The Early-Life Environment and Long-Run Human Capital Formation: Implications for Climate Change and Cross-Sectional Income Disparities*

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Abstract

We present evidence that extreme temperatures in early periods of child development have persistent influences on outcomes measured 30 years later. The tests are derived from administrative earnings records for over 12 million individuals born between 1969-1977, for whom we observe the individual's exact date of birth, county of birth, and labor market outcomes between the ages of 28 and 32. We link this data to fine-scale, daily weather data to estimate models of temperature response in various periods of early childhood development. The econometric models are purposely flexible in nature to account for the significant non-linearities in temperature-response relationship. An extra day with mean temperatures above 32°C (89.6F) in the 9 months leading up to birth and the 12 months after birth is associated with a 0.2% reduction in annual earnings between the ages of 29-31. This effect is evident in multiple periods of a child development, ranging from the first trimester to 6-12 months post-birth. Lastly, household air conditioning adoption, which increased dramatically over this time period, mitigates nearly all of the estimated temperature sensitivity, suggesting a key role for AC in climate change mitigation. JEL: H40, I12, I14, J17, J18, Q51, Q54

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1 Introduction

This paper explores the long-run impacts of early-life exposure to extreme temperature, using data on over 12 million individuals born in the United States between 1969-1976 and observed 30 years later. While a burgeoning literature across several disciplines documents lasting impacts of prenatal and early childhood interventions on long-run outcomes (Almond and Currie, 2011a,b; Barker, 1990; Cunha and Heckman, 2007), to our knowledge, this is the first paper to trace the origins of adult well-being to early-life exposure to the climate.

The possibility that extreme temperature can have lasting impacts on human development may be particularly consequential in light of the growing consensus that climate change is contributing to a gradual warming of the earth. Researchers predict an increase in global mean temperatures, largely driven by a rightward shift in the upper tail of the temperature distribution. For example, the number of days with mean temperature above 32 degrees Celsius in the average county in the United States is forecasted to increase from about 1 per year to about 43 per year by 2070-2099 (Intergovernmental Panel on Climate Change, 2007).[1] While there is evidence that exposure to extreme temperatures has harmful contemporaneous effects on human health (see, e.g., Intergovernmental Panel on Climate Change, 2007; Basu and Samet, 2002; Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2013; Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011), much less is known about whether these impacts persist many years later or whether they translate into effects on other measures of human capital such as adult earnings.[2]

We address these questions using a newly available resource on labor market outcomes linked to location and exact date of birth for over 12 million workers in the United States. We combine these longitudinal earnings records with fine-scale, daily weather data that spans the United States on a 2.5km×2.5km grid. The weather data allow us to construct the length of time an individual is exposed to each 1-degree Celsius temperature interval in particular focal windows of early childhood development. We then use these data to estimate flexible econometric models designed to identify non-linearities and breakpoints in the long-run effect of temperature on human capital measures.

Since individual place and season of birth are not randomly assigned, early-life exposure to temperature is potentially correlated with other determinants of human capital development. The empirical challenge of this paper is therefore to isolate a *causal* long-run relationship between temperature and adult outcomes. We address this challenge by focusing on the following thought experiment that we observe in our data many thousands of times: Consider two children of the same gender and same race, and who are born in the same county and on the same day of the year but in *different* years. Now, suppose that one child experienced an extreme heat wave in his 2nd trimester of gestation, while the other did not. Our goal is to quantify any differences in these children's labor market outcomes measured 30 years after birth. Formally, we flexibly model the relationship between early-life temperature exposure and long-run outcomes using a series of estimators that allow for (possibly) non-linear effects of temperature on later-life outcomes, and controlling for county×day-of-year×race×sex (e.g. African American males born into Harris County, TX on November 18th) and year fixed effects. Thus, estimates are purged of time-invariant observed and unobserved determinants of long-run human capital formation in a

[1] The error-corrected Hadley 3 A1FI predictions indicate that the typical person will experience 38 additional days per year where the mean daily temperature is between 26°C and 32°C and 42 additional days per year for which the mean temperature *exceeds* 32°C. Currently, the average person in the United States experiences 29 days with a mean temperature between 26-32°C and 1 days for which the mean temperature exceeds 32°C (Deschênes and Greenstone, 2011).

[2] Indeed, the lack of empirical estimates of this sort have been highlighted in recent empirical work in this area: "The important question left unanswered by this paper is whether these [temperature induced] changes in birth weight are related to welfare losses; for example, through changes in health, human capital, income, or neonatal mortality. If there is indeed a relationship between in utero exposure to high temperature and welfare measures, then these impacts should become part of the calculations of the benefits of greenhouse gas reductions. This is an important topic for future research" Deschênes, Greenstone, and Guryan (2009). See also Deschenes (2012).

given county, any seasonal determinants of fertility that may also be correlated with later-life outcomes such as compulsory schooling laws (Angrist and Krueger, 1999) and socio-economic status (Buckles and Hungerman, 2008), and overall time trends.

Our paper provides several contributions. First, one advantage of studying temperature is that it exhibits a great deal of variability, both over time and across space. A child born in a given county on June 23rd may be exposed to more extreme temperature events *in utero* or in early childhood than a child born in the same county on June 23rd the year before. We use this variation to better understand "critical periods" in child development; i.e. is the first trimester more sensitive to extreme temperatures relative to the third trimester? Is the *in utero* period more "critical" than the first year of life?

Second, we believe our results can shed light on an important policy parameter; a well-identified causal relationship may help us better understand the social welfare costs associated with climate change. Third, our estimates may speak to the degree to which the persistent correlations between cross-sectional disparities in income and extreme temperatures around the world may operate through a causal link between early-life exposure and adult productivity.[3]

Fourth, we also analyze the role adaptation plays in mitigating any observed responses. A useful feature of our particular setting is the rapid increase in air conditioning (AC) adoption over the course of our sample period that varies across both time and space. We examine whether individuals born in counties with higher levels of household AC penetration exhibit different long-term responses to extreme temperatures relative to individuals born in counties with lower rates of AC adoption. As much of the developing world currently experiences relatively low levels of AC adoption, this exercise is useful for predicting the future role of adaptive behavior in low-income countries. While the dose-response relationship between temperature and long-run human capital formation in the United States is likely to differ from the dose-response relationship in the developing world, our analysis may nevertheless highlight the extent to which adaptation could mitigate temperature-induced health and human capital externalities.

