejad 2017; Frijters et al. 2020; Levinson 2012; Lucas and Lawless 2013).While these studies have investigated the relationship between weather and well-being in the US and in Canada, there is no reason to think that the relationship should be any different in the UK. The inclusion of individual fixed effects allows us to control for potential time-invariant confounding effects, which strengthens the analysis. Second, in line with the studies using the UKHLS covid waves to document a decline of well-being in the UK population (e.g. Banks and Xu 2020; Chandola et al. 2020; Davillas and Jones 2020; Pierce et al. 2020), we find a robust and negative relationship of the covid wave indicators across all specifications. The size of the effect is quite similar whatever the controls we include, with roughly a 0.2 standard-deviation drop in well-being as compared to UKHLS wave 9 for all three months of the covid module. Lastly, as Feddersen et al. (2016) discuss, the effect of weather on self-reported well-being decreases with panel experience, so it is not surprising to find no effect of weather on well-being in our panel data.

A final point to consider is that weather might not be fully exogenous given that respondents themselves chose when to take the survey, within the one-week survey period. Reassuringly, Figure A.3 shows the expected downward trend in completion over the survey week for all three surveys with a small peak when reminders are being sent. This, together with the weather variation across waves (see Figures 2 and 3) makes it less likely that weather is an important determinant of survey taking time and more plausible that weather is exogenous.

5 Conclusion

We study the effect of weather, in terms of temperature and rainfall, on mobility and well-being during the spring lockdown in the UK. We find that weather affects mobility, especially in parks, with effect sizes similar to those found for the US (Wilson 2020). Conversely, we find no sizable effect of weather on well-being, either during the lockdown or before.

While the zero effect of weather on well-being in the pre-covid survey could have been expected based on previous findings, it is interesting that we do not find a relationship during lockdown either. This is especially surprising given the effects of weather on mobility during this period. In combination with the (mainly correlational) evidence that being outdoors is linked to enhanced well-being, both in general (Collins et al. 2020) and during the pandemic (Lades et al. 2020), one could have expected a non-negligible effect of weather on well-being. Nonetheless, we clearly replicate the sizable and consistent within-individual drop of well-being in March, April and May 2020. We therefore hypothesize that the pandemic is affecting well-being through other channels than mobility restrictions. This is consistent with Brodeur et al. (2020) who document an increase in boredom and loneliness during lockdowns in Europe and the US, as well as Chandola et al. (2020) and Etheridge and Spantig (2020) who find that the decrease in well-being in the UK is associated with increased feelings of loneliness. The latter studies additionally find a significant, albeit smaller, association between decreasing well-being and increasing domestic work demands such as childcare and home schooling.[27]

The null effect of weather on well-being implies that a winter lockdown would not affect well-being through the lack of physical mobility. However, it should be noted that well-being itself can be seasonal (see e.g. the discussion in Banks and Xu 2020) and thus might fall in the coming months, even absent further lockdowns. It should also be taken into account that economic impacts will likely manifest themselves more clearly and for a broader range of the population in the future than in the spring. In addition, rising numbers of infections itself can also lead to economic anxiety and thus decreases in well-being (Fetzer et al. 2020a). Moreover, this climate of economic downturn and uncertainty will likely be exacerbated by the effects of Brexit.

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Appendix

A Additional Tables and Figures

Table A.1: Descriptive Statistics

	No.	Mean	Std.Dev	Min.	Max.
Well-being					
Likert score	46,969	-0.05	1.04	-4.07	2.04
Weather					
Mean temp. (F)	40,812	56.63	9.09	21.40	80.50
Temp. range (F)	40,810	18.08	7.21	0.90	40.20
Rainfall (inches)	40,812	0.04	0.13	0.00	4.72
Δ Mean temp.	40,798	-0.66	3.68	-16.10	17.80
Δ Temp. range	40,796	16.16	6.76	-1.06	37.66
Δ Rainfall	39,031	0.01	0.13	-3.26	2.41
Mobility					
Retail and recreation	25,530	-15.70	14.65	-80.00	52.00
Grocery and pharmacy	25,349	-47.78	28.42	-100.00	58.00
Parks	18,950	17.98	43.96	-82.00	456.00

Notes: "Difference" versions of the weather variables capture the change since the previous day. The measure of mobility captures the change in visits to and length of stay in parks compared to January 03-February 06 2020. The sample used in calculating the descriptives for well-being include observations with complete information. The values of the weather variables correspond to the statistics for the weather merged with the UKHLS dataset. Survey weights are used when computing the descriptives of the Likert score and weather variables, and population weights are used when computing the mobility descriptives.

