The Relationship Between Season of Birth, Temperature Exposure, and Later Life Well-Being, Supplementary Appendix

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Supporting Information (SI). This supplementary appendix begins by providing additional details regarding data construction. We then present and discuss additional results that support the main conclusions of our study:

Additional Data Discussion.

Longitudinal Employer Household Dynamic Files. Although the LEHD provides essential information for studying the long-run effects of early-life circumstances for a large fraction of the U.S. worksforce, several limitations exist. First, the LEHD is assembled by combining various state's administrative earnings records. This means that states have varying degrees of temporal coverage in the main dataset, with most participating states entering the sample by the late 1990s. The second challenge is that it is not possible to distinguish between unemployment and non-participation. For example, we would observe a missing earnings record for an individual both if he/she were to move to a state not covered in the LEHD and if he/she became unemployed or self-employed in a given year. Since our treatment variable may also covary with this form of sample attrition, we are careful to construct a sample that tries to address such concerns.

Specifically, we limit our sample to the 24 states that continuously contain earnings records between 1998-2007.[*] Furthermore, we limit the analysis sample to individuals who were born in one of those 24 states.[†] Workers are able to move from their state of birth to other states, but they are only in our sample if they ever work in one of these 24 states between 1998-2007.

Fine-Scaled Weather Data. The underlying data come from a 2.5km×2.5km grid for the contiguous United States and were produced by (23). In order to preserve the influence of temperature extremes, we first count the number of days in each of the respective temperature bins for every 2.5km×2.5km grid×day, and then we average the grids to the county×day, weighting by the 2000 Census Block population in which the grid centroid is located. Lastly, for each county×date-of-birth, we sum the temperature bins over the various focal periods (e.g., the total number of days with mean temperature between 20-24C in the first trimester).

[*]We exclude the year 2008 from our analysis both because some states only have partial quarterly coverage in 2008. The states in our sample include: CA, CO, FL, GA, ID, IL, IN, LA, MD, ME, MT, NC, NJ, NM, OR, RI, TX, WA, WI, WV, TN, SC, NV, and VA. Total non-farm employment in these 24 states accounted for 61 percent of the total U.S. non-farm workforce in 2000.

[†]Formally, we take the full sample of individuals who ever worked in one these 24 states in the years for which the state is covered within the LEHD by pooling over the individuals in the LEHD Individual Characteristics Files for all 24 states.

Additional Results. Below, we present and discuss additional results that support the main conclusions of our study: (1) exposure to days with very hot temperatures in the prenatal period and in the first year of life lowers average annual earnings at ages 29-31, and (2) household AC adoption mitigates nearly all of this observed reduction.

Table S1 presents summary statistics, both for the overall sample and also by region. We classify our data into regions based on the Census Bureau's definition of a Census Region. There is substantial heterogeneity in temperature and average annual earnings between ages 29 and 31. Areas in the Northeast experience far fewer days above 32C than areas in the Southwest. These translate to differences in the average number of days during various critical periods of a child's development spent in different temperature bins (Panel B). In addition, the Western states in our sample experienced some of the smallest changes in AC penetration relative to the states with hotter climates in the South.

In Fig. S1, we examine the residual variation in earnings by month of birth and correlate it with the residual variation in extreme temperatures experienced during gestation by birth month. Fig. S1a plots average days during gestation for which the average daily temperature exceeded 32C, conditional on county-of-birth×race×sex fixed effects. Fig. S1b similarly plots the conditional average earnings by month of birth for individuals in our sample.[‡]

Next, while Table 1 presented results from a single regression model that included all critical periods jointly, Table S2 instead shows coefficients from *separate* regression models, one for each critical period indicated in each row. The magnitudes reported in Tables 1 and S2 are similar, suggesting that the effects of a temperature episode in one period of development may be independent of temperature variation in other periods.

