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WORKING PAPER SERIES

THE IMPACT OF WEATHER ON TIME ALLOCATION TO PHYSICAL ACTIVITY AND SLEEP OF CHILD-PARENT DYADS

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A more recent version of this paper was published as Nguyen HT, Christian H, Le HT, Connelly L, Zubrick SR, Mitrou F. (2023) The impact of weather on time allocation to physical activity and sleep of child-parent dyads. Science of The Total Environment, 880, 163249. DOI: 10.1016/j.scitotenv.2023.163249

No. 2021-11

July 2021

NON-TECHNICAL SUMMARY

Regular physical activity supports healthy functioning of individuals across all ages. However, children and adults are not physically active enough. Much research has investigated the barriers to children and adults being more physically active. One of the commonly documented barriers is unfavourable weather conditions (i.e., too hot, cold or wet). However, it remains unclear whether unfavourable weather conditions have a differential impact on physical activity and sleep in children compared with adults. This study explores the differential impact of weather on time allocation to physical activity and sleep by young adolescents and their middled-aged parents.

We use nationally representative data with time use indicators objectively measured from accelerometers and activity cards on multiple occasions for more than 1,100 child-parent pairs, coupled with daily meteorological data. Employing an individual fixed effects regression model to estimate the causal impact of weather, we show that unfavourable weather conditions, as measured by cold or hot temperatures or rain, cause children to reduce the time allocated to physical activities, mainly by increasing the sedentary time. However, we do not find any noticeable weather impact on the time that children allocate to sleeping or the way their parents spend their own time. Our results also show that the differential weather impact observed for these child-parent dyads is statistically significantly different and meaningful.

In addition to the potential role of age differences between children and their parents, our results further suggest that children's school commitments or parental work schedules contribute to this differential weather impact because weather impact varies substantially by weekdays/weekends and parental employment status. We also find evidence of adaptation and acclimatization, as children living in colder regions or surveyed in colder months are more sensitive to warmer temperatures. Our findings are robust to a wide range of sensitivity checks, including controlling for individual heterogeneity and using alternative model specifications.

The finding of a more pronounced weather impact on the time allocation by children enriches existing evidence suggesting that climate change affects individuals differently depending on their age and stage of development. This finding also calls for mitigation policies to protect vulnerable populations, especially children, from adverse consequences of extreme weather conditions. The results suggest that extreme weather conditions, including those associated with climate change, could make children vulnerable to reduced physical activity.

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Acknowledgements

This research was partly funded by the Australian Research Council Centre of Excellence for Children and Families over the Life Course (#CE140100027, Zubrick) and Australian National Heart Foundation Future Leader Fellowship (#102549, Christian). This paper uses unit record data from Growing Up in Australia, the Longitudinal Study of Australian Children. The study is conducted in partnership between the Department of Social Services (DSS), the Australian Institute of Family Studies (AIFS) and the Australian Bureau of Statistics (ABS). The findings and views reported in this paper are those of the authors and should not be attributed to the DSS, the AIFS or the ABS.

ABSTRACT

This study explores the differential impact of weather on time allocation to physical activity and sleep by children and their parents. We use nationally representative data with time use indicators objectively measured on multiple occasions for more than 1,100 child-parent pairs, coupled with daily meteorological data. Employing an individual fixed effects regression model to estimate the causal impact of weather, we find that unfavourable weather conditions, as measured by cold or hot temperatures or rain, cause children to reduce physical activity time and increase sedentary time. However, such weather conditions have little impact on children's sleep time or the time allocation of their parents. We also find substantial differential weather impact, especially on children's time allocation, by weekdays/weekends and parental employment status, suggesting that these factors may contribute to explaining the differential weather impact that we observed. Our results additionally provide evidence of adaptation, as temperature appears to have a more pronounced impact on time allocation in colder months and colder regions. The results suggest that extreme weather conditions, including those associated with climate change, could make children vulnerable to reduced physical activity.

Keywords: weather, time allocation, physical activity, sleep, family, dyad

Suggested citation: Nguyen, H.T., Christian, H., Le, H.T., Connelly, L., Zubrick, S.R., and Mitrou, F. (2021). 'The Impact of Weather on Time Allocation to Physical Activity and Sleep of Child-Parent Dyads', Life Course Centre Working Paper Series, 2021-11. Institute for Social Science Research, The University of Queensland.

1. Introduction

It has been argued that time is increasingly the most important resource a person has at their disposal (Hamermesh 2016). Although longevity, in rich countries, has increased by about 20% over the last 60 years, per capita GDP has tripled in that time; thus, relative to goods, the scarcity of time has increased (Hamermesh 2016). Not only does this render the study of time use as between market activities and household production (Becker 1965) of increasing economic relevance, but also the allocation of time to the production of health and other things (Grossman 1972, 2000), as well as the effect of exogenous factors (e.g., taxes, the climate) on those activities, and their implications for child and adult health.

Regular physical activity (PA) supports healthy functioning of individuals across all ages (Poitras *et al.* 2016; Carson *et al.* 2017). However, children and adults are not physically active enough (WHO 2020). Much research has investigated the barriers to children and adults being more physically active (Biddle *et al.* 2011; Janke *et al.* 2016). One of the commonly documented barriers is unfavourable weather conditions (i.e., too hot, cold or wet). While weather impact estimates on PA vary widely, depending on the applied methodology and datasets analysed, current literature typically finds that unfavourable weather conditions discourage PA by individuals of all ages (Tucker & Gilliland 2007; Nguyen *et al.* 2021). However, it remains unclear whether unfavourable weather conditions have a differential impact on PA in children compared with adults.

This lack of robust evidence can be explained by noticeable differences in datasets and methods employed by existing studies, making it hard to directly compare the estimated weather impacts for individuals of different ages across these studies. In particular, the studies to date have focused on groups of individuals of largely similar ages, such as children (Duncan *et al.* 2008; Harrison *et al.* 2017), adolescents (Bélanger *et al.* 2009), middle-aged individuals (Chan *et al.* 2006) or elderly (Prins & van Lenthe 2015; Aspvik *et al.* 2018). Furthermore, studies have used variable measures of PA and/or weather conditions. Existing studies have also employed various empirical models (more on this in subsequent sections). These methodological issues, independently or jointly, pose challenges to a direct comparison of the weather impacts on different age groups observed in previous studies. Such a direct comparison is further complicated by the fact that studies often employ datasets collected at different times and locations, and evidence suggesting that the weather impact varies by climate regions (Harrison *et al.* 2017; Nguyen *et al.* 2021) and seasons (Harrison *et al.* 2015).

This paper contributes to the literature by exploring the impact of weather on time allocation by children and their parents. In particular, we employ a nationally representative dataset containing various time use indicators, including PA and sleep, for more than 1,100 child–parent pairs (Clifford *et al.* 2019). For each of them, we have various time use indicators which are measured using the same instruments (i.e., accelerometers and activity cards), on the same dates, and on multiple occasions. This unique feature of our data allows us to contrast the responses by two groups within the same family (i.e., young adolescents and their parents) who share the same environment, including climate and survey time. We augment this high-quality dataset with an individual fixed-effects (FE) model to estimate the causal impact of weather on time allocation of these child-parent dyads. Our data and empirical method allow us, for the first time in this literature, to directly answer if weather affects the time allocation of children and adults differently. This represents our first and primary contribution. By providing more robust evidence on the likely heterogenous weather impact for children and their parents, this study helps inform policies that aim to mitigate the negative impact of unfavourable weather conditions on time allocation and hence subsequent outcomes on various population groups (Watts *et al.* 2019). These policies are of increasing relevance for regions that are affected adversely by climate change and extreme weather scenarios (Dell *et al.* 2014).