Our results point to a robust relationship between the early-life environment and long-run human capital formation. We also show that this relationship is both non-linear and heterogeneous. In particular, extreme heat exposure in early life has lasting adverse effects on adult earnings, and this relationship is highly responsive to adaptive behavior (i.e., air conditioning). A single day with a mean temperature above 32°C during gestation or within the first year after birth is associated with a reduction in age-30 earnings of around 0.2 percent of the average annual salary (about $40). This effect is fairly constant across early-life critical periods between conception and age one.[4] Additionally, we find evidence of heterogeneous responses across the earnings distribution—about half of our estimated mean effect is driven by the extensive margin of labor force participation, while the other half manifests through a shift in mass from the top half to the bottom half of the income distribution.

Assuming a constant earnings effect over the lifecycle, we estimate that our results translate to a per-person loss of $870 in lifetime earnings associated with each day of early-life exposure to an above 32°C day. Thus, if the number of such days per year increases in the subsequent decades as predicted by scientists, climate-change-induced long-run costs of exposure to hot temperatures could be fairly substantial. However, the results described above do not incorporate the role of adaptation in mitigating these possible costs. In fact, we find substantial scope for adaptation through household air conditioning penetration. Moving from 0 to 100 percent

[3]The relationship between the environment and broader measures of economic development have been studied within economics starting with Gallup, Sachs, and Mellinger (1999). Recent work exploring the contemporaneous and persistent influences of rainfall, temperature, and/or cyclones on economic development include Barrios, Bertinelli, and Strobl (2010); Dell, Jones, and Olken (2012); Hsiang (2010); Maccini and Yang (2009); Graff-Zivin and Neidell (Forthcoming); Hsiang and Jina (2012); Heal and Park (2013).

[4]We cannot reject the null hypothesis that the coefficients for exposure in different critical periods are the same. We do see some suggestive evidence that the effect after six months post-birth is smaller (and insignificant), but the confidence intervals are large enough that we cannot statistically distinguish this coefficient from the coefficients for other critical periods.

AC penetration in a county is associated with a 90 percent reduction in the marginal impact of a degree day above 32°C.

Our analysis relies on the identifying assumption that, holding constant the county of birth, birth day of year, race, and gender of an individual, there are no unobserved variables that are systematically correlated with both temperature exposure in early life and adult labor market outcomes. While this assumption is inherently untestable, we provide several pieces of evidence suggesting that it is unlikely to be violated. In particular, we observe that (i) leads in temperature episodes occurring before conception are not correlated with later-life outcomes; (ii) controlling for our set of fixed effects described above, there is no correlation between early-life exposure to temperature and contemporaneous economic shocks driven by temperature (e.g. agriculture), and (iii) temperatures, conditional on our fixed effects, are not correlated with observable characteristics of individuals born during this time period.

We also examine the sensitivity of our estimated adaptation responses. We first show that more aggregate variation in household AC adoption (i.e., state level), which is likely to be more exogenous than county-level adoption rates, delivers similar results. Second, we show that our results our robust to controlling for county per-capita income and interacting income with our temperature vector.

The rest of the paper proceeds as follows: Section 2 describes an overview of the climate-health literature, with a focus on the underlying biological theory and the evidence motivating our research questions. Section 3 discusses the primary data sources we use for our analysis, and Section 4 discusses the baseline econometric specifications. Sections 5 delivers our main results and discusses their implications. Section 6 concludes.

2 The Environment's Role in Human Capital Development

How can temperature impact human capital development? Individuals are able to cope with both high and low temperatures through various heat regulation mechanisms of the body. However, extreme temperatures may overload the capacity of the body to self-regulate. While there are various biological implications of this overload, hot temperatures are generally associated with increases in blood viscosity and blood cholesterol levels, leading to cardiovascular stress (Huynen, Martens, Schram, Weijenberg, and Kunst, 2001). This stress can in turn have adverse implications for human morbidity and mortality (Deschênes and Greenstone, 2011; Deschenes and Moretti, 2009), and an extensive literature has documented that the relationship between temperature and mortality/morbidity is typically non-linear (see e.g., Basu and Samet, 2002).

There is also some evidence that the temperature-health relationships are more pronounced for both very young and very old populations (Deschênes and Greenstone, 2011; Deschenes and Moretti, 2009). The excess sensitivity of infants to heat may stem from the fact that their thermoregulatory systems are not yet fully functional (Knobel and Holditch-Davis, 2007). Additionally, a small set of studies points to adverse impacts of fetal exposure to extreme heat, finding a non-linear relationship between temperature and birth weight (Deschênes, Greenstone, and Guryan, 2009).

The fact that fetal and infant health may be especially sensitive to temperature is important in light of recent evidence pointing to the persistent impacts of early-life environmental conditions on long-run outcomes (Isen, Rossin-Slater, and Walker, 2013; Black, Butikofer, Devereux, and Salvanes, 2013; Almond, Edlund, and Palme, 2009; Sanders, 2012). Almond and Currie (2011a) and Almond and Currie (2011b) provide recent surveys of the broader literature examining the importance of early-life influences in determining long-run development. In summary, the evidence points to the *in utero* stage and the first few years of life as being critical periods in human capital development, and dynamic complementarities in skill acquisition and skill formation may make

early-life insults both cumulative and persistent (Cunha and Heckman, 2007).[5]

The above discussion focuses on the direct biological effects of temperature on human capital formation. However, exposure is a function of both prevailing weather conditions and any adaptive responses to extreme temperatures. Adaptation to extreme temperatures could occur through short-run temporal substitution between activities (i.e., limiting time spent outside) (Graff-Zivin and Neidell, Forthcoming) or through the adoption of more permanent measures of temperature mitigation such as air conditioning (Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2013; Rogot, Sorlie, and Backlund, 1992). There may also be scope for physiological acclimatization, arising through changes in skin blood flow, metabolic rate, oxygen consumption, and core temperatures (Armstrong and Maresh, 1991).

In sum, the evidence on the pathways through which temperature influences human health suggests that our econometric models must be flexible enough to account for the presumed non-linearities. In addition, the ways in which populations can respond or adapt to temperature are important both for interpreting results and for understanding the potential scope for future mitigation responses. In Section 4, we outline our flexible econometric models designed to deliver insight into both the temperature-health relationship and the role for adaptation. Before doing so, we first describe the data used in the analysis.

3 Data

We use a newly available data resource that allows us to observe both the location and exact date of birth for 12 million individuals as well as their longitudinal earnings history 30 years later. We combine this data with fine-scaled, daily weather measures on a 2.5×2.5 mile grid for the entire United States. This section briefly describes these data and reports basic summary statistics. Appendix B describes these data sources in additional detail.