Table A.2: Descriptive Statistics - Mobility by Period

	Parks	Grocery and Pharmacy	Retail and Recreation
Pre-lockdown	-0.11	4.39	-5.88
Lockdown	11.90	-23.61	-67.33
Eased-restrictions	58.14	-13.72	-34.70

Notes: Mean mobility by period and location.

Table A.3: Mobility Regression Estimates - Additional Mobility Categories

	Stations	Workplaces	Residential
Mean temp. (tens of F)	-0.178	0.207	-0.237***
	(0.370)	(0.139)	(0.0630)
Temp. range (tens of F)	1.106***	0.207***	-0.383***
	(0.211)	(0.0653)	(0.0669)
Rainfall (tenths of an inch)	-0.289***	-0.117***	0.0557***
	(0.0560)	(0.0245)	(0.0101)
Pre-lockdown × Mean temp.	0.996	-1.569*	0.594**
	(0.826)	(0.794)	(0.290)
Pre-lockdown × Temp. range	-0.0921	0.490	-0.194
	(0.692)	(0.504)	(0.212)
Pre-lockdown × Rainfall	0.204	0.523***	-0.268***
	(0.138)	(0.152)	(0.0890)
Eased restrictions × Mean temp.	-1.464	-1.214***	-0.0204
	(0.921)	(0.266)	(0.0992)
Eased restrictions × Temp. range	-0.640**	-0.0334	-0.0798
	(0.317)	(0.137)	(0.0639)
Eased restrictions × Rainfall	-0.0259	0.241***	-0.0236
	(0.193)	(0.0422)	(0.0217)
N	17,208	17,893	14,586
DV mean	20.50	-13.75	-42.95
Location and date fixed effects	✓	✓	✓
Location-day of the week interaction	✓	✓	✓
Location-lockdown interaction	✓	✓	✓
Adj. R^2	0.971	0.992	0.993

Notes: Sample covers February 15-August 7 2020. The lockdown period is specified as March 23-July 3. The measure of mobility captures the change in visits to and length of stay in places specified in the dependent variable compared to January 03-February 06 2020. Weather variables have been centered. Weights are used to account for population. Standard errors are robust and clustered at the mobility zone level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Mobility Regression Estimates - Lockdown Eased in May

	Parks	Grocery and Pharmacy	Retail and Recreation
Mean temperature (tens of F)	9.076***	1.677***	0.00882
	(2.422)	(0.193)	(0.405)
Temperature range (tens of F)	13.18***	1.058***	0.857***
	(1.566)	(0.128)	(0.250)
Total precipitation (tenths of an inch)	-0.977**	-0.0395	-0.134**
	(0.416)	(0.0411)	(0.0567)
Pre-lockdown × Mean temp.	-5.796**	1.091	-0.699
	(2.345)	(0.715)	(0.698)
Pre-lockdown × Temp. range	-4.436**	0.0943	0.682
	(2.023)	(0.584)	(0.817)
Pre-lockdown × Rainfall	1.076**	0.0744*	0.402**
	(0.509)	(0.0431)	(0.199)
Strict lockdown × Mean temp.	-2.729	-1.708***	0.351
	(2.253)	(0.343)	(0.615)
Strict lockdown × Temp. range	-6.227***	0.0839	-0.255
	(1.409)	(0.237)	(0.367)
Strict lockdown × Rainfall	0.0585	-0.0519	0.122
	(0.496)	(0.0698)	(0.0831)
Eased restrictions × Mean temp.	0.104	-1.693***	-3.621***
	(5.702)	(0.509)	(1.292)
Eased restrictions × Temp. range	-4.796**	-0.745***	-0.817***
	(1.908)	(0.193)	(0.290)
Eased restrictions × Rainfall	-0.770	0.00800	0.00681
	(0.778)	(0.0754)	(0.119)
N	13,211	17,525	17,406
DV mean	20.39	-13.74	-45.01
Location and date fixed effects	✓	✓	✓
Location-lockdown interaction	✓	✓	✓
Location-day of the week interaction	✓	✓	✓
Adj. R^2	0.926	0.980	0.989

