Fetal temperature exposure on long term cognitive and economic individual outcomes

Sonia Bhalotra, *[1], Irma Clots-Figueras, †[2], Joseph Flavian Gomes, ‡[3], and Alessio Mitra §[4]

[1] *University of Warwick*
[2] *University of Kent*
[3] *UCLouvaint*
[4] *University of Kent*

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Abstract

This paper studies the impact of fetal exposure to unusual hot days on long-term individual outcomes such as personal income, education attainment and adult cognitive capabilities in the UK. Merging individual level data from the UK's Longitudinal Household Survey (UKHLS) with gridded weather data from the Met Office Integrated Data Archive System (MIDAS) we find that exposure to hot temperatures during pregnancy leads to lower income, education and cognitive abilities in adulthood. Such results bring support to the fetal origins" hypothesis.

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*University of Warwick
†University of Kent
‡UCLouvain
§University of Kent

1 Introduction

Extensive medical research as reported how adverse in utero experiences can affect the pre-natal development of the human embryos (Zeng et al. 2017, Yang et al. 2006), up to the point of affecting the weight at birth (Deschênes et al. 2009, Yitshak-Sade et al. 2021, Camacho 2008, Andalón et al. 2016, Rangel & Vogl 2016, Larsen et al. 2017, Aizer 2011), which is a strong predictor of normal growth and healthy development (Belbasis et al. 2016, Goldenberg & Culhane 2007).

In particular, excess heat in the womb is associated with physical defects, delay in brain development, and lead to a host of central nervous system problems that may make it harder to accumulate human capital in the long run (Zivin & Shrader 2016). This is often referred to as the "fetal origins" hypothesis (Almond & Currie 2011).

More recently, a growing body of research looks at the long-lasting effects of such adverse pre-natal shocks. It is shown that adverse in utero and early childhood weather experiences can have lasting effects on later-in-life human capital outcomes such as health, education and labour market achievements (Almond et al. 2018, Randell & Gray 2016, 2019, Almond et al. 2018). Yet, most of the empirical evidence is concentrated in developing countries where cushion factors may be less determinant. Climate change is likely to play a crucial role on this regards, as the emissions of greenhouse gases due to human activity will alter global temperatures, precipitation levels, and overall weather stability (Thornton et al. 2014).

The aim of this paper is to measure the effect of exposure to unusual hot temperatures during pregnancy, in a developed country such as the UK, on long-term individual outcomes such as personal income, education attainment and adult cognitive capabilities. Using individual-level data on more than 20 thousand births, we find that exposure to hot temperatures during pregnancy leads to lower income, education and cognitive abilities in adulthood. We also explore the effect of rainfall and sunnshine on the same long term outcome variables, finding less clear results.

2 Data Sources and Summary Statistics

To implement the analysis, we collected the most detailed and comprehensive data available on individual characteristics and historical weather conditions in the UK. This section describes these data and reports summary statistics. See in the Appendix for further details.

2.1 UK's Longitudinal Household Survey

We take individual level data from the UK's Longitudinal Household Survey (UKHLS). The data include date of birth, county of birth, race, sex, as well as adult cognitive abilities, education level and net personal income achieved. We use UKHLS waves 1-9 (2009-2018), and follow 38,242 unique individuals that reported all: year, month and county of birth in the UK. Across all waves, we can count on 218,046 observations.

2.2 CEDA weather data

We obtain the weather data from the Met Office Integrated Data Archive System (MIDAS). The gridded climate variables are derived from the network of UK land surface observations. The dataset covers the UK at 1 km x 1 km resolution, spans the period from 1960 to 2018, with a daily frequency of observations. The key variables for our analysis are the daily minimum and maximum temperature, which we average to construct daily average temperature.