Longitudinal Employer Household Dynamic Files

The main data source for this analysis comes from the U.S. Census Bureau's Longitudinal Employer Household Dynamic Files. These files consist of quarterly administrative earnings records for approximately 98 percent of the U.S. workforce. The files provide detailed information on workers such as race, sex, location and date of birth, while also providing a detailed longitudinal earnings history for each worker.[6] While these data are comprehensive in nature, there are a few caveats worthy of mention. 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 states entering the sample by the late 1990's. The second challenge associated

[5]The "fetal origins hypothesis", originally put forth by British epidemiologist David J. Barker, focused on the consequences of prenatal malnutrition. Barker argued that poor nutrition *in-utero* "programs" the fetus to have metabolic characteristics that can lead to future disease in adulthood (Barker, 1990). A number of studies have leveraged a variety of shocks to the *in utero* environment to provide evidence in support of the hypothesis. See, e.g., Van den Berg, Lindeboom, and Portrait (2006); Almond, Edlund, Li, and Zhang (2010); Almond and Mazumder (2012); Hoynes, Schanzenbach, and Almond (2012); Scholte, van den Berg, and Lindeboom (2012) on malnutrition; Almond (2006); Barreca (2010) on disease outbreaks; Almond, Edlund, and Palme (2009); Black, Butikofer, Devereux, and Salvanes (2013) on radiation; Sanders (2012); Isen, Rossin-Slater, and Walker (2013) on air pollution; and Black, Devereux, and Salvanes (2014); Persson and Rossin-Slater (2014) on stress from family bereavement. Additionally, other work has focused on the long-term returns to interventions targeting children in their first few years of life, such as the HighScope Perry Preschool program (Heckman, Moon, Pinto, Savelyev, and Yavitz, 2010) and Head Start (Currie and Thomas, 1995; Garces, Thomas, and Currie, 2002; Ludwig and Miller, 2007).

[6]Race and place of birth information comes from the Social Security Administration's numident file which the Census Bureau has merged to their own internal LEHD files. We aggregate the race codes in the numident file to three different race codes corresponding to White/Caucasian, African American, and Other.

with the LEHD 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.[7] Furthermore, we limit ourselves to examining earnings records of individuals who were *born* in one of those 24 states.[8] Workers are able to move from their state of birth to other states, but they will only be in our sample if they ever work in one of these 24 states between 1998-2007. We use the data to construct various measures of labor market outcomes as measured between the ages of 29-31. Our main outcomes of interest are average annual earnings and average annual quarters worked of an individual between the ages of 29-31. The focus on labor market outcomes averaged over a set of years, rather than outcomes in a particular year is meant to (i) minimize the residual variance in the observed unemployment/earnings distribution and (ii) help to ameliorate concerns that any effects we see are driven by a contemporaneous economic shocks in one particular earnings year.

We express all monetary variables in real 2008 dollars using the Consumer Price Index. For each cohort, we cap earnings at age-28 equivalent $100,000 allowing for 2% annual growth in earnings in order to limit the influence of outliers.[9] Our baseline sample consists of earnings records between the years 1998-2007 for 12 million individuals born between the 1969 and 1976. The mean annual earnings between the ages of 29-31 is $24,117 in our sample (in 2008 dollars). See Appendix B for additional details on the LEHD and data construction.

Fine-Scaled Weather Data

As mentioned above, we combine our longitudinal earnings records with fine-scaled, daily weather measures using information on county and exact date of birth. We begin by constructing the number of days for which the daily mean temperature fell into one of 10 temperature bins (<0, 0-4, 4-8, 8-12, 12-16, 16-20, 20-24, 24-28, 28-32, 32+ degrees Celsius) over the course of a particular "focal" period. We examine exposure in the following "focal" periods: the 1st, 2nd, and 3rd trimesters of gestation, and 0-3, 3-6, and 6-12 months post-birth.

The underlying data come from a 2.5km×2.5km grid for the contiguous United States and were produced by Schlenker and Roberts (2009). 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.[10] 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 20-24°C in the first trimester).

[7] 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.

[8] 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.

[9] Specifically, we cap earnings at $100,000 for 28-year-olds, $102,000 for 29-year-olds, $104,040 for 30-year-olds, $106,121 for 31-year-olds, and $108,243 for 32-year-olds.

[10] Ideally, we would like to weight by the 1960 Census Block population estimates. However, to the best of our knowledge, these boundary files do not exist in a usable digitized format. Due to migration shifts between 1970 and 2000, we also present unweighted results in Appendix A.

Additional Datasets

We supplement our data on the early-life environment and long-run human capital measures with a variety of other population and demographic data from the Bureau of Economic Analysis Local Area Personal Income files. We also use county-level data on household air conditioning penetration rates in the United States between 1960-1980 from the U.S. Census of Population. Barreca, Clay, Deschenes, Greenstone, and Shapiro (2013) show how AC penetration significantly reduced the estimated impacts of contemporaneous exposure to extreme temperatures on child and adult mortality rates over the course of the 20th century. In 1960, about 10 percent of U.S. households had a room with AC or central AC; by 1980, this fraction had increased to 50 percent.

3.1 Summary Statistics

Table 1 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. The table highlights the cross-sectional disparities in both income and climate. Areas in the Northeast experience far fewer days above 32°C than areas in the Southwest. The Western states in our sample also experienced some of the smallest changes in AC penetration relative to the states with hotter climates in the South.

To get a sense for the possible scale and scope of the influence of extreme temperature on human capital formation, we examine the residual variation in earnings by month of birth and correlate this with the residual variation in extreme temperatures experienced during gestation by birth month. Appendix Figure A1a plots the average earnings by month of birth for individuals in our sample, conditional on county-of-birth×race×sex fixed effects. Appendix Figure A1b similarly plots the conditional average days during gestation for which the average daily temperature exceeded 32°C.[11]

The R-squared from a regression of these conditional earnings measures on the conditional temperature measures is 0.25, suggesting that 25 percent of the conditional variation in age-30 earnings by month of birth is explained by exposure to extreme temperatures during gestation. Of course, there may be other unobserved determinants of long-run human capital formation that co-vary with month of birth. Below we outline a set of econometric models that attempt to address these issues while also attempting to more flexibly model the temperature-human capital relationship.