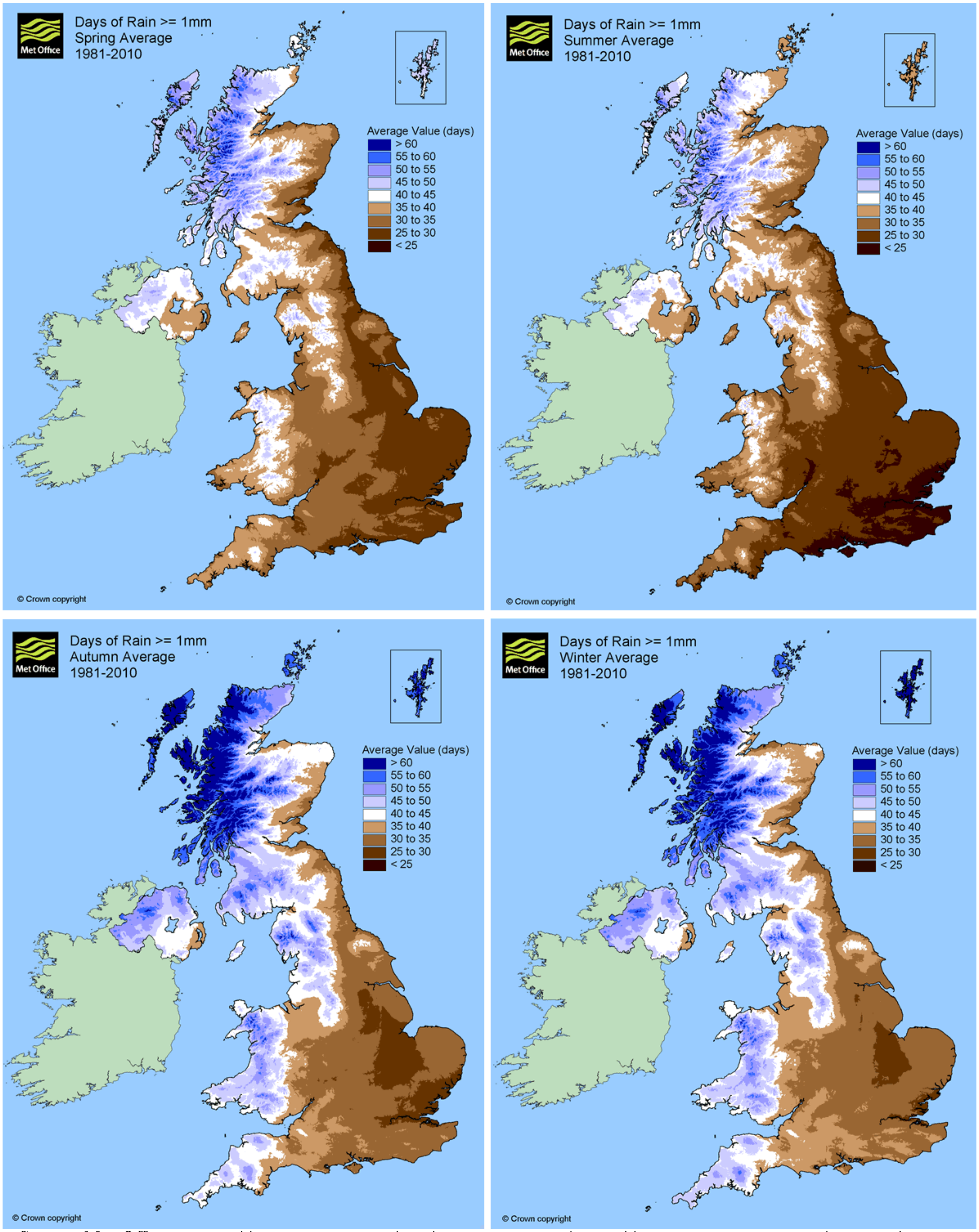
Notes: The sample used in the estimation covers February 15-August 07 2020. The strict lockdown period is specified as March 23-May 10. The (omitted) unlimited exercise period is specified as May 11-July 3 2020. The measure of mobility captures the change in visits to and length of stay in places specified in the dependent variable compared to January 3-February 6 2020. Weather variables have been centered. Weights are used to account for population. Standard errors are robust and clustered at the mobility zone level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Well-being Regression Estimates - Lockdown Eased in May

	(1)	(2)
Mean temp. (tens of F)	-0.000671	-0.00821
	(0.0140)	(0.0266)
Temp. range (tens of F)	-0.00747	0.00500
	(0.0165)	(0.0237)
Rainfall (tenths of an inch)	-0.00260	-0.00936
	(0.00512)	(0.0151)
Wave (Wave 9 UKHLS omitted)		
Covid wave 1	-0.187***	-0.204***
	(0.0601)	(0.0699)
Covid wave 2	-0.181***	-0.192***
	(0.0633)	(0.0642)
Covid wave 3	-0.195***	-0.192***
	(0.0639)	(0.0659)
Pre-lockdown × Mean temp.		0.00352
		(0.0297)
Pre-lockdown × Temp. range		0.00543
		(0.0377)
Pre-lockdown × Rainfall		0.00960
		(0.0165)
Strict lockdown × Mean temp.		-0.0165
		(0.0373)
Strict lockdown × Temp. range		-0.0364
		(0.0250)
Strict lockdown × Rainfall		0.00217
		(0.0195)
N	41,041	41,041
Mean of DV	0.02	0.02
Wave and region fixed effects	✓	✓
Controls	✓	✓
Individual fixed effects	✓	✓
Sample	Full	Full
Adj. R^2	0.0283	0.0286