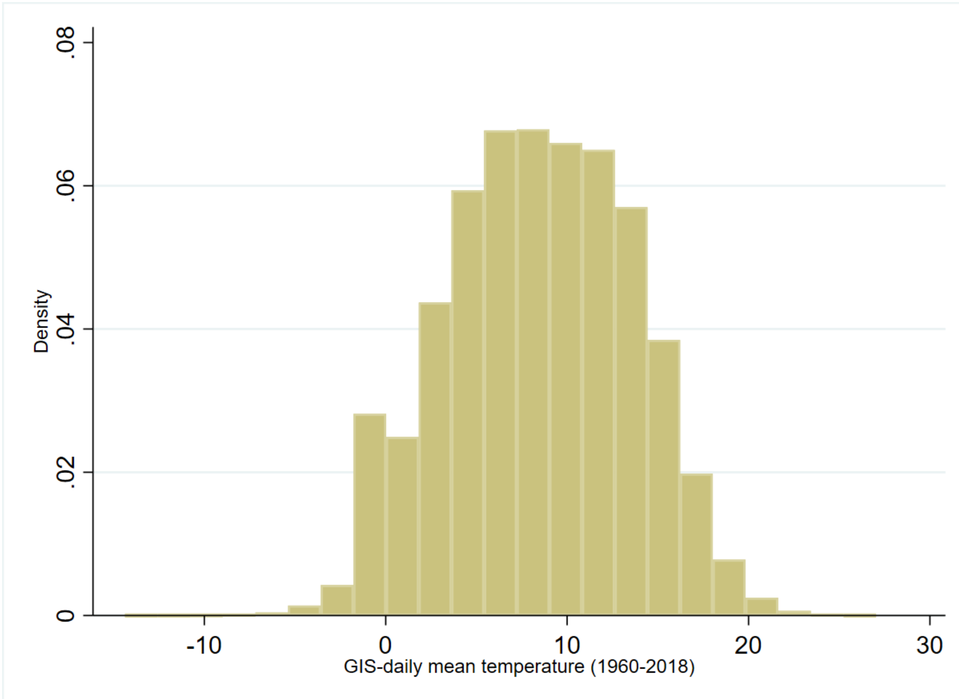
2.3 UK's Household Weather at birth Linked Survey

We link UKHLS individual data to CEDA weather gridded data using date and county of birth of individuals. Since historical UK counties borders slightly changed over time, we match individuals' county of birth with a geographic information system (GIS) following the "Great Britain Historic GIS Project". Then, we match CEDA weather data to the resulting GIS coordinates.

Overall, all 121,200 UKHLS observations are matched with a GIS and the CEDA weather variables (all individuals born after 1960 are matched). The so built UK's Household Weather at birth Linked Survey (UKHWLS) bring to the literature a much needed novel data source to study the impact of early age exogenous weather shocks on a wide range of individual level outcome variables.

Figure 1 depicts the distribution of daily temperature from 1960 until 2018. The fact that the UK is a rich, with typically mild weather, country should not be seen as a draw back, on the contrary, this allows to assess the impact of moderately high temperature in a setting where high temperature is not associated with shortage of food and malnutrition, hence allowing to exclude the malnourishment mechanism. Furthermore, what the UK may lack in term of extreme temperatures, more than compensate with quality of the data.

Figure 1: Temperature histogram



Note: The hystogram represents the distribution of the daily mean temperature in the UK at GIS level from 1960 to 2018.

Table 1 shoes the descriptive statistics of the main individual level variables employed in our analysis. Individual socio-economic outcomes are available for almost all waves of the UKHLS, while cognitive ability measurements comes from the wave 3. Personal net income represents the total net personal income with no deductions, education qualification is a dummy with 1 if the individual has obtained any education qualification and 0 otherwise, while job confidence measure the perceived confidence of individuals in having a successful career. During the third waves a special survey was added to the UKHLS, participants were asked a set of cognitive questions with pre-defined correct and wrong answers. During the interviewing process, the interviewers registered the correct answers with value 1 and the wrong answers with value 2.