This study also makes two additional contributions to the literature. First, it is one of a few studies investigating the impact of weather on activities beyond PA. In particular, like some studies which employed data from time-use diaries (Connolly 2008; Graff Zivin & Neidell 2014; Nguyen *et al.* 2021), we explore the weather impact on sleep outcomes.[1] This is possible since our data contain measures of time contributed to both physical activities (objectively collected from accelerometers) and sleeping (recorded from activity cards). This contribution is particularly important because time allocation among different activities has been found to have dissimilar effects on health and developmental outcomes (Fiorini & Keane 2014; Del Boca *et al.* 2017; Nguyen *et al.* 2020; Bessone *et al.* 2021) so focusing on PA alone would not capture the full impact of weather on time allocation and its outcomes. Second, this is the first study to examine the association between weather conditions

[1] This paper is also related to a seemingly separate literature focusing on the relationship between climate change related events and sleep. Studies from that literature commonly report diminished total sleep times and sleep disruption are associated with rising temperature, extreme weather events, floods or wildfires (see, for example, Rifkin *et al.* (2018), for a review). However, it remains unclear whether such climate change related events have a differential effect on sleep of children and adults, mainly due to differences in empirical models and data used in these studies.

and objectively measured PA using a nationally representative child-parent dataset from Australia. Previous Australian studies were mostly done within one city (Badland *et al.* 2011; Ridgers *et al.* 2018) or one region (Remmers *et al.* 2017).[2] Owing to its wide coverage, our dataset allows a more extensive investigation of the differential weather impact by various sub-populations, including those identified by climate regions.

We present four main findings. First, we confirm the well-documented negative impact of unfavourable weather conditions, as measured by cold or hot temperatures or rain, on physical activity. However, we do not find any significant weather impact on the time that children spend on sleeping or the way their parents allocate their own time. Second, we present new evidence that the impact of weather on the time allocated to PA is mainly driven by the effect of weather on children's time allocation; and, this differential weather impact is statistically significantly different and meaningful. Third, our heterogeneous analysis suggests that children's school commitments or parental work schedules partly contribute to this differential weather impact since weather impact varies by weekdays/weekends and parental employment status. Fourth, our results provide evidence of adaptation and acclimatization, as the level of PA of children living in colder regions or surveyed in colder months is more responsive to temperatures.

This paper proceeds as follows: Section 0 describes our data and empirical model. Section 0 presents the empirical results while Section 0 documents the results from numerous robustness checks. Section 0 examines heterogeneous effects and Section 0 concludes the paper.

2. Data and empirical model

2.1 Data

Our primary dataset was the Longitudinal Survey of Australian Children (LSAC). The LSAC is a biennial nationally representative survey with sampling frame of all children born between March 2003 and February 2004 (Birth or B-Cohort, 5,107 infants aged 0–1 year in 2004) and between March 1999 and February 2000 (Kindergarten or K-Cohort, 4,983 children aged 4–5 years in 2004) (AIFS 2018). The LSAC was initiated in 2004 and, in 2015-16, it dedicated an one-off biophysical module, called the Child

[2] In particular, their datasets were collected in Perth (Badland *et al.* 2011), Melbourne (Ridgers *et al.* 2015; Harrison *et al.* 2017; Ridgers *et al.* 2018), Adelaide (Lewis *et al.* 2016), or Southeast Australia (Remmers *et al.* 2017).

Health CheckPoint, to collect information on physical health and biospecimens from 1,874 B-cohort children and their parents (Davies *et al.* 2018). Thus, when CheckPoint data were collected, B-cohort children were around 12-13 years old.

2.2 Time allocation measures

This study mainly uses the Child Health CheckPoint data because they provide common and highly reliable measures of time allocation by both children and their parents, allowing us to document and contrast the impact of weather on time allocation of them both. In particular, LSAC collected objective measures of their time allocation using triaxial, wrist-worn GENEActiv accelerometers (Clifford *et al.* 2019). The study child and participating parent were provided accelerometers to wear for 8 consecutive days following their visit at the health check point. They were also given a take home pack, including an activity card for them to record wake and sleep times, and activities during periods of non-wear. Collected information then has been processed to produce measures of time allocation across various activities by both children and their parents (Davies *et al.* 2018).[3]

We employ eight daily measures of time allocation by children and their parents. The first measure is "sleep duration" which is calculated as the difference between sleep onset and sleep offset. The second measure, called "sleep efficiency", indicates the percent of minutes scored as sleep between onset and offset. Depending on the intensity of physical activities undertaken, we use four other measures to capture the time spent on physical activities each day, namely "sedentary duration", "light PA duration", "moderate PA duration", and "vigorous PA duration".[4] We combine the time attributed to the last two physical activities in one group, denoted by "moderate-to-vigorous physical activity (MVPA) duration", and use it as another measure of time use. Finally, we employ the daily

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[3] LSAC also has some objective time allocation measures obtained from time-use diaries (AIFS 2018; Nguyen *et al.* 2021) or Multimedia Activity Recall for Children and Adults (MARCA) program (Davies *et al.* 2018) but these measures are available for children only.

[4] In principle, the sum of "sleep duration", "sedentary duration", "light PA duration", "moderate PA duration", and "vigorous PA duration" should add up to 24 hours per day. However, it is not always the case, probably due to non-wear time or other measurement errors. It is likely that individuals shift the timing of activities within the day in response to weather conditions (Graff Zivin & Neidell 2014; Nguyen *et al*. 2021). We do not specifically model this "avoidance" behaviour because we do not know the time when PA is undertaken from the accelerometer data. The weather impact on time allocation presented in this paper includes the impact of weather on such an "avoidance" behaviour, if any.

average counts[5] per minute, denoted as "average counts", as another indicator to investigate the impact of weather on the intensity of physical activities.

2.3 Meteorological measures

To measure local weather, we assign daily weather elements from three spatially closest weather stations to the respondent's residential postcode centroid.[6] Historical weather data were obtained from the Australian Bureau of Meteorology (BoM). These data have information on meteorological elements at all monitoring stations throughout Australia. Our spatial matching results indicate that, at the median, the first-, second-, and third-closest weather stations are within 5, 10, and 13 miles, respectively, of the respondent's residential location. This close spatial distance matching warrants that the respondent's activities are affected by local weather conditions.

We employ the following meteorological elements to gauge the impact of local weather. The first element is temperature. To capture the potential heterogenous impact of daily temperature on different activities undertaken during the day (e.g., sleep usually occurs at night when temperature reaches its minimum while physical activities typically take place during the day when temperatures are higher) and follow previous studies (Graff Zivin & Neidell 2014; Nguyen *et al.* 2021), we consider both maximum and minimum daily temperature. Furthermore, to examine the possible non-linear impact of maximum daily temperature on time allocation, we introduce a quadratic form of temperature, which is purposely represented in degrees Fahrenheit (°F) to transform all negative degree Celsius (°C) temperature values in our data to positive °F temperature values, in all regressions. The second weather element is daily precipitation (in inches). We also investigate the impact of relative humidity (reported as a percentage), wind speed (in miles per hour) and wind direction (in degrees to the north) on time allocation. For these variables, we introduce their daily maximums.