4 Econometric Specification

Equation (1) describes the primary estimation equation of interest:

$$y_{irscdt} = \sum_k \sum_j (\theta_j^k Temp_{cdtj}^k) + Prec_{cdt}^k \Phi + \gamma_{cdrs} + \lambda_t + \epsilon_{icdt}. \quad (1)$$

We regress a labor market outcome y_{icdt} measured between the ages of 29-31 for person i of race r and sex s born into county c on day-of-year d in year t against a series of temperature bins j that describe the total number of days the average daily temperature in a county fell within bin j during critical period k for an individual born on each day.[12] Temperature bins are defined in 4°C intervals (i.e. $j \in [<0$, 0-4, 4-12, 12-16, 16-20, 20-24, 24-28, 28-32, 32+]), and critical periods k are defined as $k \in$ [1st, 2nd, or 3rd Trimester; 0-3, 3-6, and 6-12 months]. The

[11] The conditional average measure in both Figures A1a and A1b 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. Figures A1a and A1b plot the coefficients from the birth month fixed effects, all measured relative to December births.

[12] To calculate the number of days falling into each temperature bin during pregnancy, we assume a 40-week gestation period.

ten temperature bins j are meant to model the effect of temperature in a non-linear, semi-parameteric fashion. Similar estimators have been used in recent work by Schlenker and Roberts (2009); Graff-Zivin and Neidell (Forthcoming); Barreca, Clay, Deschenes, Greenstone, and Shapiro (2013); Deschênes and Greenstone (2011); Deschênes, Greenstone, and Guryan (2009), albeit in the context of different outcomes. This particular estimation strategy is fairly flexible with respect to the relation between temperature and long-run outcomes, except that we are restricting the marginal effect of temperature to be the same within 4°C ranges.

For each critical period k, we also include a flexible polynomial (up to a cubic) in mean precipitation $Prec^k_{cdt}$ for the county over that time period.[13] The model also includes county×day-of-year×race×sex fixed effects γ_{cdrs} to control for time-invariant observed and unobserved determinants of long-run outcomes that vary across space, separately by race and sex. At the same time, county×day-of-year×race×sex are designed to control for location-specific seasonal patterns in fertility that may also be correlated with later-life earnings (e.g. compulsory schooling laws). In order to capture overall trends across years, we include year fixed effects λ_t. The parameter ϵ_{icdt} is the error term.

Since our temperature bins span the full range of possible temperature outcomes, they are not all separately identified, and we are forced to make a normalization. We normalize the coefficients on $j \in [20 - 24°\text{C}]$ to be equal to zero. The virtue of equation (1) is that we can examine the independent relationship between extreme temperatures and later-life outcomes at various critical periods *while holding other critical periods constant.* The large amount of conditionally random temperature variation provides us with the unique opportunity to examine which periods of child development are most critical for predicting long-run outcomes.

We present several auxiliary specifications that include: results in which we estimate equation (1) separately for each k; results in which we aggregate over j to examine more parsimonious forms of temperature heterogeneity $j \in [< 0,$ 0-24, 24-28, 28-32, $32+]$; results for outcomes at different follow-up ages; and results using different sets of outcome variables. Finally, we estimate regressions that include additional interaction terms between $Temp^k_{cdtj}$ and our county×year measure of AC adoption, while also including the main effects of county AC exposure.[14] This specification implicitly tests the extent to which AC can mitigate the effects of extremely hot temperature days on long-run outcomes.[15]

The baseline econometric model delivers a set of 54 regression coefficients (9 temperature bins j and 6 critical periods k). We attempt to summarize our results graphically whenever possible in order to better interpret the large number of coefficients. Our table-form results rely on more parsimonious specifications with fewer temperature bins. We conduct inference using standard errors clustered at the state level to account for various forms of both spatial and temporal dependence in the data.[16]

[13] It is possible that other aspects of daily weather influences the temperature-health channel through unobserved channels. For example, Barreca (2012) finds that humidity (independent of temperature) is an important predictor of adult mortality. It may also be the case that air pollution covaries with both extreme temperatures and health outcomes. Lack of comprehensive data on both air pollution and humidity preclude us from directly controlling for the possible confounding effects. In this sense, the observed temperature estimate may be thought of as a reduced-form relationship of temperature, inclusive of possible confounding sources of weather variation that covary with extreme temperatures.

[14] County level household AC adoption varies at the county-year level and thus is not absorbed by the county×day-of-year×race×sex fixed effects.

[15] Adoption of AC is not random and likely correlated with other county-level characteristics. As such, these specifications may also be picking up other forms of heterogeneous treatment effects with regard to county time-varying factors correlated with AC adoption. However, as discussed below, we show that the results are similar when we use state-level aggregation of AC adoption, which is arguably more exogenous than county-level adoption. Moreover, our results are robust to controlling for county per-capita income and interacting income with our temperature vector.

[16] Clustering at the state-level gives comparable standard errors to approaches that more specifically model the covariance of error terms between counties as a function of distance (Conley, 1999), while also remaining computationally easier to implement (Fisher, Hanemann, Roberts, and Schlenker, 2012).

5 Results

Figure 1 plots the baseline temperature response estimates from Equation (1), where the outcome is average annual age 29-31 earnings in real 2008 dollars. The solid blue line in each panel plots the coefficients on exposure to an additional day with mean temperature falling in various bins during the critical period indicated in the panel title. Thus, Panel A of Figure 1 shows the estimated impact of an extra degree day in the first trimester of gestation, holding other critical periods fixed and where degree days between 20-24°C have been normalized to 0. The dotted line presents 95% confidence intervals associated with the estimates, where inference comes from standard errors clustered by state.

There are two key take-aways from this figure. First, the effect of exposure to temperature during gestation and in the first year of life is highly non-linear—while there are no statistically significant coefficients on exposure to days with cold or moderate temperatures, exposure to hot days with average temperatures above 28 and, more strongly, above 32 degrees has disproportionately large negative impacts on adult earnings. Second, the effect across different critical periods between conception and age one is fairly homogeneous, and the negative effect of exposure to temperature above 32°C on earnings exists in nearly all of the early-life stages we consider. That is, we cannot reject the null hypothesis that a day with mean temperatures above 32°C in the first trimester is significantly different from a day with mean temperatures above 32°C in the third trimester.

To facilitate relative comparisons, Figure 2 plots all of the critical period response estimates in a single graph. As presaged by Figure 1, the responses in all critical periods are non-linear, however the relationship between early-life temperature exposure and adult earnings in terms of functional form and magnitude is fairly similar across critical periods.