Table S3 explores the robustness of our results to a variety of different control variables. In order to economize on reported coefficients, we report estimates for a single "summary" critical period, gestation. We focus on different variants of model 2, which includes interactions with AC penetration. Column (1) presents the cross-sectional OLS results relating earnings at ages 29-31 to temperature exposures during

[‡]The conditional average measures in both Figs. S1a and S1b come from a regression using the individual microdata, where the dependent variable is either earnings or temperature, and we include a set of fixed effects for birth month, a set of fixed effects for county-of-birth×race×sex, and a set of year fixed effects. Figs. and S1a and S1b plot the coefficients from the birth month fixed effects, all measured relative to December births.

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Table S1. Summary Statistics

Panel A: Sample Means By Region							
	Earnings	Air Conditioning		Temperature Descriptives			
	Age 29-31	1960	1980	Mean	Min	Max	# of Days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Overall	24117.69	14.70	57.88	14.66	8.48	20.85	0.32
Census Region							
Midwest	26314.44	10.97	58.19	9.95	4.43	15.46	0.01
Northeast	25489.36	13.14	52.90	10.68	5.22	16.15	0.00
South	22705.62	20.05	72.19	17.50	11.37	23.62	0.75
West	24734.85	8.76	35.70	13.91	7.03	20.79	0.23
Panel B: Average Number of Days By Focal Period							
	1st Trimester	2nd Trimester	3rd Trimester	Total Gestation	0-3 Months	3-6 Months	6-12 Months
Days below 0C	6.92	6.53	6.47	20.08	6.99	7.20	14.05
Days 0-24C	66.94	65.83	64.79	199.05	67.83	67.73	137.56
Days 24-28C	12.24	12.67	12.78	37.98	12.42	12.33	26.93
Days 28-32C	2.80	2.86	2.85	8.57	2.65	2.64	6.25
Days above 32C	0.10	0.11	0.11	0.32	0.10	0.10	0.21

Note: Panel A presents summary statistics for the overall sample and by region. Column (1) is the primary dependent variable in the paper, which is measured as mean annual earnings of an individual between 29-31 and comes from the LEHD. Columns (2) and (3) of Panel A report the average fraction of households in our sample in 1960 and 1980 who have air conditioning as reported in the Decennial Census. These averages are constructed by taking the population weighted average over the county level variable. Columns (4)-(6) report the population weighted temperature moments in our sample. Column (7) reports the population weighted average number of days above 32C per year. Panel B reports the average number of days during various critical periods of a child's development (indicated in column) spent in each of the respective temperature bins (indicated in rows). The temperature data come from (23).