[5] A 'count' is the sum of acceleration magnitude over 1 minute epochs (Davies *et al.* 2018). We use the daily average counts for all activities, including sleeping, undertaken during the accelerometer day.

[6] As suggested by Hanigan *et al.* (2006), instead of using weather elements from the closest weather station, we use the geographic centroid inverse distance weighted average of weather elements from three nearest weather stations. We use the restricted version of the LSAC which contains the respondent's residential postcode. Postcodes are the finest geographical identifiers available in our data. As of 2011, there were about 8,500 persons per postcode (among around 2,500 postcodes) in Australia. There were about 800 weather stations in Australia at the study time. For a small number of days (i.e., less than 5% of the final sample) when weather elements from the closest weather stations are not available, we assign weather elements from the closet rainfall district (among all 109 rainfall districts as identified by the BoM).

Finally, as time allocation across various activities may vary by the length of time between sunrise and sunset time, we consider a variable named "day length" (in hours).[7]

Error! Reference source not found. – Panel A shows large variations of temperature within the same days (i.e., maximum versus minimum daily temperature) and across all accelerometer dates in our final sample. Similarly, **Error! Reference source not found.** indicates substantial variations in all weather elements measured on various accelerometer dates by the same individuals (see within-individual standard deviations), supporting the use of an individual FE model to draw robust evidence on the causal impact of weather. We note that weather statistics reported in this study are largely similar to yearly weather figures in Australia (Nguyen *et al.* 2021). This similarity is likely to be explained by the fact that geographical distribution of individuals in our data mirrored the broader Australian population and the survey time was relatively evenly distributed across all months (Clifford *et al.* 2018). Likewise, in line with the fact that more than 90% of children and their parents in our final sample have their accelerometers recorded on the same dates, **Error! Reference source not found.** additionally shows identical distributions of daily temperature and precipitation by children and their parents. This unique feature of our data allows us to contrast the responses by two groups (i.e., children and their parents) who share the same environment, including climate and survey time. This is important given other studies have identified the differential impacts of weather on the time allocation by individuals living in different climate regions and surveyed at different seasons (Harrison *et al.* 2017; Nguyen *et al.* 2021).

2.4 Sample

From an original sample of 1,874 parent–child pairs participated in the LSAC Child Health CheckPoint module, 1,317 children and 1,402 parents returned valid accelerometer records (Davies *et al.* 2018).[8] Since one of our main objectives is to compare the weather impact on time allocation by children and their parents, we restrict the sample to parent-child pairs with valid accelerometer records for both of them. This sample restriction leads to a sample of 1,164 unique child-parent pairs. We additionally exclude individuals with missing information on any variable used in our empirical model.

[7] This variable is calculated using an astronomical formula proposed by Forsythe *et al.* (1995). We only include this variable in regressions which do not control for individual FE because of a lack of within-individual variations in day length in our data (See **Error! Reference source not found.**).

[8] Specifically, a valid day consisted of at least 10 hours of wear time (excluding sleep) and at most 6 hours of non-wear during wake time (Clifford *et al.* 2018).

Furthermore, as we mainly employ an individual FE model in this analysis, we necessarily restrict the sample to individuals who have at least two valid accelerometer days during the study period. These restrictions result in a final sample of 1,140 unique parent-child pairs, with 6,738 accelerometer days from children and 6,838 days from their parents.

2.5 Descriptive results

Table 1 demonstrates apparent differences in time allocation by 12–13-year-old children and their middle-aged parents. Specifically, children spent more time sleeping (by 69 minutes each day) but they had lower sleep efficiency (by 2%) than their parents. As compared to their parents, children in our sample also allocated more time to sedentary activities (by 133 minutes per day) and less time to physically light (by 103 minutes) and moderate (by 95 minutes) activities. By contrast, children spent about 3 minutes more per day on vigorous physical activity than their parents. Similarly, children had a much higher number of average counts per minute (191) than their parents (153). However, as vigorous physical activity represented a very small proportion of MVPA undertaken by both children and parents, on average, children still spent much less time on MVPA (by 91 minutes per day) than their parents. These time allocation patterns lend support to separate analyses of time allocation by children and parents.

Table 1: Sample means of outcomes and key covariates

	Child	Parent	Child - Parent (1) - (2)
	(1)	(2)	(3)
Age (years)	11.96	44.54	-32.58***
Male [(a)]	0.49	0.12	0.37***
Any health condition [(a)]	0.27	0.34	-0.07***
Two-parent family [(a)]	0.81	0.81	0.00
Parent worked part time [(a)]	0.41	0.41	0.00
Parent worked full time [(a)]	0.41	0.41	0.00
Sleep duration (minutes per day)	567.16	498.60	68.56***
Sleep efficiency (%)	83.99	85.72	-1.73***
Sedentary duration (minutes per day)	678.56	545.62	132.94***
Light PA duration (minutes per day)	163.42	266.82	-103.41***
Moderate PA duration (minutes per day)	22.47	117.05	-94.58***
Vigorous PA duration (minutes per day)	11.04	7.71	3.33***
MVPA duration (minutes per day)	33.52	124.76	-91.25***
Average counts	190.81	152.63	38.18***
Max temperature (°F)	71.83	71.92	-0.08
Min temperature (°F)	51.34	51.35	-0.01
Precipitation (inches)	0.10	0.09	0.00
Max humidity (%)	89.11	89.05	0.06
Max wind speed (mph)	16.22	16.19	0.03
Max wind direction (degree to the north)	301.40	301.38	0.02
Day length (hours)	12.01	12.02	-0.01
Number of observations	6,738	6,838	

Notes: Figures are sample means. [(a)] indicates dummy variables. Tests are performed on the significance of the difference between the sample mean for children and parents. The symbol *denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 1 additionally suggests noticeable differences between parents and children in some individual characteristics such as age, gender and health conditions.[9] For instance, as expected, children are healthier on average than their parents as they have not yet had time to accumulate lifestyle diseases or diseases of aging. Furthermore, in line with the sampling design of LSAC (AIFS 2018), mothers are over-represented as parents in our data while sons and daughters appear equally. However, consistent with the data structure and our research design,

[9] Health conditions for the study child or parent are captured using a binary variable that takes the value of one if an individual had any on-going conditions at the survey time, and zero otherwise. On-going conditions include allergy, asthma, blood clotting, bone disorder, broken bone, chronic or recurring pain, diabetes, difficulty gripping/holding, hearing loss (not corrected), heart condition, high blood pressure on medication, high cholesterol on medication, incomplete use of arms/fingers, incomplete use of feet or legs, pacemaker, restricted physical activity/exercise, shortness of breath causing restriction, and vision loss (not corrected) (Le & Nguyen 2017). These variables are measured once at the time of health check point visit, so they are invariant during the observed accelerometer window. As such, it is not included in regression equation (1). Similarly, other time-invariant variables such as age, gender, family structure and parental working status are excluded from equation (1).

Table 1 shows no difference between parents and children on some household-level characteristics, including family structure. Similarly, as discussed above, there is no apparent difference in weather conditions recorded on accelerometer dates for children and their parents.