Table 1: Individual characteristics

	Min	Max	Mean	SD	Observations	Available waves
Socio-economic outcomes						
Personal net income	-17741.34	387060.7	1514.846	1878.988	121200	1-9
Education qualification	0	1	0.9562508	0.2045374	121168	1-9
Cognitive abilities						
ns207d1	1	2	1.888645	.3146869	1365	3
ns210j1	1	2	1.49455	.5000839	2202	3
ns221g2	1	2	1.793828	.4045846	6999	3
ns235o2	1	2	1.421053	.4938634	1824	3
nacar	1	2	1.660475	.4735647	14373	3
nainterest	1	2	1.554955	.4970052	7215	3
Individuals' characteristics controls						
Gender	1	2	1.573087	.4946315	121198	1-9
Marital status	0	10	3.225671	3.147462	121061	1-9
Age	16	60	37.04145	10.59022	121197	1-9
Race	1	97	2.197388	4.932918	121127	1-9
Ethnicity	1	97	2.202876	4.966293	121192	1-9
Urbanization neighbour	1	2	1.220042	.4142766	121154	1-9
N. children	0	9	.7973267	1.048032	121200	1-9
Ethnicity father	1	97	2.863396	9.224964	19897	1-9
Ethnicity mother	1	97	2.765274	9.384794	19985	1-9
Religiousness	1	5	3.939636	1.283478	42956	1-9

Note: Education qualification = 0 if individual does not hold any qualification. Education qualification = 1 if individual holds a qualification. Cognitive ability = 1 if individual gave wrong answer during standardized test. Cognitive ability = 2 if individual gave correct answer during standardized test. For cognitive abilities, in the raw data, the classification was: correct answer = 1 and wrong answer = 2. In the final data is has been inverted for easier interpretation.

Questions ns207d1 ns210j ns221g2 and ns235o2 all require the respondent to look at a series of numbers with a number missing from the series. The Respondent must determine the numerical pattern, and then provide the missing number in the series. Each participant was given up to six number series problems to solve. These tests are adaptations from Woodcock Johnson III Tests of Achievement: Number Series by Woodcock et al. (2001)

The question nacar has as text: A second hand car dealer is selling a car for £6,000. This is two thirds of what it cost new. How much did the car cost new? While the question nainsterest has as text: Let's say you have £200 in a savings account. The account earns ten percent interest each year. How much would you have in the account at the end of two years?

3 Econometric strategy

We are interested in estimating the effect of temperatures during pregnancy on adult outcomes, such as education, income, health and mental health. Given that the relationship between temperature and these variables can be nonlinear, in order to estimate the effects of temperature in a flexible way, we use different temperature bins, similar to the approach taken in many studies in the literature, see, for example (Deschênes & Greenstone 2011, Burgess et al. 2014). The UK is a relatively cold country, that in contrast with more southern countries has not been exposed to very large temperature shocks. As we can see in **??**, the average daily temperature for the period we consider is below 10 degrees, with only a few observations above 23 degrees or below -4 degrees. Given our interest in understanding the effects of these extreme temperatures, we construct 5 bins of approximately the same distance for those temperature values that are more frequent.

The econometric approach is based on the fitting of the following equation:

$$Y_{i,c,t,m} = \sum_{j} \beta^{PRG} \cdot TEMPMEAN^{PRG}_{c,t,j,m} + \alpha_{c,t} + \epsilon \tag{1}$$

Our outcome variable Y_{ict} would be income, education, or the health measure for individual i, born in grid c in year t and month m. The variables of interest $TEMPMEAN^{PRG}_{c,t,j,m}$ represent how many times (days) the mean temperature was within the j bin ($j = 1, 2, 3, 4, 5$) during the gestation period of the individual.

We employ 5 bins, that capture the distribution of temperatures in the grid of birth during the gestation period: $]-\infty; -4]$, $]-4; 5]$, $]5; 14]$, $]14; 23]$ and $]23; +\infty[$. The temperature bin $j = 3$ is our reference bin, given that it contains the average temperature. Hence, each coefficient measures the impact of an additional day in a given bin, during the pregnancy, on the outcome variable, relative to the impact of a day within the third bin, with usual temperatures.

We control for grid of birth, year of birth, month of birth and survey FE, together with individual characteristics, such as: gender, age, race, and urban-rural area.

4 Results

Table 2 shows the results of cumulative hot days during the whole pregnancy by employing equation 1 on different socio-economic outcomes. Each coefficient measures the impact of an additional day, during the entire pregnancy, in a given bin on the outcome variable of interest, relative to the impact of a day with temperature in between 5C and 14C. The estimates show that cumulative high-temperature days during the pregnancy strongly and negatively affects future individuals' net income, education attainment and job confidence.