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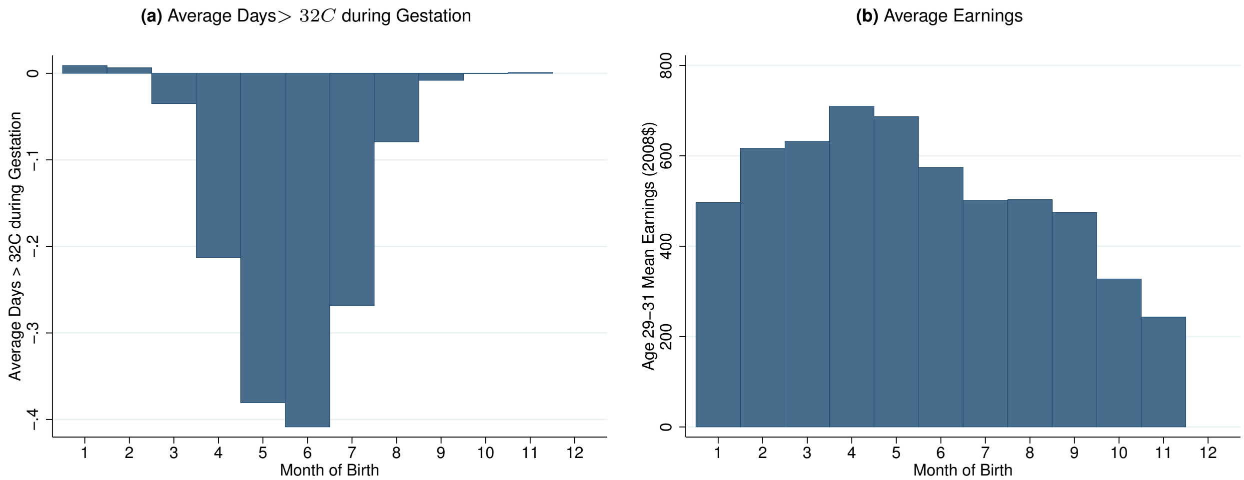
gestation, controlling for race, sex, and year of birth fixed effects. Column (2) adds county of birth fixed effects which reduce some of the residual variation in the cross-sectional estimates, while also controlling for time-invariant, observed or unobserved county-level determinants of later-life well-being. Column (3) adds fixed effects by month of birth to attempt to control for any seasonal determinants of earnings (such as socio-economic status and compulsory schooling laws); results remain similar. Column (4) adds fixed effects for county×day-of-year to control more granularly for seasonality in later life outcomes by day of year. Column (6) adds county×day-of-year×race×sex fixed effects, as in our main specifications. Column (6)adds birth-state-specific linear time trends, while Column (7) includes birth-state×birth-year fixed effects in addition to the race×sex×birth-county×birth-day-of-year fixed effects. In sum, Table S3 suggests that the non-linear influence of temperature exposure *in utero* is robust across model specifications—the number of days during gestation for which the average daily temperature exceeded 32C predicts worse outcomes measured 30 years later, but a large fraction of this effect is mitigated by AC adoption.

Next, we explore how temperature exposure during gestation affects the shape of the income distribution for affected cohorts relative to a counterfactual.[§] We begin by constructing a counterfactual earnings distribution for each county×race×sex by focusing on individuals in each county×race×sex cell for which the daily average temperature during gestation did not exceed 32C. We then calculate the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentiles of the earnings for this set of individuals (separately by county×race×sex). We then classify all individuals into bins based on their place in the "counterfactual" earnings distribution of a particular county×race×sex. Thus, the dependent variable represents the fraction of all individuals in the specified percentile of the sub-32C earnings distribution. Table S4 presents results from 10 separate regressions, one for each quantile. The estimates suggest that the number of days with average temperatures exceeding 32C during gestation is correlated with an increase in the likelihood of being in the bottom half of the earnings distribution and a decrease in the likelihood of being in the top half of the earnings distribution. One interpretation of this result is that the observed mean earnings impacts are driven both by the extensive and the intensive margins.

[§]Our very large sample sizes preclude us from estimating quantile treatment effects directly using our micro data.

Fig. S1. Conditional Temperature Exposure and Average Earnings by Month of Birth



Note: Each figure plots the coefficient estimates from month of birth indicators, with December the representing the excluded category. Panel A plots the month of birth coefficients coming from a regression of number of days during gestation for which the daily average temperature exceed 32C regressed against county×race×sex fixed effects, year fixed effects, and month fixed effects. Panel B plots the month of birth estimates from a regression of average earnings between 29-31 years old (2008$), controlling for county×race×sex fixed effects, year fixed effects, and month fixed effects. An auxiliary regression comparing the 11 observations in Panel B with the 11 observations in Panel A delivers an R-squared of 0.25.

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Table S2. Effects of Temperature over Different Critical Periods on Age 29-31 Annual Earnings

	# Days <0C	# Days 24-28C	# Days 28-32C	# Days 32+C
	(1a)	(1b)	(1c)	(1d)
Gestation	1.303	-0.534	-3.434	-28.230*
	(4.051)	(1.719)	(3.941)	(14.714)
1st Trimester	1.912	-0.489	-2.997	-43.252**
	(4.407)	(2.577)	(4.623)	(19.966)
2nd Trimester	3.632	-0.369	-0.091	-9.526
	(4.036)	(2.186)	(5.248)	(22.160)
3rd Trimester	-1.334	0.422	-5.492	-34.572**
	(4.167)	(2.701)	(4.438)	(16.933)
0-3 Months	-1.469	-2.643	-7.185	-30.439**
	(3.010)	(2.632)	(4.966)	(13.507)
3-6 Months	-2.888	-1.115	-6.521	-33.225**
	(3.839)	(2.585)	(6.498)	(16.124)
6-12 Months	-2.936	-1.654	-3.248	-34.316
	(3.176)	(2.188)	(2.745)	(23.271)