2.6 Empirical model

The following econometric model is employed to investigate the impact of local weather conditions on the time allocated to activity A by individual i, who resides in postcode p, on accelerometer date t:

$$A_i = \alpha + \beta Z_{p(i),t(i)} + \gamma X_{i,t} + \delta_i + \varepsilon_{i,t} \quad (1)$$

where $Z_{p(i),t(i)}$ is a set of local meteorological elements, as described above. $X_{i,t}$ is a set of time-variant control variables, including day-of-week and month indicators. δ_i is an individual time-invariant unobservable factor and $\varepsilon_{i,t}$ is the random error term. α, β and γ are parameters to be estimated. As we observe multiple observations per individual, we apply an individual FE regression technique which controls for individual heterogeneity, including individual residential location preferences, to equation (1). Our estimates of the weather impact (β) are identified from daily fluctuations in weather within a postcode for the same individuals. The results from this individual FE model can be viewed like those obtained from a "natural" experiment which locates the same individuals to different climate regions. This model, together with the fact that weather conditions are exogenous to individual time allocation, facilitates a causal interpretation of the estimated results. We estimate aquation (1) separately for children and parents.

3. Empirical results

Table 2 reports individual FE estimates of various weather elements on time allocation measures for children and their parents.[10, 11] We begin with the estimates of daily maximum temperature which demonstrate a statistically significant temperature impact on four outcomes for children: sedentary duration, light PA duration, moderate PA duration and average counts. Moreover, the statistically significant estimates of the quadratic term suggest that the impact of daily maximum temperature on these measures is non-linear. Specifically, the results show the relationship between daily maximum temperature and children's light PA duration, moderate PA duration and average counts follows an inverted U-shaped pattern while the link between daily maximum temperature and children's sedentary duration exhibits a U-shaped pattern (See Figure 1 – Panel A). The results suggest that children's time allocated to light or moderate PA first increases with daily maximum temperature before starting to fall after 78°F and 64°F, respectively. Likewise, children's number of average counts increases with daily maximum temperature up to 68°F and starts to decrease afterwards. By contrast, their sedentary duration reaches a minimum at around 76°F, and increases either side of that ambient temperature.

[10] To formally test whether coefficients are equal in separate FE regressions for children and parents, we run a FE regression on a pooled sample of children and parents. We include in this regression a list of all explanatory variables as described in the text and interactions between a child dummy variable and all variables in this list. The test after the interaction effects is the test whether the coefficients are equal. Test results (reported on the first row in **Error! Reference source not found.**) give strong support for separate regressions for children and parents.

[11] Estimation results for other control variables, reported in **Error! Reference source not found.**, show noticeable differences in time allocation by days of week and months for children or their parents. Furthermore, parents and children spend their time very differently (with the difference is statistically significant at least at the 5% level as shown in row 5 of **Error! Reference source not found.**) by days of week and months.

Table 2: Impact of weather on time allocation by children and parents

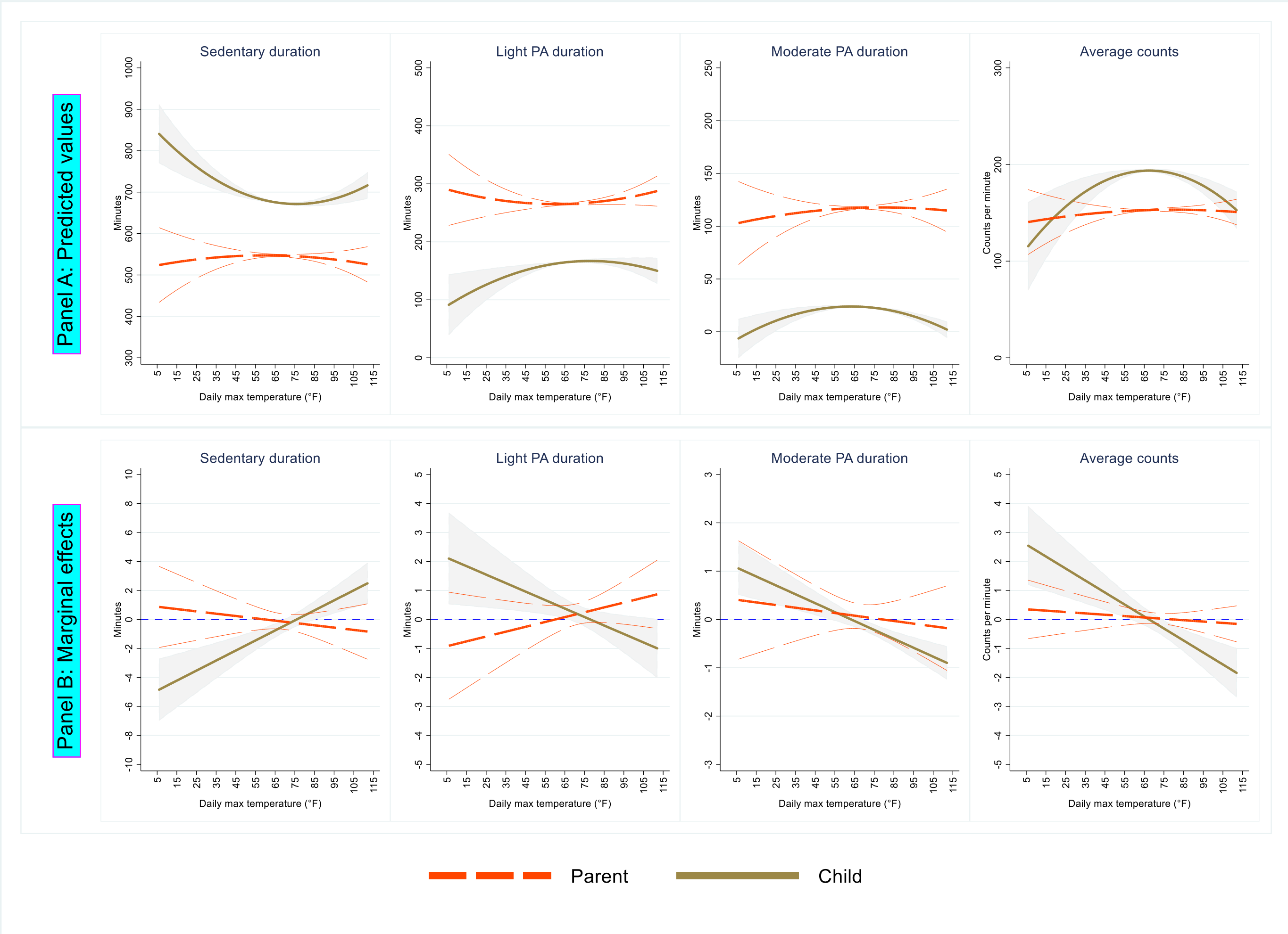
	Sleep duration		Sleep efficiency		Sedentary duration		Light PA duration	
	Child	Parent	Child	Parent	Child	Parent	Child	Parent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max temperature (°F)	-0.42	0.61	-0.01	0.03	-5.54***	1.02	2.40***	-1.07
	[1.18]	[1.19]	[0.09]	[0.11]	[1.24]	[1.65]	[0.92]	[1.08]
Max temperature squared	0.00	-0.01	0.00	-0.00	0.03***	-0.01	-0.01**	0.01
	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Min temperature (°F)	-0.56**	-0.10	-0.00	-0.09***	1.00***	0.11	-0.30	0.30
	[0.23]	[0.25]	[0.02]	[0.02]	[0.29]	[0.35]	[0.20]	[0.22]
Precipitation (inches)	-4.00	-2.47	0.26	-0.25	6.78*	3.74	-3.67	-3.40
	[3.03]	[3.86]	[0.32]	[0.32]	[3.97]	[4.89]	[2.89]	[2.83]
Max humidity (%)	0.15	0.12	-0.01	-0.02	-0.05	-0.23	0.05	0.19
	[0.13]	[0.14]	[0.01]	[0.01]	[0.16]	[0.19]	[0.10]	[0.13]
Max wind speed (mph)	0.25	0.53**	-0.04**	-0.03	0.11	-0.38	0.09	0.22
	[0.22]	[0.23]	[0.02]	[0.02]	[0.25]	[0.33]	[0.16]	[0.21]
Max wind direction	0.02	-0.02	-0.00	0.00	0.04	0.07**	0.01	-0.00
	[0.02]	[0.02]	[0.00]	[0.00]	[0.03]	[0.03]	[0.02]	[0.02]
Observations	6,738	6,838	6,732	6,838	6,738	6,838	6,738	6,838
No of unique individuals	1,140	1,140	1,139	1,140	1,140	1,140	1,140	1,140
R-squared	0.011	0.042	0.006	0.007	0.025	0.032	0.036	0.012
Sample mean	567.2	498.6	83.99	85.72	678.6	545.6	163.4	266.8