A one day more with temperature above 23C during pregnancy will decrease the individual net monthly income by £25, reduce the likelihood of getting any education qualification by 0.25 percentage points. It is reassuring to observe that the estimates are not sensitive to the inclusion of survey wave fixed effects and Individuals' characteristics controls, with magnitude and statistical significance rising with their addition.

Table 2: Effect of cumulative hot days during whole pregnancy on long term individual socio-economic outcomes

	(1)	(2)	(3)	(4)
	total net personal income		Formal qualification	
Whole pregnancy				
n. days whole pregnancy with meantemp in bin 1	-4.300	-0.168	-0.000729	-0.00115
	(4.517)	(5.122)	(0.000918)	(0.00115)
n. days whole pregnancy with meantemp in bin 2	0.958	-0.0210	-0.0000878	-0.000177
	(1.056)	(1.090)	(0.000204)	(0.000216)
n. days whole pregnancy with meantemp in bin 4	-0.348	0.375	-0.0000268	-0.0000758
	(0.675)	(0.589)	(0.000120)	(0.000191)
n. days whole pregnancy with meantemp in bin 5	-25.20**	-30.13**	-0.00241*	-0.00414**
	(9.832)	(9.637)	(0.00130)	(0.00207)
Constant	1477.2***	582.9	0.965***	1.046***
	(72.12)	(356.8)	(0.0144)	(0.0795)
Observations	118477	19448	118445	19442
GIS FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Survey wave FEs	No	Yes	No	Yes
Individuals' characteristics controls	No	Yes	No	Yes

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at GIS level. Each model includes GIS, year and month of birth FEs. Individuals' characteristics controls includes: gender, marital status, age, race, ethnicity, urban-rural area, n. children in household, father ethnicity, mother ethnicity and religiousness. Temperature bins employed are: $]-\infty; -4]$, $]-4; 5]$, $]5; 14]$, $]14; 23]$ and $]23; +\infty[$

Table 3 shows the results of cumulative hot days during the whole pregnancy by employing equation 1 on cognitive abilities. A one day more with temperature above 23C during pregnancy will reduce the probability of giving the correct answer on different UKHLS cognitive questions by around 2 percentage points. Table 4 highlight that the estimates are not sensitive to the inclusion of survey wave fixed effects and individuals' characteristics controls, with magnitude and statistical significance rising with their addition. The results of pre-natal high temperature on education attainments are in line with what found by Randell & Gray (2016) in Ethiopia, by Aguilar & Vicarelli (2011) in Mexico and by Randell & Gray (2019) in South-east Asia. To the best of our knowledge, instead, no other paper has reported the effect of fetal exposure to high temperatures on long-term personal income.

Table A1 (see Appendix) shows the same estimations on more outcome variables such as self reported health, trust in others and satisfaction with life. Most of these estimates are statistically insignificant, most likely due to the subjective nature of the measurements. Table A2 and Table A3 (see Appendix) show the impact of pregnancy average rainfall and pregnancy average sunshine on socio-economic and cognitive outcomes, with unclear results.

With regard to the potential mechanisms, the literature presents an economic and biological channel. The economic channels mainly go through the impact of extreme whether conditions on agricultural production, leading to malnutrition and worsened individual development. The biological channel instead focus on the direct physical or mental impairment effects from heat stress on the body. Heat stress is classified among the many environmental stress that can damper cognitive development at the early stages of life. From here, lower education and cognitive achievement are likely to lead to lesser job market outcomes.

Table 3: Effect of cumulative hot days during whole pregnancy on long term individual cognitive outcomes (baseline results)