Note: This table reports regression coefficients from 7 separate regressions, one per row, each corresponding to a version of Equation (1) in the text. Robust standard errors, clustered by state, are in parentheses. All regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***p< 0.01, **p< 0.05, *p< 0.1.

Table S3. Effect of Temperature During Gestation on Age 29-31 Annual Earnings: Model Sensitivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# Days <0C	-51.992***	11.971***	6.723**	18.266**	15.883**	-3.551	0.748
	(11.808)	(2.612)	(2.857)	(7.661)	(7.364)	(3.212)	(3.644)
# Days 24-28C	-28.765*	-1.527	0.021	-3.436	-2.539	0.302	-0.059
	(14.819)	(2.657)	(2.996)	(4.931)	(4.989)	(3.999)	(3.791)
# Days 28-32C	-58.183***	-23.008**	-19.816**	-39.094***	-40.384***	-24.971**	-34.672***
	(21.880)	(9.420)	(9.011)	(14.779)	(15.438)	(11.653)	(9.688)
# Days 32+C	-308.052*	-99.802***	-101.148***	-111.547***	-95.758**	-46.944*	-58.610**
	(160.648)	(34.924)	(34.217)	(40.950)	(40.853)	(27.097)	(25.451)
# Days <0C ×AC	182.060***	-13.207**	-16.498***	-55.537***	-50.048***	-0.051	-3.433
	(27.876)	(6.497)	(5.830)	(13.981)	(13.091)	(8.089)	(8.553)
# Days 24-28C ×AC	34.116	-4.071	-1.007	6.063	4.873	0.008	3.987
	(24.323)	(4.847)	(4.922)	(8.477)	(8.491)	(6.017)	(5.996)
# Days 28-32C ×AC	102.875***	32.517**	29.721**	66.277***	66.339***	44.111**	59.158***
	(33.650)	(13.604)	(13.015)	(21.944)	(22.840)	(18.664)	(16.997)
# Days 32+C ×AC	327.112	123.156***	127.810***	157.236***	127.144**	67.111	83.064**
	(215.972)	(47.215)	(46.786)	(54.320)	(54.329)	(42.917)	(41.110)
Race and Sex FE	X	X	X	X			
County FE		X	X				
Birth Month FE			X				
County×DOY FE				X			
County×DOY×Race/Sex FE					X	X	X
State-Trends						X	
State×Year FE							X

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NOTE: This table reports regression coefficients from 7 separate regressions, one per column, each corresponding to a version of Equation (2) in the text. Robust standard errors, clustered by state, are in parentheses. All regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***p< 0.01, **p< 0.05, *p< 0.1.

Table S4. Effect of Temperature During Gestation on the Distribution of Earnings at Age 29-31

	(1) $0 \leq p \leq 1$	(2) $1 < p \leq 5$	(3) $5 < p \leq 10$	(4) $10 < p \leq 25$	(5) $25 < p \leq 50$	(6) $50 \leq p \leq 75$	(7) $75 < p \leq 90$	(8) $90 < p \leq 95$	(9) $95 < p \leq 99$	(10) $99 < p \leq 100$
# Days < 0C	-0.003	-0.029	-0.015	0.050	-0.002	-0.004	0.026	-0.010	-0.020	0.008
	(0.010)	(0.025)	(0.023)	(0.036)	(0.040)	(0.039)	(0.044)	(0.025)	(0.019)	(0.012)
# Days 24-28C	0.008	0.002	-0.014	-0.024	0.016	0.030	-0.041	0.018	0.003	0.001
	(0.007)	(0.013)	(0.016)	(0.025)	(0.029)	(0.029)	(0.026)	(0.015)	(0.015)	(0.008)
# Days 28-32C	0.002	-0.025	0.005	0.009	0.085*	0.011	-0.066	0.010	-0.021	-0.010
	(0.012)	(0.026)	(0.025)	(0.042)	(0.043)	(0.057)	(0.047)	(0.024)	(0.025)	(0.017)
# Days 32+C	0.118	-0.114	0.037	0.478**	0.401***	-0.353*	-0.407***	-0.001	-0.007	-0.153
	(0.100)	(0.091)	(0.120)	(0.189)	(0.149)	(0.199)	(0.136)	(0.074)	(0.114)	(0.122)