Table 2 presents table form estimates of the responses shown in Figures 1 and 2. In order to economize on space, we present parsimonious versions of Equation (1) that include 4 temperature bins ($<$ 0, 24-28, 28-32, 32+) rather than 9 temperature bins per critical period. We normalize the temperature bin 0-24°C to be equal to zero in each critical period. The estimates of the $\widehat{\theta}_j^k$ parameters associated with high daily temperatures (i.e., 28-32°C and 32°C+) are very similar to those in the baseline 9-bin model; thus, the more parsimonious specification does not significantly affect our conclusions. The choice of these particular temperature bins is motivated by the estimates in Figures 1 and 2 that suggest that the $\widehat{\theta}_j^k$ were approximately equal in the 0-24°C categories. Panel A presents coefficients from 7 separate regressions (one in each row), where we estimate the response function separately for each critical period. Panel B presents coefficients from a single regression that estimates the critical periods jointly. The gestation period in Panel B is not included as it is contained within the 1st-3rd trimester estimates of the joint critical period model. The magnitudes in Panel A and Panel B are very similar, suggesting that the effects of a temperature episode in one period may be independent of temperature variation in other periods. As a result, subsequent results will sometimes focus on total gestation as a summary critical period to economize on reported coefficients.

The average estimate across all critical periods suggests than an extra day of exposure to temperatures above 32°C *in utero* or in early childhood is associated with around $40 (2008$) lower earnings at ages 29-31, which translates to a 0.2 percent effect size when evaluated at the sample mean. To interpret the magnitude of this effect, we calculate the lifetime earnings impact implied by our estimates. We assume that the percentage loss in earnings remains constant at 0.2 percent over the life-cycle and that earnings are discounted at a 3 percent real rate (i.e., a 5 percent discount rate with 2 percent wage growth) back to age zero.[17] Under these assumptions, the mean present value of lifetime earnings at age zero in the U.S. population is approximately $434,000. We

[17] This exercise using similar assumptions is conducted in Chetty, Friedman, Hilger, Saez, Schanzenbach, and Yagan (2011) and Chetty, Friedman, and Rockoff (2011) to evaluate the long-term benefit of having a high value-added teacher in the classroom for an additional year.

calculate this number using the mean wage earnings from the March 2008 Current Population Survey to obtain an earnings profile over the lifecycle.[18] Thus, the financial loss associated with being exposed to an additional very hot day with temperature above 32°C during gestation or in the first year of life is 0.2 percent of $434,000 or $870 per person. While today, the average person is exposed to about one such hot day per year, this number is expected to increase substantially in the next several decades (Intergovernmental Panel on Climate Change, 2007). Our estimates thus suggest that the long-run human capital costs associated with the predicted global temperature increases in the U.S. may be non-neglible.

This discussion, however, neglects the role for adaptation to mitigate such negative effects. One particularly useful technology that can lessen the influence of extreme temperature is air conditioning. Recent work suggests that air conditioning reduces the influence of extreme temperatures on health outcomes such as mortality (Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2013) and on contemporaneous measures of cognitive performance such as math test scores (Graff-Zivin, Hsiang, and Neidell, 2013).

A unique feature of the particular time period we study is the rapid expansion in the prevalence of in-home air conditioning. In 1960, only about 10 percent of households had access to an in-home air conditioner. By 1980, 50 percent did. AC adoption also varied significantly by county. We utilize county-level data on household AC adoption from the 1960, 1970, and 1980 Decennial Censuses to examine the extent to which AC mitigates the observed impacts of extreme temperature. Formally, we augment Equation (1) to include an interaction between county-level AC adoption and each of the 24 temperature bins of interest (i.e. 6 critical periods and 4 temperature bins):[19]

$$y_{icdt} = \sum_k \sum_j \left[(\Theta_j^k Temp_{cdtj}^k) + \beta_j^k (Temp_{cdtj}^k \times AC_{ct}) + Prec_{cdt}^k \phi \right] + \delta AC_{ct} + \Gamma_{cd} + \Lambda_t + \iota_{icdt}. \quad (2)$$

where the new set of coefficients β_j^k provide an estimate of the dose-response relationship of earnings at ages 29-31 to early childhood temperature exposure in various critical periods and in hypothetical counties that have 100 percent of households with air conditioning in the county×year.

Table 3 presents results of both $\widehat{\Theta_j^k}$ and $\widehat{\beta_j^k}$ from a single regression where each column indexes a particular temperature bin and each row indexes a particular critical period. Focusing on the estimates in Column (1d), the baseline coefficients in the top half of the table deliver the estimated impact of an extra day of mean temperatures above 32°C for a county with 0 percent of households having AC. These estimates are larger than the corresponding estimates in Table 2, consistent with AC adoption being a critical determinant of treatment effect heterogeneity. The corresponding interaction terms in the bottom half of Table 3, deliver estimates for the hypothetical county with 100 percent household AC penetration. Results suggest that much of the attenuated response in Table 2 is driven by the mitigating capabilities of air conditioning. Namely, moving from 0 to 100 percent household AC adoption attenuates the estimated impacts in column (1d) by nearly 90 percent.[20] These results are consistent with recent evidence showing the possibility for AC to mitigate the effect of extreme temperatures, albeit not completely. There may be alternative explanations of these results, which we turn to in the subsequent section.

[18] Based on this exercise, the cumulative (non-discounted) average lifetime earnings is around $1.5 million (2008$). Poterba, Venti, and Wise (2010) estimate that average lifetime earnings in the United States are $1.6 million (2010$).

[19] We follow Barreca, Clay, Deschenes, Greenstone, and Shapiro (2013) by imputing missing county-level air conditioning adoption in non-Census years by using within-county, linear interpolation. In additional specifications, we have interacted household AC in 1970 with our temperature vector, producing similar results (not reported).

[20] This is calculated by taking the average ratio between each critical period k that is statistically different from zero at conventional levels and the corresponding AC interaction. The average in the ratio of coefficients across the three statistically significant critical periods is 0.91.

5.1 Additional Results and Robustness Checks

We conduct a number of sensitivity analyses while also presenting some additional sources of treatment heterogeneity. Appendix Table A1 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. Column (5) of Table A1 presents our preferred specification as a benchmark, which is the same estimate as the one found in Row 1, Panel A of Table 2. Column (1) presents the cross-sectional OLS results relating earnings at ages 29-31 to temperature exposures during gestation, controlling for race, sex, and year fixed effects. Column (2) adds county 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. Relative to Columns (1) and (5), the coefficients in Column (2) are smaller in absolute magnitude, but they are statistically significant at conventional levels. 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. The results in Column (4) are most similar to our preferred model in terms of both magnitude and statistical significance. In sum, Appendix Table A1 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 32°C predicts worse outcomes measured 30 years later.