Notes: Results for each outcome and sub-group are from an individual FE regression. Other explanatory variables include day-of-week and month dummies (Their estimates are reported in **Error! Reference source not found.**). Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Table 2: Impact of weather on time allocation by children and parents (continued)

	Moderate PA duration		Vigorous PA duration		MVPA duration		Average counts	
	Child	Parent	Child	Parent	Child	Parent	Child	Parent
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Max temperature (°F)	1.24***	0.46	-0.63	-0.75	0.61	-0.30	2.96***	0.39
	[0.32]	[0.72]	[0.63]	[0.60]	[0.71]	[1.00]	[0.79]	[0.59]
Max temperature squared	-0.01***	-0.00	0.01	0.01	-0.00	0.00	-0.02***	-0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.00]
Min temperature (°F)	-0.05	-0.22	0.00	0.13	-0.05	-0.09	-0.11	-0.09
	[0.07]	[0.16]	[0.12]	[0.09]	[0.14]	[0.19]	[0.17]	[0.10]
Precipitation (inches)	-2.64**	-2.02	-2.63	-1.66**	-5.27***	-3.69	-6.00**	-2.35
	[1.07]	[2.32]	[1.87]	[0.69]	[1.93]	[2.54]	[2.74]	[1.45]
Max humidity (%)	-0.01	0.04	0.05	-0.02	0.05	0.01	-0.00	0.05
	[0.04]	[0.09]	[0.07]	[0.04]	[0.08]	[0.10]	[0.09]	[0.06]
Max wind speed (mph)	0.01	-0.04	-0.13	-0.14**	-0.12	-0.18	0.04	-0.03
	[0.06]	[0.16]	[0.10]	[0.06]	[0.11]	[0.18]	[0.15]	[0.11]
Max wind direction	0.00	-0.02	0.03***	0.00	0.03**	-0.02	0.01	-0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]
Observations	6,738	6,838	6,738	6,838	6,738	6,838	6,738	6,838
No of unique individuals	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140
R-squared	0.041	0.007	0.012	0.004	0.010	0.006	0.057	0.008
Sample mean	22.47	117	11.04	7.713	33.52	124.8	190.8	152.6

Figure 1: Impact of weather on time allocation by children and parents



Notes: Results (coefficients and 95% confidence intervals) for each outcome are from separate individual FE regressions. Detailed regression results are reported in Table 2.

The estimates of daily maximum temperature reported in Table 2 and Figure 1 highlight the marked differences in the effect of temperature impact on activities undertaken by children compared with their parents. For example, the impact of daily maximum temperature on time allocation for the four elements of PA described above is statistically significant for children only, not parents. Furthermore, when statistically significant, the estimates for children usually run in the opposite direction to that observed for parents.[12] Indeed, test statistics show that the estimates of temperature and precipitation on sedentary duration, light PA duration and average counts are statistically significantly different for children and parents (as shown in **Error! Reference source not found.** – rows 3 and 4). However, we do not observe any statistically significant difference in the impact of daily maximum temperature on the time allocated to sleeping, vigorous PA or MVPA by children and their parents as the estimates are statistically insignificant for them both. Our finding of a more visible temperature impact on children's time allocation to lighter intensity PA suggests that the effect of temperature depends on whether PA is structured (usually MVPA, as shown in the literature (Caspersen *et al.* 1985)) or unstructured.

Table 2 also shows that daily minimum temperature has a statistically significant effect on some activities. For instance, daily minimum temperature decreases sleep duration (children only) or sleep efficiency (parents only). By contrast, it increases the sedentary duration for children. However, as compared to the estimates of daily maximum temperature on non-sleeping activities, the estimates of daily minimum temperature are much less pronounced, both in terms of the statistical significance level and magnitude.

Turning to the estimates of precipitation (reported in row 4 of Table 2), we observe that, while the estimates are typically of the same sign for children and parents, they are often more pronounced for children with respect to the magnitude or statistical significance level. For example, precipitation has a statistically significant impact on sedentary duration, moderate PA duration, MVPA duration and average counts for children only. Moreover, for these outcomes, the estimates are substantially greater in magnitude for children than for parents. Similarly, while the estimate on vigorous PA duration is statistically significant (at the 5% level) for parents only, the estimate is slightly higher for children (minus 2.63) than for parents (minus 1.66). Overall, the results, when statistically significant,

[12] An exception is observed for estimates on moderate PA duration which have the same sign for children and parents.

suggest that precipitation is negatively (positively) associated with PA (sedentary) time, especially for children.

The remaining results in Table 2 suggest that, in line with previous studies (Graff Zivin & Neidell 2014; Nguyen *et al.* 2021), other weather elements play little role in explaining the time allocation by children and parents because most of the estimates are not highly statistically significant. There are two noticeable exceptions though. First, daily maximum wind speed tends to increase sleep duration (for parents only) but decrease sleep efficiency (for children only) and vigorous PA duration (for parents only).[13] Second, daily maximum wind direction appears to increase sedentary duration (for parents only) and the time allocated to vigorous PA or MVPA (for children only).

In sum, the above results indicate that unfavourable weather conditions, as represented by cold or hot temperatures or rain, have a more pronounced and negative impact on the time allocated to PA by children than their parents. To the best of our knowledge, this evidence is novel to the literature. This finding when viewed with the fact that children, on average, are much less physically active than their parents, suggests that children may be disproportionally and negatively affected by extreme weather conditions, compared with their parents. This evidence of a more noticeable weather impact for children is reached when we have controlled for some factors which (i) are shared between parents and their children and (ii) have been shown to influence how individuals allocate their time in response to weather (Nguyen *et al.* 2021),[14] suggesting other non-shared factors are behind this differential impact.

One such factor could be the heterogeneity in their ages. Young adolescents (aged 12-13 years old) in our sample were still growing, making them more sensitive to environmental hazards related to extreme weather events than their middle-aged parents (WHO 2003). To this end, our finding is consistent with evidence from other related literature demonstrating that children are more sensitive to heat waves than adults (Ye *et al.* 2012). It is also consistent with evidence from a wider literature suggesting that climate change affects individuals differently depending on their age and stage of

[13] To check the possible non-linear impact of wind speed on time allocation, we experimented with additionally including it squared term in the regressions and found no such evidence.

[14] Examples of shared factors include genetic traits common to parents and their children or shared residential homes (Le & Nguyen 2018). It should be noted that our individual FE regression approach helps mitigate the role of such factors in driving the results by controlling for all unobservable factors that do not change during a short time duration (i.e., less than a month).

development (Watts *et al.* 2019). Other non-shared environmental factors include parental work schedules and children's school commitment (Matricciani *et al*. 2019). We will explore the potential role of some non-shared factors in following sections.