NOTE: This table reports the results from 10 separate regressions, one per column, each corresponding to a version of Equation (1) in the text. The dependent variable changes in each regression and is indicated in the column headings. The dependent variable corresponds to the fraction of individuals in a county that fall into the indicated quintile of the "counterfactual" earnings distribution. The "counterfactual" earnings distribution is calculated separately by each county×race×sex for those individuals in each county×race×sex for which the daily average temperature did not exceed 32C during gestation. Robust standard errors, clustered by state, are in parentheses. All regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***p< 0.01, **p< 0.05, *p< 0.1.

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We have also explored later ages of exposure to see whether we continue to observe effects of days with mean temperature above 32C. Table S5 presents estimates where we include temperature exposures experienced between 12 and 36 months post-birth. We see very little effect of exposure in these later ages. Moreover, effects at 6-12 months are also not statistically significantly different from zero, albeit with larger standard errors. To sum up, effects are apparent during the fetal stage and shortly after birth, and then fade out towards the end of the first year of life.

Table S5. Effects of Temperature over Different Critical Periods on Age 29-31 Annual Earnings, Additional Ages of Exposure

	# Days <0C	# Days 24-28C	# Days 28-32C	# Days 32+C
	(1a)	(1b)	(1c)	(1d)
1st Trimester	-6.059**	-4.064	-10.95**	-56.48**
	(2.738)	(5.223)	(5.069)	(27.62)
2nd Trimester	-2.235	0.291	-7.823	-23.28
	(2.899)	(3.874)	(8.149)	(15.81)
3rd Trimester	-3.322	-1.064	-13.70***	-58.51***
	(4.906)	(2.717)	(4.443)	(18.60)
0-3 Months	-1.954	-2.271	-19.28***	-30.55***
	(3.234)	(4.513)	(6.361)	(10.98)
3-6 Months	-1.769	-2.120	-14.74**	-78.81***
	(3.093)	(5.124)	(6.542)	(13.71)
6-12 Months	1.730	-0.737	-6.915**	-22.12
	(4.543)	(2.513)	(3.280)	(18.92)
1-3 Years	-4.889**	-4.964	-2.446	0.462
	(2.442)	(3.474)	(3.778)	(6.364)

NOTE: This table reports regression coefficients from a version of Equation (1) in the text. Robust standard errors, clustered by state, are in parentheses. Regressions control for daily mean total suspended particulate pollution, birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***p< 0.01, **p< 0.05, *p< 0.1.

We further explore the sensitivity of our results to measuring earnings at different follow-up ages. Table S6 presents results, where each column corresponds to a different regression using earnings at age 28 through 32 as outcomes. Column (6) replicates estimates from Table 1 as a basis for comparison. In each earnings year, the results are qualitatively consistent with the baseline results from before; a day with mean temperature exceeding 32C predicts reductions in earnings at all of the ages we consider. While there is some heterogeneity across age categories, the confidence intervals overlap across all groups.