Appendix Table A2 examines heterogeneity in our baseline results across different outcome variables. As before, we report coefficients on the effects of temperature during gestation to economize on reported coefficients. In Column (1), the outcome is the average annual quarters not employed between ages 29 and 31. The mean annual quarters not employed for an individual in our sample is around 0.86, and a day above 32°C is associated with a 0.2 percent increase in the likelihood of non-employment at ages 29-31. Column (2) explores whether the baseline earnings results in the paper are driven purely by the "extensive" margin effects in Column (1). The dependent variable in Column (2) consists of earnings only for the individuals for whom we observe positive earnings in each quarter of each year at ages 29-31. Results suggest that the adverse impacts of > 32°C days are not only driven by quarters worked. Columns (3) and (4) explore logarithmic transformations of earnings as outcomes. Conclusions from the logarithmic earnings transformations in terms of both signs and magnitudes are similar, although we lack the precision to reject the null of a zero effect for most of the temperature variation.

The results thus far have focused on the mean impact of temperatures on adult labor market outcomes, with evidence above suggesting that some of the mean impacts on earnings are driven by the extensive margin of labor force participation. We explore these distributional implications further by examining how temperature exposure during gestation affects the shape of the income distribution for affected cohorts relative to a counterfactual.[21] 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 32°C. 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 classify individuals into bins based on their place in the "counterfactual" earnings distribution of a particular county×race×sex. Appendix Table A3 presents results from 10 separate regressions, one for each quantile. The estimates suggest that the number of days with average temperatures exceeding 32°C 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. Thus, our observed mean earnings impacts are driven both by the extensive and the intensive margins.

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

We also explore the sensitivity of our results to measuring earnings at different follow-up ages. Appendix Table A4 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 2 (Row 1 of Panel A) 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 32°C 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 age groups. These results may reflect the fact that earnings are highly correlated across ages, but they also provide some degree of assuredness that (i) earnings impacts are found at more than one (somewhat arbitrary) age category, and (ii) our results are not confounded by some contemporaneous change in earnings determinants in later years. As evidence of the latter point, consider that Columns (1)-(5) are estimated using the same individuals, but the earnings are collected at different years (i.e. cohorts born in 1970 show up between 1998 (Column 1) and 2002 (Column 5)). Our preferred earnings measure in Column (6) serves as a type of "summary-index" over the various age categories while also reducing the residual variance in annual earnings. The constant effects over different ages is similar to the findings in Isen, Rossin-Slater, and Walker (2013), who show that early-life exposure to air pollution has a constant and lasting effect on labor market outcomes between the ages of 28 and 32.

As discussed in Section 3, we use 2000 Census block population weights to aggregate 2.5×2.5km gridded weather data to the county level as that is the earliest year for which we were able to obtain geocoded block level population estimates. As population may have changed differentially across counties between 1970 and 2000, Appendix Table A5 presents estimates where we simply take an unweighted average over all grid cells within a county×day when creating the data. The results are slightly more imprecisely estimated, which may be due to the increased measurement error associated with the unweighted county-level temperature variable.[22]

One additional concern for our econometric model is that our temperature variation is picking up some unobserved differential time-varying trends across counties. We investigate this possibility in a number of ways. First, Appendix Table A6 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 been born 2 years before his actual date of birth*. We choose a two-year lead to avoid confounding our estimates with any possible conception/fertility impacts of temperature (Lam, Miron, and Riley, 1994); our leads should thus be completely uncorrelated with the actual treatment effect of exposure during gestation or in the first year of life. Table A6 presents results from a single regression, where the first six rows of Table A6 show the lead coefficients, while rows 7-12 show the coefficients on exposure by trimester and through month 12 post-birth. When we consider exposure to degree days above 32°C , for which we consistently find negative impacts on adult labor market outcomes, we see that the leads in temperature are uncorrelated with earnings 30 years later, while the coefficients on actual early-life exposure to hot temperature are negative, larger in absolute magnitude, and mostly statistically significant.

Another concern is that temperature variation may be correlated with variation in economic conditions. Research has shown that extreme temperatures predict adverse economic outcomes, in particular for agricultural services (Schlenker and Roberts, 2009). In addition, there is some evidence that economic conditions in early childhood are predictive of life-long well-being (Hoynes, Schanzenbach, and Almond, 2012; Van den Berg, Doblhammer-Reiter, and C 2011; Van Den Berg, Lindeboom, and Portrait, 2006). In order to test whether the adverse impact of temperature operates through an income channel, we calculate the fraction of 1969 employment that works in the agricultural sector. We then interact this variable with our temperature variables in regression (1), and we

[22]Population weighting likely makes a considerable difference in the western United States, where counties tend to be large and can be topographically very diverse. Thus, for example, failing to population weight mountainous counties introduces substantial noise into the baseline estimates.

report the baseline coefficients in Appendix Table A7. The results are very similar to the baseline estimates, suggesting that temperature related shocks to agricultural sectors of the economy are not explaining our results.

There is also growing evidence suggesting that there is important seasonal variation in birth outcomes which correlates with demographic characteristics (Buckles and Hungerman, 2008; Currie and Schwandt, 2013; Darrow, Strickland, Klein, Waller, Flanders, Correa, Marcus, and Tolbert, 2009; Lam, Miron, and Riley, 1994). 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 county×day-of-year×race×sex 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.[23] Appendix Table A8 presents estimates from a model with county×day-of-year fixed effects (as opposed to our baseline county×day-of-year×race×sex fixed effects) to ask whether there is a relationship between observable characteristics of the population (i.e. race and sex) and the temperature variation in our data. There is suggestive evidence that more disadvantaged populations (as indicated by lower predicted earnings) disproportionately experience extreme temperatures during gestation. However, the magnitudes of the observed sorting responses are quite a bit smaller than our baseline estimates. Nevertheless, we believe that differential fertility that covaries with the observed temperature variation is an important source of bias, and we therefore control for county×day-of-year×race×sex fixed effects in all of our other regression models.

Finally, the results in Table 3 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 three 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 Appendix Table A9, 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 Appendix Table A9 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. Panel A of Appendix Table A10 presents results where we interact temperature with average state household AC adoption rates, and the results remain very similar to before. Lastly, we estimate our baseline AC model where we include an additional set of interactions between income and our vector of temperature dummies. This test is designed to control for any unobserved income effects that covary with the main temperature variation in the model. Panel B of Appendix Table A10 presents results from this model, where again we find very similar treatment effects.

[23] Specifically, we use the micro data to estimate earnings regressions controlling for sex and race indicators and county×day-of-year fixed effects. We then use the predicted values from this regression as a summary index measure of sorting as in Isen, Rossin-Slater, and Walker (2013).