4. Sensitivity analysis

This section presents results from three main sets of robustness checks.[15] The first set is to test the sensitivity of the results to different functional forms of weather variables. Initially, we experiment by excluding the daily minimum temperature from the regression and find the estimates of other remaining variables (reported in Panel B of **Error! Reference source not found.**) are largely similar to the baseline results (re-reported in Panel A). This stability in the results is probably explained by the fact that physical activities, which are typically performed during the day, are not influenced by daily minimum temperature which normally occurs at night (Nguyen *et al.* 2021). Furthermore, as has been done by Badland *et al.* (2011), we introduce daily maximum temperature in a linear form and find it has a statistically significant (at the 1% level) effect on children's moderate PA duration only (see Panel C). This lack of statistical significance in the effects of daily maximum temperature, when viewed with the high statistical significance of the temperature estimates from the baseline analysis, suggests that the quadratic specification appears to be well-suited to capture the non-linear impact of daily maximum temperature on time allocation, particularly for children.

We find further evidence supporting our modelling choice when employing a cubic functional form for daily maximum temperature since none of the estimates of the cubic polynomial is statistically significant (Panel D). An exception is observed for the estimate of daily maximum temperature on parents' light PA duration as the estimate of its cubic term is negative and marginally statistically significant at the 10% level.[16] Moreover, following previous studies (Aibar *et al.* 2013; Edwards 2015;

[15] For brevity purposes, this section focuses on four main time use outcomes which were previously found to be statistically significantly affected by weather conditions. These outcomes are sedentary duration, light PA duration, moderate PA duration and average counts. Similarly, we only report estimates for two dominant weather elements: temperature and precipitation. Unreported results for remaining outcomes or weather elements are largely similar to the baseline estimates.

[16] While the estimate of the cubic temperature term is trivial in both the magnitude (i.e., minus 0.0004) and statistical significance level, including it in the regression turns estimates of other temperature terms from statistically insignificant to statistically significant (at least at the 10% level). However, even taking this preferred functional form into account, the discouraging marginal impact of decreasing daily maximum temperature, especially at the lower end of the observed temperature range, on light PA duration is still more pronounced for children than for parents (see **Error! Reference source not found.** – Panel B).

Harrison *et al.* 2017), we employ daily average temperature (and its square) in place of daily minimum and maximum temperature. The results (reported in Panel E) confirm our prior findings, although the temperature estimates are much less visible in terms of the magnitude and statistical significance level. The results from this experiment give additional support to our modelling choice because, as documented above, most children and their parents sleep when minimum temperatures (which we also control for in regressions) usually occur, so including daily maximum temperature in regressions better captures temperature exposure to activities other than sleeping.[17]

Finally, we include daily maximum temperature in bands, using 66-75°F as the base, with all other temperature estimates being compared to this temperature band. The results reported in Panel F confirm the well-defined non-linear relationships between temperature and children's sedentary duration, moderate PA duration and average counts. We also observe that although the estimates for temperature bands on children's light PA duration follow an inverted U-shaped pattern, they lack statistical power, possibly due to the small sample size. Importantly, the results from this experiment reaffirm that unfavourable weather conditions have a more pronounced impact on the time allocation of children compared with their parents.

The second set of robustness checks involves employing two alternative econometric models that have been used elsewhere in the literature. In particular, like Graff Zivin & Neidell (2014) or Obradovich & Fowler (2017), we do not control for individual FE by, instead, employing a pooled Ordinary Least Squares (OLS) model and found largely similar results (Panel G).[18] We reach the same conclusion when using a Random-Effects (RE) model (see Panel H), as has been employed in some previous studies (Aibar *et al.* 2013; Harrison *et al.* 2017). The stability in the results across three

[17] Meteorological data available to us are recorded at 30-minute intervals, allowing us to capture the potential impact of weather elements in a flexible way (e.g., by introducing daily minimum temperature or daily maximum temperature).

[18] In this and subsequent experiment, we additionally control for list of variables describing individual (such as age, gender, health status (for both children and parents) and labour market status (for parents only)) and household characteristics (e.g., two-parent household). We further control for day length and postcode dummies. Remaining results from the pooled OLS regressions (reported in **Error! Reference source not found.**) are as expected and in line with that from previous studies (Graff Zivin & Neidell 2014; Matricciani *et al.* 2019; Nguyen *et al.* 2021). For instance, older children spend less time on sleeping and PA and hence more time on sedentary activities. Furthermore, males are typically more physically active than females. Moreover, parental working status affects the time allocation of both parents and children. We do not control for accelerometer wear time in the regressions because it is potentially affected by weather conditions. Nevertheless, following some previous studies (Ridgers *et al.* 2015; Harrison *et al.* 2017), we experiment with additionally controlling for accelerometer wear time and find little sensitivity in the results (see Panel I).

alternative econometric models (i.e., FE, pooled OLS and RE) suggest little evidence of location selection in our data (Sinha *et al.* 2018) and that weather conditions are genuinely exogenous in the time allocation equations in our case.

Finally, we pool the sample of accelerometer days by both children and parents. Results from this exercise (reported in Panel J) confirm the well-defined weather impacts on time allocation found earlier in Section 0. Specifically, daily maximum temperature and daily precipitation remain the main weather elements driving the time allocation, particularly for sedentary or physically moderate activities, by both children and their parents. Furthermore, as expected, the estimates from the pooled sample are bounded between the estimates obtained separately for children and their parents.

5. Heterogeneity

Our results showed that children and their parents adjust their time differently in response to weather conditions. To further shed light on potential mechanisms behind these differential impacts, we explore the heterogeneity of weather impact. To do so, we estimate equation (1) separately for sub-populations, identified by some likely important characteristics. In particular, it is possible that children and their parents are more constrained in their time allocations during the week due to the children's school commitments or parental work schedules. Thus, children and their parents may have more freedom to adjust to weather conditions on weekends than weekdays. To explore this possibility, we estimate the effects of weather on time allocation on weekdays and at weekends. Similarly, parents with different work arrangements may respond to weather conditions differently. As such, we estimate equation (1) by parental employment status (i.e., full-time employment versus part-time or non-employment).[19]

[19] We combine part-time employment and not-in-labour-force as one group to have a reasonably large sample for this heterogenous analysis. It should be noted that some sub-population analyses lack statistical power due to small sample sizes. To keep the sample sizes reasonably large to obtain reliable estimates, we do not disaggregate the original sample further, for example, by estimating the weather impact by weekends and parental work status. For concentration purposes, this section focuses on estimates of daily maximum temperature and precipitation. It also mainly concerns four outcomes which have been shown to be mostly affected by these weather elements.