An important concern for our analysis is that the temperature variation is picking up some unobserved, differential, time-varying shocks across counties. We investigate this possibility in a number of ways. First, Table S7 presents results from our baseline model in which we include leads in temperature data for the same county-day two years prior to birth. In other words, for each individual, we calculate his hypothetical exposure to temperature in each critical period *had he or she been born 2 years before his or her actual date of birth.* Our leads should thus be uncorrelated with the actual treatment effect of exposure during gestation or in the first year of life. Table S7 presents results from a single regression, where column (1a) of Table S7 shows the lead coefficients, while column (1b) shows the coefficients on exposure by trimester and through age 12 months. For parsimony, we only report coefficients on the 32C temperature bin (we are not able to reject the null hypothesis from an F-test that the non-32C and above temperature coefficients are equal to zero). We find that exposure to extreme heat two years before birth is uncorrelated with age-30 earnings, while the coefficients on actual early-life exposure to hot temperature remain negative, larger in absolute magnitude, and mostly statistically significant.

There is also growing evidence suggesting that there is important seasonal variation in birth outcomes which correlates with demographic characteristics (22, 32–35). If certain populations give birth in periods of very warm temperatures and those groups are more economically disadvantaged for reasons unrelated to temperature, then we could falsely attribute temperature variation to this omitted variable. For this reason, all of the results we have presented attempt to control for this differential seasonality by including race×sex×birth-county×birth-day-of-year fixed effects. Nevertheless, we investigate how differential fertility that is correlated with extreme temperatures may affect conclusions or lead to biases in models without county×day-of-year×race×sex fixed effects. We begin by using the LEHD earnings records to form a predictive earnings index based on sex and race of workers: We use the individual-level data to estimate earnings regressions controlling for sex and race indicators and county×day-of-year fixed effects, and then use the predicted values from this regression as a summary index measure of demographic change or sorting as in (31). We estimate a regression model using this index as the outcome and with birth-county×birth-day-of-year fixed effects (as opposed to our baseline race×sex×birth-county×birth-day-of-year fixed effects) to ask whether there is a relationship between observable characteristics of the population and the temperature variation in our data. Table S8 provides mixed evidence on whether more disadvantaged populations (as indicated by lower predicted earnings) disproportionately experience extreme temperatures during gestation. Namely, only one out of the six estimates for very hot days is significant at 10%, and while four out of six signs are negative, the magnitudes of the estimates are much smaller than our baseline estimates. Nevertheless, we believe that differential fertility that covaries with the observed temperature variation may be an important source of bias, and we therefore control for race×sex×birth-county×birth-day-of-year fixed effects in all of our other regression models.

It is also worth noting that we would be most concerned with direct fertility responses biasing the trimester 1 estimates, given such responses would occur due to temperature swings during and immediately preceding conception. However, the positive auto-correlation in temperature would imply that if the first trimester was downwardly biased, a regression with separate coefficients for each trimester would then likely lead to upwardly biased estimates for the second and third trimesters and other critical periods. Yet, we also find negative earnings effects in these other periods, which further suggests this issue is not driving our results.

Another concern is that temperature exposure is correlated with exposure to air pollution, which, in prior work, we have found to impact adult earnings (31). To address this possibility, we have investigated how the inclusion of controls for

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Table S6. Effect of Temperature During Gestation on Adult Annual Earnings: Different Ages of Follow-up

	(1) Age 28	(2) Age 29	(3) Age 30	(4) Age 31	(5) Age 32	(6) Age 29-31
# Days < 0C	1.862	2.532	1.882	1.226	2.442	1.303
	(5.770)	(5.130)	(4.002)	(3.579)	(4.905)	(4.051)
# Days 24-28C	1.187	-0.314	-0.814	-0.630	-0.501	-0.534
	(1.872)	(1.988)	(1.826)	(1.969)	(3.174)	(1.719)
# Days 28-32C	5.200	2.730	-2.592	-7.789*	-20.959**	-3.434
	(4.477)	(3.860)	(4.268)	(4.543)	(10.184)	(3.941)
# Days 32+C	-37.747**	-26.518*	-27.253*	-27.647**	-61.154***	-28.230*
	(18.632)	(14.931)	(14.455)	(13.234)	(23.690)	(14.714)

NOTE: This table reports the results from 6 separate regressions, one per column, each corresponding to a version of Equation (1) in the text. Robust standard errors, clustered by state, are in parentheses. All regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***p< 0.01, **p< 0.05, *p< 0.1.