6 Conclusion

Recent work has shown how exposure to very high temperatures influences contemporaneous health outcomes, including adult and infant mortality, as well as the incidence of low birth weight in children (see e.g. Intergovernmental Panel on Cl (2007); Basu and Samet (2002); Barreca, Clay, Deschenes, Greenstone, and Shapiro (2013); Deschenes and Moretti (2009); Deschênes and Greenstone (2011); Deschênes, Greenstone, and Guryan (2009)). A separate line of research has explored how shocks to the early-life environment translate into long-run human capital disparities (Almond and Currie, 2011a,b). However, while the existing literature has investigated the lasting impacts of fairly large and devastating events such as disease outbreaks, disasters, and famines (e.g., Almond, 2006; Almond, Edlund, and Palme, 2009; Almond, Edlund, Li, and Zhang, 2010), to date, there is little evidence on the possible long-term consequences of the climate. Thus, an important question left unanswered is whether the observed temperature-induced impacts on contemporaneous morbidity may translate into even larger welfare losses through human capital and lifetime income channels.

This paper attempts to fill this gap by presenting some of the first evidence on the persistent impact of early-life extreme temperature episodes on later-life well-being. We accomplish this task by combining new U.S. administrative earnings records data that contains information on individuals' counties and dates of birth with fine-scale daily weather data. We estimate a series of flexible econometric models that allow us to observe the possible non-linear relationship between early-life temperatures and adult labor market outcomes. We find that, while exposure to cold or moderate temperatures during gestation or in the first year of life has no impact on human capital accumulation, later-life outcomes are disproportionately sensitive to early-life exposure to very hot days with mean temperatures exceeding 32°C. Lastly, we find that much of the estimated adverse affects are mitigated by household AC adoption, which suggests a role for adaptation in alleviating the possibly severe and lasting impacts of extreme temperatures *in utero* and in early childhood.

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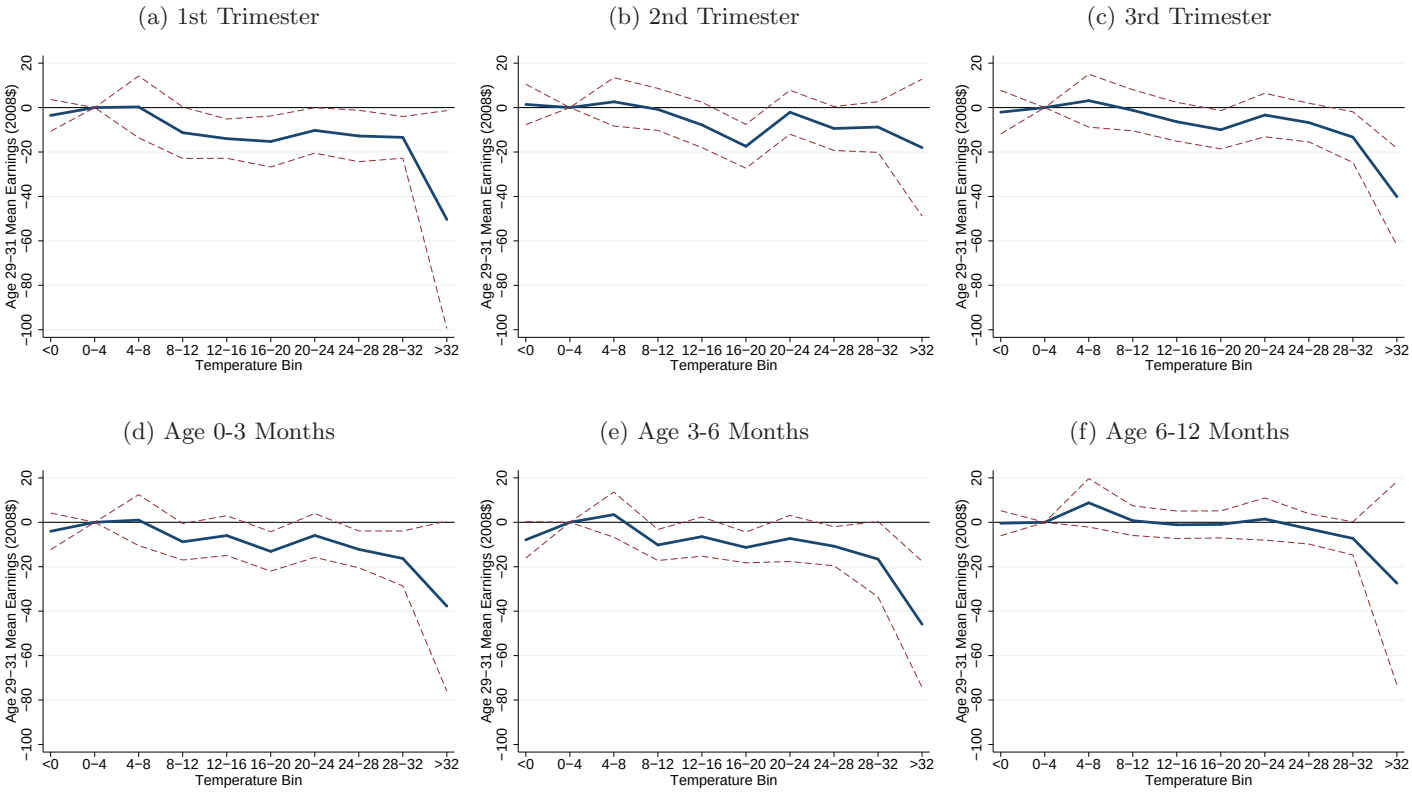
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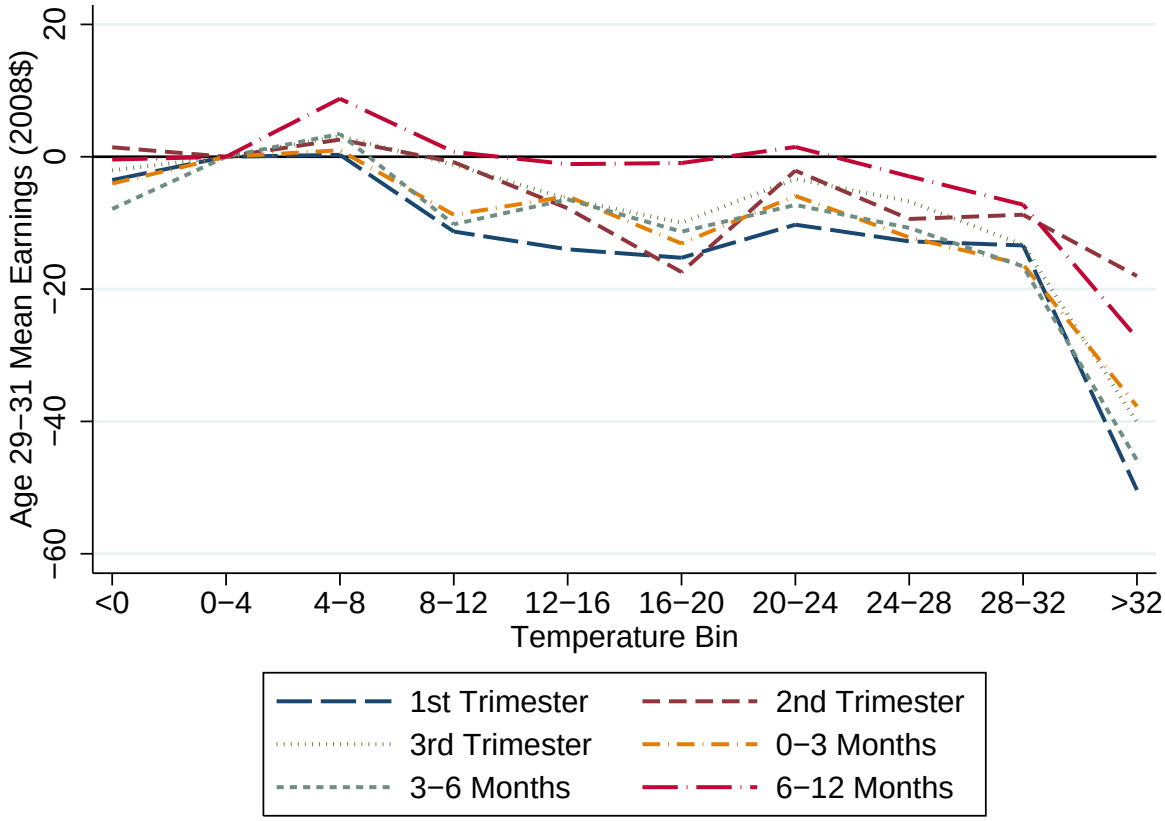
Figures and Tables