Table 3: Heterogeneity

	Sedentary duration				Light PA duration				Moderate PA duration				Average counts			
	Child		Parent		Child		Parent		Child		Parent		Child		Parent	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Weekend (No = Weekdays; Yes = Weekends)																
Max temperature (ºF)	-7.25***	-3.55	0.08	-1.65	2.56**	2.18	-2.02*	6.66**	1.08***	2.09**	0.07	0.67	2.76***	3.66	0.52	-0.16
	[1.42]	[4.74]	[1.81]	[5.13]	[1.00]	[2.99]	[1.13]	[3.08]	[0.32]	[1.01]	[0.71]	[2.33]	[0.78]	[2.38]	[0.60]	[1.50]
Max temperature squared	0.05***	0.02	-0.00	0.00	-0.02**	-0.01	0.01*	-0.04**	-0.01***	-0.01**	-0.00	-0.00	-0.02***	-0.02	-0.00	0.00
	[0.01]	[0.03]	[0.01]	[0.03]	[0.01]	[0.02]	[0.01]	[0.02]	[0.00]	[0.01]	[0.00]	[0.02]	[0.01]	[0.02]	[0.00]	[0.01]
Precipitation (inches)	4.35	30.22***	-1.58	16.26	-1.02	-16.39**	-2.56	-17.60***	-3.14**	-6.90***	-1.01	1.63	-5.48	-18.08***	-1.13	-0.71
	[5.02]	[10.32]	[5.63]	[10.43]	[3.22]	[6.47]	[3.24]	[6.27]	[1.38]	[2.60]	[2.42]	[5.32]	[3.41]	[4.81]	[1.52]	[3.44]
Observations	4,947	1,406	5,012	1,448	4,947	1,406	5,012	1,448	4,947	1,406	5,012	1,448	4,947	1,406	5,012	1,448
No of unique individuals	1,136	698	1,137	718	1,136	698	1,137	718	1,136	698	1,137	718	1,136	698	1,137	718
R-squared	0.021	0.089	0.006	0.013	0.020	0.029	0.008	0.066	0.022	0.033	0.010	0.019	0.023	0.035	0.008	0.021
Sample mean	678	680.3	555.1	521.1	167.8	151.6	268.3	262.9	24.09	18.34	117.1	116.6	196.2	176.8	153.4	149.9
Panel B: Parental full-time employment (No = Part-time employment or unemployment; Yes = Full-time employment)																
Max temperature (ºF)	-5.17***	-7.14***	0.45	1.90	1.87*	4.21**	-2.49**	2.56	1.19***	1.32**	0.65	0.34	2.40***	4.39***	0.72	-0.15
	[1.42]	[2.67]	[1.96]	[3.09]	[1.10]	[1.82]	[1.20]	[1.92]	[0.37]	[0.64]	[0.85]	[1.47]	[0.91]	[1.53]	[0.73]	[1.03]
Max temperature squared	0.03***	0.04**	-0.00	-0.01	-0.01	-0.03**	0.02**	-0.01	-0.01***	-0.01**	-0.00	-0.00	-0.02***	-0.03***	-0.01	0.00
	[0.01]	[0.02]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]
Precipitation (inches)	7.97*	5.76	7.37	-1.92	-3.92	-3.56	-4.17	-1.84	-3.13***	-2.10	-1.59	-2.58	-6.53**	-5.56	-2.40	-2.13
	[4.81]	[6.63]	[5.47]	[8.48]	[3.87]	[4.26]	[3.72]	[4.52]	[1.04]	[2.06]	[2.65]	[4.21]	[2.92]	[4.99]	[1.69]	[2.55]
Observations	3,999	2,739	4,038	2,800	3,999	2,739	4,038	2,800	3,999	2,739	4,038	2,800	3,999	2,739	4,038	2,800
No of unique individuals	673	467	673	467	673	467	673	467	673	467	673	467	673	467	673	467
R-squared	0.025	0.036	0.021	0.066	0.037	0.049	0.015	0.018	0.048	0.041	0.015	0.013	0.062	0.063	0.022	0.011
Sample mean	676	682.3	535.5	560.2	164	162.5	271.4	260.3	22.54	22.37	118	115.7	191.7	189.4	153.1	152

Notes: Results for each outcome and sub-group are from an individual FE regression. "Yes" indicates the coefficient estimate in the regression for the sub-population mentioned on each panel while "No" represents the estimate for the other sub-population. Other explanatory variables include daily minimum temperature, maximum humidity, maximum wind speed, maximum wind direction, day-of-week and month dummies. Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Table 3: Heterogeneity (continued)

	Sedentary duration				Light PA duration				Moderate PA duration				Average counts			
	Child		Parent		Child		Parent		Child		Parent		Child		Parent	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel C: Warmer months (No = June to November; Yes = December to May)																
Max temperature (ºF)	-8.78***	-0.18	1.41	1.67	4.23***	0.03	-2.49**	0.89	2.06***	0.45	0.53	0.17	4.89***	1.10	0.39	0.38
	[1.69]	[2.39]	[2.17]	[2.88]	[1.29]	[1.61]	[1.14]	[1.90]	[0.43]	[0.61]	[0.93]	[1.33]	[1.09]	[1.47]	[0.82]	[0.88]
Max temperature squared	0.06***	0.00	-0.01	-0.01	-0.03***	0.00	0.02**	-0.00	-0.02***	-0.00	-0.00	-0.00	-0.04***	-0.01	-0.00	-0.00
	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Precipitation (inches)	6.14	6.82	-3.45	5.67	-1.03	-4.39	0.40	-4.67	-2.26	-2.90***	3.32	-5.00*	-4.13	-7.31***	0.60	-4.24**
	[6.97]	[4.38]	[8.40]	[5.55]	[4.74]	[3.28]	[4.56]	[3.70]	[2.01]	[0.93]	[3.36]	[2.96]	[5.04]	[2.50]	[2.25]	[1.84]
Observations	3,630	3,099	3,643	3,186	3,630	3,099	3,643	3,186	3,630	3,099	3,643	3,186	3,630	3,099	3,643	3,186
No of unique individuals	616	535	615	536	616	535	615	536	616	535	615	536	616	535	615	536
Sample mean	679.2	677.8	547.5	543.4	163.2	163.6	264.1	270.0	22.5	22.4	117.1	117.0	190.2	191.6	151.8	153.6
Panel D: Warmer regions (No = colder regions; Yes = warmer regions (i.e., postcode with latitude greater to the median))																
Max temperature (ºF)	-5.46***	-7.39**	2.43	-2.73	2.65**	3.00	-1.72	0.44	1.52***	1.37*	0.29	0.84	3.45***	3.52*	0.23	1.14
	[1.43]	[3.42]	[1.95]	[4.12]	[1.05]	[2.32]	[1.14]	[2.92]	[0.35]	[0.79]	[0.84]	[1.80]	[0.87]	[2.02]	[0.70]	[1.25]
Max temperature squared	0.03***	0.05**	-0.02	0.02	-0.02**	-0.02	0.01*	-0.00	-0.01***	-0.01*	-0.00	-0.01	-0.02***	-0.02*	-0.00	-0.01
	[0.01]	[0.02]	[0.01]	[0.03]	[0.01]	[0.01]	[0.01]	[0.02]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]
Precipitation (inches)	12.82**	-0.85	14.23**	-4.66	-8.57**	1.54	-5.80	-0.95	-4.09***	-1.04	-5.55**	1.00	-10.83***	-0.98	-5.19***	-0.15
	[5.06]	[6.10]	[6.26]	[6.81]	[3.93]	[3.79]	[4.12]	[3.98]	[1.00]	[1.73]	[2.70]	[3.39]	[2.88]	[4.18]	[1.89]	[2.05]
Observations	3,393	3,345	3,428	3,410	3,393	3,345	3,428	3,410	3,393	3,345	3,428	3,410	3,393	3,345	3,428	3,410
No of unique individuals	569	571	569	571	569	571	569	571	569	571	569	571	569	571	569	571
Sample mean	670.1	687.2	543.8	547.4	166.3	160.5	266.8	266.9	25.2	19.7	119.6	114.5	196.5	185.1	153.7	151.6