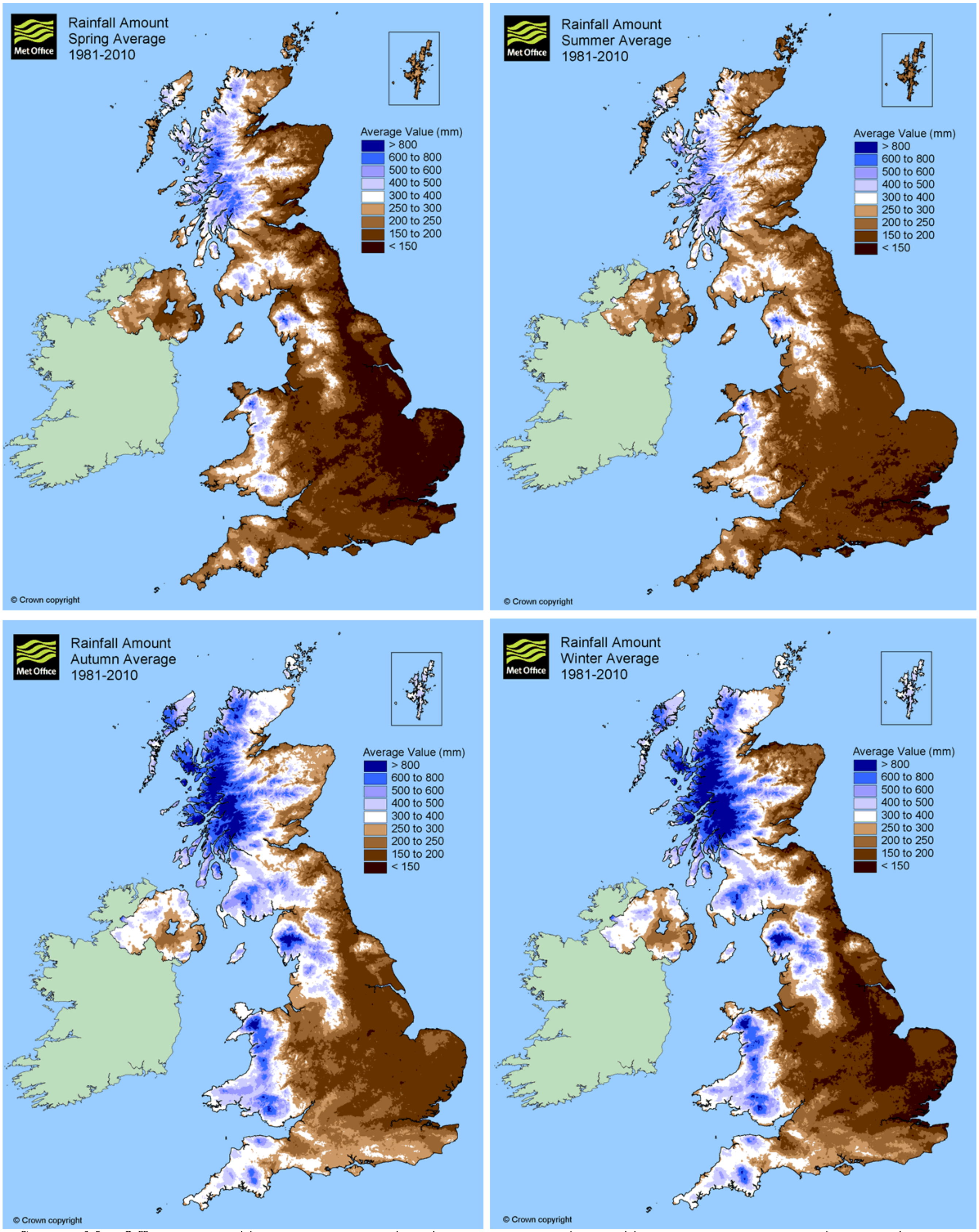
Notes: The strict lockdown period is specified as between March 23-May 10. The omitted period corresponds to the period of unlimited exercise, May 11-July 3. Controls include age, age squared, race, sex, level of education, a dummy capturing whether the individual co-resides with a partner, a dummy capturing own children in the household dummy, the season of UKHLS interview and whether the day of response was during a weekend. Likert score is inverted, so that a greater value implies greater well-being, and rescaled by dividing by 10. Cross sectional weights are used. For the estimates of models with individual fixed effects estimates, weights from the April UKHLS Covid survey are used. Weather information is assumed to be missing if the weather station is more than 30km away from the LSOA the individual lives in. Standard error are clustered at the primary sampling unit level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.1: Number of Rainy Days by Season