Table S7. Leads in Temperature Do Not Predict Later-Life Outcomes

	# Days 32+C (t-2) (1a)	# Days 32+C (t) (1b)
1st Trimester	-6.053	-44.090**
	(10.616)	(18.300)
2nd Trimester	9.321	-6.844
	(14.944)	(19.160)
3rd Trimester	-9.073	-27.558*
	(13.829)	(15.137)
0-3 Months	2.540	-25.878*
	(13.559)	(13.757)
3-6 Months	-8.601	-34.787***
	(14.724)	(12.278)
6-12 Months	-16.145	-33.280
	(10.805)	(22.069)

NOTE: This table reports the results from a single regression corresponding to a version of Equation (1) in the text. We augment Equation (1) by including leads in the temperature response variables for temperatures experienced two years prior to birth. Robust standard errors, clustered by state, are in parentheses. All regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***p< 0.01, **p< 0.05, *p< 0.1.

air pollution affects our findings. It is important to note that only 60 percent of the county×day observations in our original sample have data on daily pollution monitor readings. For this sub-sample, we merge on data on the only monitored pollutant during this time period—total suspended particulates (TSP). We then estimate our baseline regressions, controlling for the daily mean TSP pollution level. The results, presented in Table S9, remain very similar to our main estimates. We thus conclude that our baseline results are robust to including controls for air pollution. Additionally, this analysis suggests that pollution levels are not strongly correlated with our temperature variation (conditional on our controls).

Finally, the results in Table 2 suggest that county-level household AC penetration mitigates nearly all of the observed long-run effect of extremely hot temperature. One concern when interpreting these results, is that household AC adoption may be correlated with other unobservable determinants of later-life well-being, such as income. We investigate this hypothesis in two ways. First, we estimate whether county-level changes in household AC adoption are correlated with other observed changes in that county that may predict later life outcomes (e.g., per-capita income and population size) using data from the Bureau of Economic Analysis local area employment statistics file. In Column (1) of Table S10, we regress the change in the fraction of households in a county that have AC between 1970 and 1980 on the log change in per-capita income over the same time period. We repeat this exercise using instead the log difference in population growth between 1970 and 1980 as the explanatory variable in Column (2). Lastly, Column (3) of Table S10 includes both the log change in population and the log change in per-capita income jointly in the regression model. In all three specifications, we observe little relationship between within-county changes in per-capita income, changes in population, and changes in household AC adoption.

The second way in which we test the robustness of our finding that AC mitigates the effects of temperatures is to use state-level AC penetration, which is likely to be more exogenous (conditional on our baseline controls) than county-level AC adoption. Table S11 presents results where we interact temperature with average state household AC adoption rates, and the results remain very similar to before.

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Table S8. The Conditional Relationship Between Temperatures and Predicted Earnings

	# Days <0C (1a)	# Days 24-28C (1b)	# Days 28-32C (1c)	# Days 32+C (1d)
1st Trimester	-1.225*	-0.246	-0.642	5.212
	(0.649)	(0.592)	(0.869)	(3.227)
2nd Trimester	-0.100	-0.058	-2.547**	-4.905*
	(0.656)	(0.956)	(1.072)	(2.840)
3rd Trimester	-1.238*	-1.001	-3.304***	-6.438
	(0.695)	(0.716)	(1.026)	(4.115)
0-3 Months	-0.811	-0.536	-1.894*	-3.189
	(0.719)	(0.720)	(1.034)	(3.488)
3-6 Months	-0.697	-0.105	-0.754	-2.748
	(0.598)	(0.743)	(1.139)	(3.206)
6-12 Months	0.451	0.549	-0.299	1.326
	(0.610)	(0.445)	(0.683)	(2.617)

NOTE: This table reports the results from a single regression corresponding to a version of Equation (1) in the text. The dependent variable in the regression is a predicted earnings index created in an auxiliary regression of age 29-31 earnings on a series of indicator variables for race and sex. We use the predictions from the auxiliary regression as the dependent variable in this table as a summary index measure of demographic sorting/change. Robust standard errors, clustered by state, are in parentheses. All regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***$p< 0.01$, **$p< 0.05$, *$p< 0.1$.