Heterogenous results by weekends/weekdays are reported in Panel A of Table 3. Summary statistics (reported at the bottom of Panel A) show that children and their parents spend their time quite differently by weekends/weekdays. In particular, children allocated more time to light or moderate PA on weekdays but more time (5 minutes) to vigorous PA on weekends. By contrast, parents spent more time (30 minutes) on sleeping and less time (33 minutes) on sedentary activities on weekends. These differential time allocation patterns are consistent with the idea that children and their parents are more constrained in their time allocations during the week due to the children's school commitments or parental work schedules. Sub-group regression results suggest noticeable differences in weather impacts on some activities that children and their parents perform on weekdays or weekends. For instance, daily maximum temperature appears to have a more pronounced impact on children's time spent on sedentary or physically light activities undertaken on weekdays because the estimates are more statistically significant or of a higher magnitude on weekdays. By contrast, and by a similar reasoning, daily maximum temperature has a more pronounced effect on children's time contributed to moderate PA on weekends. Likewise, precipitation tends to have a more pronounced effect on children's time allocation on weekends and this pattern is observed for all four measured outcomes.[20]

However, we do not observe any substantial difference in the weather impact on parents' time allocation by weekdays/weekends since, consistent with the baseline results, sub-group estimates are not highly statistically significant. An exception is the noticeable heterogeneity in the weather impact on parents' light PA duration (columns 7 and 8). In particular, the relationship between daily maximum temperature and parent's light PA duration, which is statistically significant (at least at the 10% level) in both cases, displays a U-shaped pattern on weekdays and an inverted U-shaped pattern on weekends (see **Error! Reference source not found.**).[21] Furthermore, taking the statistical significance level and magnitude of the estimates into account, the results indicate that daily maximum temperature has a more pronounced marginal impact on the time parents allocate to light PA on weekends than on weekdays. We also observe that precipitation has a substantially greater effect on

[20] Using detailed time-use diaries of LSAC children, Nguyen *et al.* (2021) find that types of activities, even though they may result in the same PA counting using some instruments such as accelerometers, undertaken on weekdays and weekends are not the same (Nguyen *et al.* 2021). These activities may be affected differently by weather conditions.

[21] We experimented with employing a cubic functional form for daily maximum temperature in the regressions of parents' light PA duration and found no evidence supporting the use of such a model.

parents' light PA duration on weekends because the estimate is about 7 times greater on weekends and is statistically significant (at the 1% level) for weekends only.

Our heterogeneity analysis above, while inclusive with respect to the directional differences by weekdays/weekends for children, suggests that children's school commitments or parental work schedules influence how they allocate their time as well as the way they respond to weather conditions (Nguyen *et al.* 2021). Our finding of a more pronounced weather impact on parents' light PA performed on weekends is in line with the view that parental work arrangements may curtail their capacity to respond to unfavourable conditions on weekdays (Connolly 2008; Graff Zivin & Neidell 2014).

To further our understanding of the potential role of parental work commitments, we explored the weather impact by parents' labour force status. Heterogenous results, reported in Panel B of Table 3, demonstrate that, as compared to unemployed or part-time employed parents, full-time employed parents allocated less time to sleeping (by 9 minutes) and light PA (by 11 minutes) but noticeably more time on sedentary activities (by 25 minutes). Moreover, consistent with the pooled OLS results, children's time allocations appear to be affected by their parents' work status as children of full-time employed parents spent less time sleeping (by 8 minutes) and more time on sedentary activities (by 6 minutes). Sub-group regression results suggest that children of full-time employed parents tend to be affected more by temperature since the temperature estimates are more statistically significant or greater in the magnitude for them. However, they seem to be less influenced by precipitation than children of unemployed or part-time employed parents. In line with the baseline results, sub-group regression results show a statistically insignificant weather impact on parents' time allocation. An exception is that the relationship between daily maximum temperature and unemployed/part-time employed parents' light PA duration is statistically significant (at the 5% level) and follows a U-shaped pattern.[22] This result, when viewed alongside a previous finding that weather has a more pronounced effect on parents' time allocated to light PA on weekends, further supports our starting hypothesis that work commitments limit parents' capacity to adjust to weather conditions.

[22] Consistent with this prediction, unreported results show precipitation has a negative and statistically significant (at the 1% level) effect on vigorous PA duration of unemployed or PT employed parents only.

Following previous studies (Graff Zivin & Neidell 2014; Nguyen *et al.* 2021), to explore the likelihood of short-run adaptation to weather conditions, we compare the impact of weather by seasons (i.e., warmer months versus colder months). We assign June to November as colder months and other remaining months as warmer months.[23] Furthermore, to seek evidence of longer-run adaptation to weather, we contrast the weather impact by climate regions (e.g., warmer regions versus colder regions). Child/parent pairs are considered as living in warmer regions if they resided in a postcode with a latitude greater than the median.[24]

Table 3 – Panel C shows that children's time allocation is much more responsive to temperature in colder months since the temperature estimates are much greater in magnitude and only statistically significant in these months. We also observe that parents' light PA is statistically significantly (at the 5% level) affected by temperature in colder months only. The finding of a more pronounced temperature impact in colder months is consistent with the idea of short-run acclimatization, as found in the literature (Graff Zivin & Neidell 2014; Nguyen *et al.* 2021). By contrast, children and their parents are more responsive to precipitation in warmer months as estimates of precipitation are more statistically significant and of a higher magnitude (in absolute value) for moderate PA, and hence the average count, undertaken during warmer months.

Estimates of temperature by climate regions (Table 3 – Panel D) provide some evidence of longer-run adjustments as temperature has a more statistically significant impact on children's time allocation in colder regions. Moreover, estimates of precipitation are statistically significant in colder regions only, suggesting a compounding impact of unfavourable weather conditions (i.e., cold *and* rainy days) on time allocation, especially by children.

6. Conclusion

The unique features of our data allow us, for the first time in this literature, to directly answer whether children and their parents allocate their time differently in response to ambient weather conditions. Our results show that unfavourable weather conditions, as measured by cold or hot temperatures or

[23] Using other alternative month cut-offs, such as grouping October to March as "warmer months", does not change our finding in any significant way.

[24] As expected, unreported statistics show that temperature is statistically significantly (at the 1% level) higher in warmer months or warmer regions. However, our data display no noticeable difference in precipitation by seasons or climate regions.

rain, cause children to reduce the time allocated to physical activities, mainly by increasing the time spent on sedentary activities. However, we do not find any noticeable weather impact on the time that children allocate to sleeping or the way their parents spend their own time. Our results also show that the differential weather impact observed for these child-parent dyads is statistically significantly different and meaningful.

In addition to the potential role of age differences between children and their parents, our results further suggest that children's school commitments or parental work schedules contribute to this differential weather impact because weather impact varies substantially by weekdays/weekends and parental employment status. We also find evidence of adaptation and acclimatization, as children living in colder regions or surveyed in colder months are more sensitive to warmer temperatures. Our findings are robust to a wide range of sensitivity checks, including controlling for individual heterogeneity and using alternative model specifications.

The finding of a more pronounced weather impact on the time allocation by children enriches existing evidence suggesting that climate change affects individuals differently depending on their age and stage of development (Watts *et al.* 2019). This finding also calls for mitigation policies to protect vulnerable populations, especially children, from adverse consequences of extreme weather conditions.

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