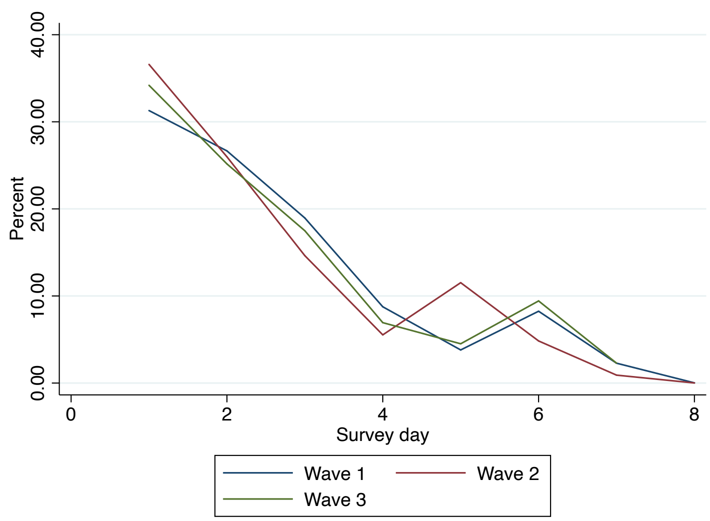
Source: Met Office. `https://web.archive.org/web/20130325145133/http://www.metoffice.gov.uk/climate/uk/averages/ukmapavge.html`, accessed Sep 28, 2020.

Figure A.2: Average Rainfall Amount by Season



Source: Met Office. `https://web.archive.org/web/20130325145133/http://www.metoffice.gov.uk/climate/uk/averages/ukmapavge.html`, accessed Sep 28, 2020.

Figure A.3: Percentage of survey responses by survey date



B Description of GHQ-12 Questionnaire

As discussed in section 2, our measure of mental well-being comes from the Likert scale derived from the 12-question GHQ questionnaire. The GHQ questions are listed below. The Likert scale is obtained by recoding so that the scale for individual variables runs from 0 to 3 instead of 1 to 4, and then summing, giving a scale running from 0 (the least distressed) to 36 (the most distressed). The questionnaire is administered to everyone.

In our analysis we standardize this variable across gender and wave to have a mean of zero and a standard deviation of one. We then multiply by -1 to obtain a scale that runs from negative (more distressed) to positive (less distressed).

Wording of the questions:

The next questions are about how you have been feeling over the last few weeks.

- ghqa [GHQ: concentration]: The next questions are about how you have been feeling over the last few weeks. Have you recently been able to concentrate on whatever you're doing?
  1. Better than usual 2. Same as usual 3. Less than usual 4. Much less than usual

- ghqb [GHQ: loss of sleep]: Have you recently lost much sleep over worry?
  1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

- ghqc [GHQ: playing a useful role]: Have you recently felt that you were playing a useful part in things?
  1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual

- ghqd [GHQ: capable of making decisions]: Have you recently felt capable of making decisions about things?
  1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less capable

- ghqe [GHQ: constantly under strain]: Have you recently felt constantly under strain?
  1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

- ghqf [GHQ: problem overcoming difficulties]: Have you recently felt you couldn't overcome your difficulties?
  1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

- ghqg [GHQ: enjoy day-to-day activities]: Have you recently been able to enjoy your normal day-to-day activities?
  1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual

- ghqh [GHQ: ability to face problems]: Have you recently been able to face up to problems?
  1. More so than usual 2. Same as usual 3. Less able than usual 4. Much less able

- ghqi [GHQ: unhappy or depressed]: Have you recently been feeling unhappy or depressed?
  1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

- ghqj [GHQ: losing confidence]: Have you recently been losing confidence in yourself?
  1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

- ghqk [GHQ: believe worthless]: Have you recently been thinking of yourself as a worthless person?
  1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

- ghql [GHQ: general happiness]: Have you recently been feeling reasonably happy, all things considered?
  1. More so than usual 2. About the same as usual 3. Less so than usual 4. Much less than usual