	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive abilities from standardized test questions					
	ns207d1_inv	ns210j1_inv	ns221g2_inv	ns235o2_inv	nacar_inv	nainterest_inv
Whole pregnancy						
n. days whole pregnancy with meantemp in bin 1	0.000744	-0.00800	0.000646	0.00248	0.00712**	-0.00279
	(0.00563)	(0.00742)	(0.00335)	(0.00830)	(0.00305)	(0.00536)
n. days whole pregnancy with meantemp in bin 2	-0.00110	0.00109	0.000865	0.000941	0.000198	0.000670
	(0.00123)	(0.00146)	(0.000581)	(0.00140)	(0.000473)	(0.000563)
n. days whole pregnancy with meantemp in bin 4	0.00105	0.000812	-0.000373	-0.000287	-0.000253	-0.0000142
	(0.000723)	(0.000963)	(0.000365)	(0.00118)	(0.000372)	(0.000451)
n. days whole pregnancy with meantemp in bin 5	-0.0195*	-0.0285**	-0.0143**	-0.0375**	-0.0112**	-0.0221**
	(0.0110)	(0.0133)	(0.00665)	(0.0171)	(0.00476)	(0.00826)
Constant	1.908***	1.395***	1.761***	1.546***	1.657***	1.521***
	(0.0826)	(0.0887)	(0.0427)	(0.0861)	(0.0355)	(0.0403)
Observations	1331	2139	6837	1778	14053	7040
GIS FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Individuals' characteristics controls	No	No	No	No	No	No

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at GIS level. Each model includes GIS, year and month of birth FEs. Temperature bins employed are: $]-\infty;-2]$, $]-2;3]$, $]3;16]$, $]16;23]$ and $]23;+\infty[$

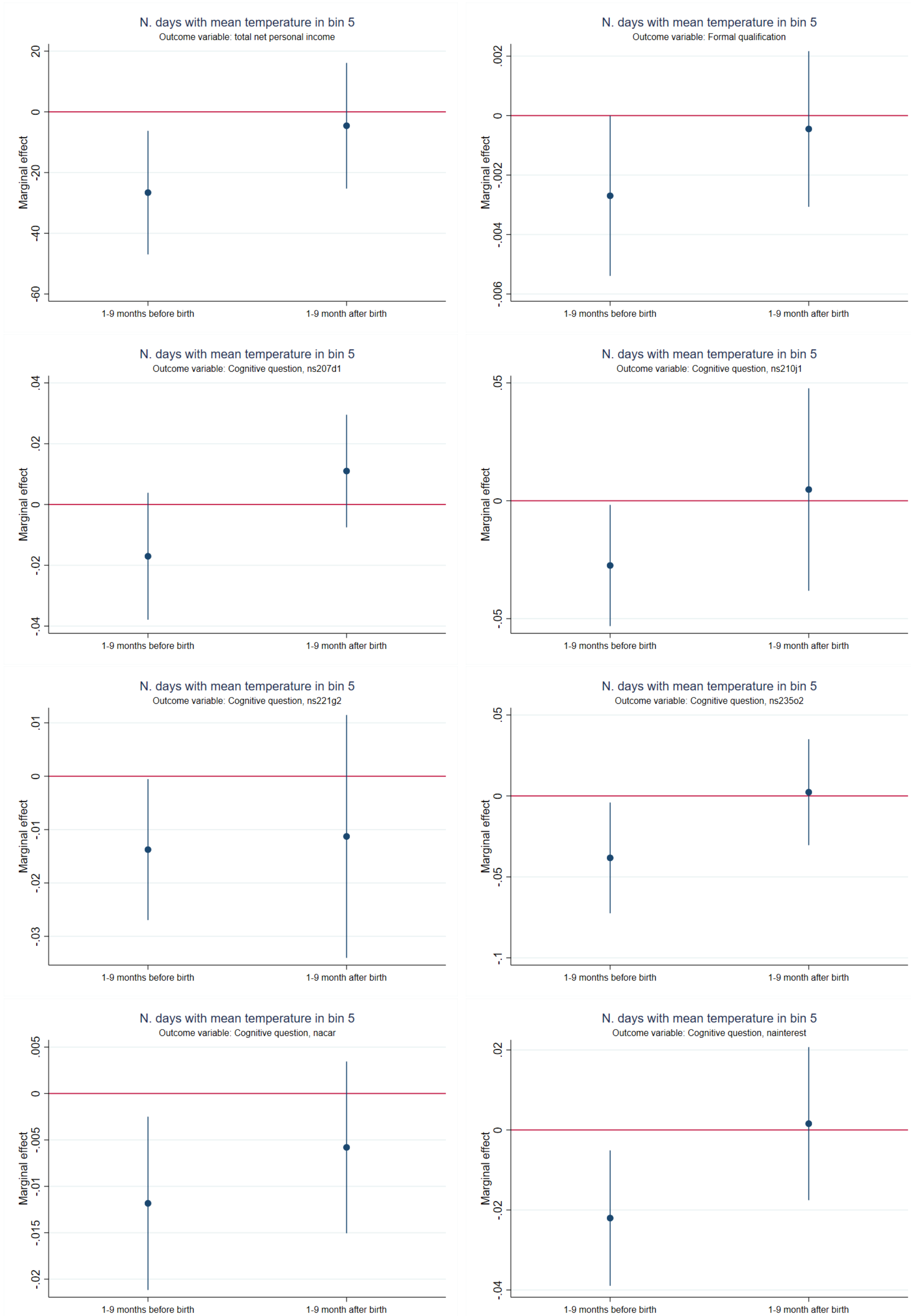
Table 4: Effect of cumulative hot days during whole pregnancy on long term individual cognitive outcomes (additional controls)