Table S9. Effects of Temperature over Different Critical Periods on Age 29-31 Annual Earnings, Controlling for Pollution

	# Days <0C (1a)	# Days 24-28C (1b)	# Days 28-32C (1c)	# Days 32+C (1d)
1st Trimester	-2.869	-5.093	-18.72***	-78.84**
	(4.045)	(4.650)	(5.987)	(31.99)
2nd Trimester	-2.422	-1.349	-13.48	-29.56*
	(3.629)	(3.750)	(8.701)	(15.98)
3rd Trimester	-7.389	-3.291	-14.62***	-77.52**
	(4.932)	(3.585)	(4.819)	(30.19)
0-3 Months	-6.708*	-1.931	-19.95***	-45.70***
	(3.443)	(4.802)	(5.804)	(17.70)
3-6 Months	-3.161	-1.096	-11.98*	-94.03***
	(2.634)	(4.758)	(6.608)	(18.78)
6-12 Months	-2.061	-0.274	-5.890*	-39.42
	(4.391)	(2.165)	(3.041)	(27.68)

NOTE: This table reports regression coefficients from a version of Equation (1) in the text. Robust standard errors, clustered by state, are in parentheses. Regression controls for daily mean total suspended particulate pollution, birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***$p< 0.01$, **$p< 0.05$, *$p< 0.1$.

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Table S10. The Relationship Between 1970-1980 Changes in County Level Household AC Adoption and Changes in Population/Income

	(1)	(2)	(3)
Δ Population	-0.006		-0.002
	(0.047)		(0.048)
Δ Income Per Capita		-0.018	-0.018
		(0.039)	(0.040)
N	3072	3072	3072

NOTE: This table reports estimates from three separate regressions where an observation is a county. The dependent variable in each regression is the county-level change in the fraction of households with air conditioning between 1970 and 1980. The independent variables are both reported in log differences, and the coefficients correspond to elasticities. Data on population and income per capita (in real 2008\$) are from the BEA's Local Area Employment Statistics file. Robust standard errors, clustered by state, are in parentheses. ***$p< 0.01$, **$p< 0.05$, *$p< 0.1$.

Table S11. Adaptation Mechanisms: Air Conditioning Exposure, State-Level AC

	# Days 28-32C (1a)	# Days 32+C (1b)	# Days 28-32C×AC (1c)	# Days 32+C×AC (1d)
1st Trimester	-6.781	-97.255	16.425	122.951
	(19.765)	(74.308)	(35.179)	(69.478)
2nd Trimester	-0.037	-24.283	16.588	105.348
	(22.337)	(39.566)	(35.179)	(69.478)
3rd Trimester	5.973	-25.627	-7.247	52.053
	(18.905)	(25.344)	(31.221)	(66.372)
0-3 Months	-38.424**	-89.775***	65.288**	171.998***
	(18.160)	(17.791)	(28.793)	(45.078)
3-6 Months	-1.092	-39.524	8.755	79.608
	(17.010)	(48.803)	(25.032)	(74.719)
6-12 Months	-39.641***	-70.785**	61.000***	135.587***
	(13.757)	(28.366)	(19.356)	(33.973)

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NOTE: This table reports the results from a single regression model corresponding to a version of Equation (2) in the text. The regression model augments Equation (1) by including an additional set of temperature response coefficients, now interacted with the fraction of households in the State that have household air conditioning. Robust standard errors, clustered by state, are in parentheses. All regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. ***$p< 0.01$, **$p< 0.05$, *$p< 0.1$.

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