	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive abilities from standardized test questions					
	ns207d1_inv	ns210j1_inv	ns221g2_inv	ns235o2_inv	nacar_inv	nainterest_inv
Whole pregnancy						
n. days whole pregnancy with meantemp in bin 1	0.0000288	-0.00783	0.0000741	-0.00168	0.00644**	-0.00347
	(0.00558)	(0.00741)	(0.00334)	(0.00853)	(0.00308)	(0.00522)
n. days whole pregnancy with meantemp in bin 2	-0.00103	0.000931	0.000805	0.000722	-0.0000174	0.000300
	(0.00122)	(0.00146)	(0.000580)	(0.00136)	(0.000444)	(0.000560)
n. days whole pregnancy with meantemp in bin 4	0.00100	0.000787	-0.000353	-0.000404	-0.000137	0.000120
	(0.000724)	(0.000954)	(0.000365)	(0.00116)	(0.000384)	(0.000465)
n. days whole pregnancy with meantemp in bin 5	-0.0199*	-0.0333**	-0.0137**	-0.0329**	-0.0115**	-0.0231**
	(0.0109)	(0.0126)	(0.00651)	(0.0152)	(0.00471)	(0.00783)
Constant	1.378**	1.790***	1.794***	0.382	2.486***	2.145***
	(0.477)	(0.493)	(0.280)	(0.740)	(0.252)	(0.319)
Observations	1330	2139	6833	1776	14041	7033
GIS FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Individuals' characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at GIS level. Each model includes GIS, year and month of birth FEs. Individuals' characteristics controls includes: gender, marital status, age, race, ethnicity, urban-rural area and n. children in household. Temperature bins employed are: $]-\infty; -2]$, $]-2; 3]$, $]3; 16]$, $]16; 23]$ and $]23; +\infty[$

Figure 2 depicts the marginal effect of cumulative hot days in the 9 months before and after birth. For all outcome variables of interest, we find a negative impact of high temperature during the pregnancy on long term cognitive and economic individual outcomes, while statistical insignificant effects of high temperatures after birth. Such results add robustness on the idea that the main findings are not driven by contextual parental or geographical characteristics, but by the exogenous changes in unusual hot days during the development period of the foetuses.

Figure 2: Effect of cumulative hot days 9-months before and after the date of birth



Note: The graphs represent the results of regression (1) where it has been included also the temperature bins for the 9 month post date of birth. Only the coefficients of interest (bin's 5 coefficients) are presented.

5 Conclusions

Using a novel dataset that links CEDA weather data to the UK's Longitudinal Household Survey, this research contribute to the growing literature on the "fetal origin" hypothesis by showing that pre natal exposure to hot temperatures decrement long term cognitive capabilities, education attainment and net personal income. Furthermore, the magnitude of the effect on personal income is economically relevant: A one day more with temperature above 23C during pregnancy is estimated to decrease the individual net monthly income by £25. The finding of relevant negative effects on education and cognitive attainment, as well as the UK centric nature of the study, helps identifying the mechanism at play. Indeed, being unlikely that UK agricultural output or import of food is affected by local extreme weather, it is plausible that the effect is almost entirely directly biological, and not through economic intermediary mechanisms.

The presented paper contribute to the literature in three ways: firstly, it represents the first empirical evidence on the effect of extreme weather from a developed countries with cushion factors and generally mild temperatures. Secondly, it shows how extreme weather conditions can negatively affect pregnancy up to the point compromising the cognitive capabilities of the new born, leading to future lower education achievements and earned income. Thirdly, it present the novel UKHWLS dataset with granular weather daily data and individuals birth and socio-economic characteristics.

Future research should use high granularity weather data to explore the same findings in other developed countries, so that upcoming research will be able to comparatively understand which institutional and policy solutions can tackle this and other challenges posed by climate change.

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A Appendix. Additional results

Table 1: Effect of cumulative hot days during whole pregnancy on other outcome variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	general health	Satisfaction(life)	depressed	SF-12 Mental	SF-12 Physical	Satisfaction(health)	Satisfaction(income)	prepared to risk	prepared to risk trusting strangers	GHQ-Likert	GHQ-Caseness	pain at work
Whole pregnancy												
n. days with meantemp in bin 1	-0.000928	-0.00189	0.000876	-0.00626	0.0252	0.00175	0.000289	-0.00967	0.00108	-0.000982	0.000774	-0.00359
	(0.00266)	(0.00280)	(0.00236)	(0.0231)	(0.0224)	(0.00343)	(0.00356)	(0.00690)	(0.00661)	(0.0130)	(0.00675)	(0.00233)
n. days with meantemp in bin 2	0.00110	-0.00206*	-0.000867	-0.00632	-0.00104	-0.00102	-0.00167	-0.00294	-0.000451	0.00714	0.00453*	0.000260
	(0.000736)	(0.00116)	(0.000791)	(0.00796)	(0.00902)	(0.00115)	(0.00135)	(0.00253)	(0.00244)	(0.00437)	(0.00246)	(0.00104)
n. days with meantemp in bin 4	0.000257	-0.000484	0.0000529	0.000406	-0.00584	-0.000112	-0.00154*	-0.00108	-0.00211	0.00101	-0.000391	0.000697
	(0.000644)	(0.000848)	(0.000664)	(0.00635)	(0.00524)	(0.000849)	(0.000917)	(0.00206)	(0.00183)	(0.00356)	(0.00207)	(0.000676)
n. days with meantemp in bin 5	0.0100	-0.0213	-0.00146	-0.0202	-0.0869	-0.0141	-0.00960	-0.0245	-0.0169	0.0599	0.0207	0.0169*
	(0.00957)	(0.0170)	(0.00935)	(0.0929)	(0.0891)	(0.0215)	(0.0240)	(0.0224)	(0.0202)	(0.0435)	(0.0252)	(0.00900)
N. observations	117849	108920	90874	109350	109350	108952	108833	18257	18258	108783	108783	90905
N. clusters	96	96	96	96	96	96	96	94	94	96	96	96
GIS FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at GIS level. Each model includes GIS, year and month of birth FEs.

Table 2: Effect of average rainfall during whole pregnancy on other outcome variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net personal income	Qualificationy	Job confidence	ns207d1	ns210j1	ns221g2	ns235o2	nacar	nainterest
Whole pregnancy									
Mean of rain for whole pregnancy	125.0	0.102**	4.275	-0.460**	-0.0739	-0.104	0.133	-0.0862	-0.159
	(175.2)	(0.0447)	(11.24)	(0.141)	(0.224)	(0.0922)	(0.236)	(0.0758)	(0.111)
N. observations	218046	217993	5557	2951	3739	12505	2996	26070	12696
N. clusters	101	101	83	87	80	94	77	98	96
GIS FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at GIS level. Each model includes GIS, year and month of birth FEs.

Table 3: Effect of average sunshine during whole pregnancy on other outcome variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net personal income	Qualificationy	Job confidence	ns207d1	ns210j1	ns221g2	ns235o2	nacar	nainterest
Tot of sunshine for whole pregnancy	0.160	0.0000247	-0.00103	0.0000607	-0.0000129	0.00000872	0.0000728	0.00000837	0.0000816
	(0.113)	(0.0000215)	(0.00567)	(0.0000857)	(0.0000816)	(0.0000541)	(0.000108)	(0.0000473)	(0.0000558)
N. observations	212383	212337	5557	2839	3677	12179	2964	25302	12491
N. clusters	101	101	83	87	80	94	77	98	96
GIS FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at GIS level. Each model includes GIS, year and month of birth FEs.

B Appendix. Data cleaning details

UKHLS.

The data is collected with Special Licence acces from UK Data Service (SN:6931). Dataset: Understanding Society: Waves 1-9, 2009-2018 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. We use data stored in a indresp, b indresp ... i indresp. These correspond to individual level data collected from interviews with responding adults (16+) in Wave 1, Wave 2 ... Wave 9.

Table 1 reports some important UKHLS variables used to merge UKHLS data with CEDA weather data.

Table 1: UKHLS variables on individuals birth info

UKHLS variable name	Label	Waves
pidp	cross-wave person identifier	1, 2, 3, 4, 5, 6, 7, 8, 9
plbornuk	county of birth UK	1, 2, 3, 4, 5, 6, 7, 8, 9
plbornuk_all	county of birth	1, 3, 4, 5, 6, 7, 8, 9
plbornc	country of birth	1, 2, 3, 4, 5, 6, 7, 8, 9
plbornc_all	county of birth	1, 2, 3, 4, 5, 6, 7, 8, 9
scdoby4	date of birth, year	1, 2
scdobm	date of birth, month	1, 2

UKHLS define missing observation with different missing categories as shown in Table 2. Date of birth is available exclusively for wave 1 and 2. Hence, only individuals entering the survey in wave 1 and 2 will be matched with the CEDA weather data.

Table 2: Missing values and labels

Value	Label
-1	”Don't know”
-2	”Refused”
-7	”Proxy”
-8	”Valid skip or inapplicable”
-9	”Missing by error or implausible”
-10	”Not available for the IEMBS”
-11	”Only available for the IEMBS”
-20	”No data from the BHPS W1-18”
-21	”No data from the UKHLS”

Informations such as date, county and country of birth are asked and reported only once (the first time/wave that an individual is interviewed). Hence, we extend such info of birth by pidp (individual) to all waves. Then, we recode as ”.” all the different missing categories (-1, -2, -7, -8, -9, -10, -11, -20, -21) for the outcome variables of interest.

Merging UKHLS with GIS.

GIS-county matches are performed using the ”Great Britain Historic GIS Project”. Not all counties of birth from UKHLS perfectly match with the counties present in the ”Great Britain Historic GIS datasets”. All the differences are small, mostly typos or different ways to refer to the same county. There are, however, a minority of cases where an arbitrary decision has to be made: this happens when UKHLS individuals gave as county of birth a macro region instead of an actual county. We assign each of these cases to the county with the larger population in the declared region.

Table 3 shows the counties mismatches and decisions taken.

Table 3: UKHLS county name changed to match with GIS datasets

UKHLS county of birth name	GIS county name
Typos/Not arbitrary decision	
ABERDEEN CITY	ABERDEEN
ANGUS - FORFARSHIRE	ANGUS
ARGYLL & BUTE	ARGYLL AND BUTE
BUTE	BUTESHIRE
DUMFRIES & GALLOWAY	DUMFRIES AND GALLOWAY
DUMFRIESSHIRE	DUMFRIES SHIRE
DUNDEE CITY	DUNDEE
EDINBURGH, CITY OF	EDINBURGH
GLASGOW CITY	GLASGOW
INVERNESS-SHIRE	INVERNESS SHIRE
ISLE OF ANGLESEY	ANGLESEY
NORTH AYRSHIRE	NORTH AYSHIRE
PEEBLESSHIRE	PEEBLES SHIRE
PERTH & KINROSS	PERTHSHIRE AND KINROSS
RHONDDA CYNON TAF	RHONDDA, CYNON, TAFF
THE VALE OF GLAMORGAN	VALE OF GLAMORGAN
Arbitrary decision	
YORKSHIRE	YORK
NORTHERN IRELAND NEC	ANTRIM
ENGLAND NEC	GREATER LONDON
MIDLANDS NEC	NOTTINGHAMSHIRE
SCOTLAND NEC	GLASGOW
STRATHCLYDE	GLASGOW
WALES NEC	POWYS