Figure 1: Impact of Temperature Degree Days on Age 29-31 Annual Earnings by Focal Period



NOTE: Plotted are the point estimates and standard errors from a single regression associated with a version of Equation (1). The dependent variable in the regression is mean annual earnings for an individual between the ages 29-31, adjusted to real 2008$. Each panel represents a different critical period in child development as indicated in the panel headings, but all panels come from the same regression model. The blue dots correspond to the predicted marginal effect of a 1 day increase in average temperatures in the associated temperature bin (indicated on the x-axis) on earnings at ages 29-31. The dotted red lines correspond to 95% confidence intervals. The regression controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. Standard errors are clustered by state.

Figure 2: Heterogeneous Impact of Temperature Degree Days on Age 29-31 Annual Earnings by Focal Period



NOTE: This overlays the marginal response of an increase in temperature at different critical periods of a child's development. This figure is created by stacking the panels in Figure 1. All of the estimates in this figure come from a single regression. The dependent variable in the regression is mean annual earnings for an individual between the ages 29-31, adjusted to real 2008$. The lines correspond to the predicted marginal effect of a 1 day increase in average temperatures in the associated temperature bin (indicated on the x-axis) on earnings at ages 29-31. The regression controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation.

Table 1: Summary Statistics

	Earnings	Air Conditioning		Temperature Descriptives			
	Age 29-31	1960	1980	Mean	Min	Max	# of Days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Sample Means By Region							
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 Degree Days By Focal Period							
	1st Trimester	2nd Trimester	3rd Trimester	Total Gestation	0-3 Months	3-6 Months	6-12 Months
Days below 0°C	6.92	6.53	6.47	20.08	6.99	7.20	14.05
Days 0-24°C	66.94	65.83	64.79	199.05	67.83	67.73	137.56
Days 24-28°C	12.24	12.67	12.78	37.98	12.42	12.33	26.93
Days 28-32°C	2.80	2.86	2.85	8.57	2.65	2.64	6.25
Days above 32°C	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. 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 Schlenker and Roberts (2009).

Table 2: Effects of Temperature over Different Critical Periods on Age 29-31 Annual Earnings

	# Days <0°C	# Days 24-28°C	# Days 28-32°C	# Days 32+°C	# Days <0°C	# Days 24-28°C	# Days 28-32°C	# Days 32+°C
	Panel A: Independent Effect				Panel B: Joint Estimation			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Gestation	1.303	-0.534	-3.434	-28.230*	—	—	—	—
	(5.522)	(2.094)	(4.269)	(14.998)	—	—	—	—
1st Trimester	1.912	-0.489	-2.997	-43.252*	1.296	-1.517	-3.593	-38.573*
	(5.636)	(2.466)	(4.571)	(23.415)	(5.948)	(3.013)	(3.721)	(23.094)
2nd Trimester	3.632	-0.369	-0.091	-9.526	2.769	-2.807	-3.491	-8.665
	(5.153)	(2.362)	(5.578)	(18.354)	(5.537)	(3.588)	(5.709)	(15.487)
3rd Trimester	-1.334	0.422	-5.492	-34.572***	-1.43	-1.386	-7.882	-33.119***
	(5.173)	(2.438)	(4.924)	(12.536)	(5.617)	(3.288)	(4.927)	(11.393)
0-3 Months	-1.469	-2.643	-7.185*	-30.439	-2.29	-3.339	-7.530*	-29.180*
	(2.913)	(2.723)	(4.195)	(19.019)	(4.148)	(3.747)	(4.244)	(17.679)
3-6 Months	-2.888	-1.115	-6.521	-33.225*	-4.283	-2.054	-7.052	-36.009**
	(3.566)	(2.967)	(7.386)	(18.174)	(4.037)	(3.941)	(7.331)	(14.546)
6-12 Months	-2.936	-1.654	-3.248	-34.316	-3.676	-2.249	-3.696	-32.745
	(2.896)	(1.328)	(1.996)	(27.742)	(2.819)	(2.402)	(2.353)	(22.898)

NOTE: Panel A reports regression coefficients from 7 separate regressions, and Panel B reports coefficients from a single regression, each corresponding to a version of Equation (1) in the text. The dependent variable in each regression is the mean annual earnings between ages 29-31 in real 2008$. Each cell in each panel corresponds to a separate regression coefficient, reporting the marginal effect of an increase in the number of days for which average temperature fell in one of the respective temperature bins during a period indicated in the row headings. Panel A estimates the marginal effect of an increase in temperatures for each critical period separately (i.e. 7 separate regressions). Panel B reports estimates from the combined model. All regressions controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. Each regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table 3: Does the Marginal Effect of Temperature on Age 29-31 Earnings Vary with Household Air Conditioning Adoption?

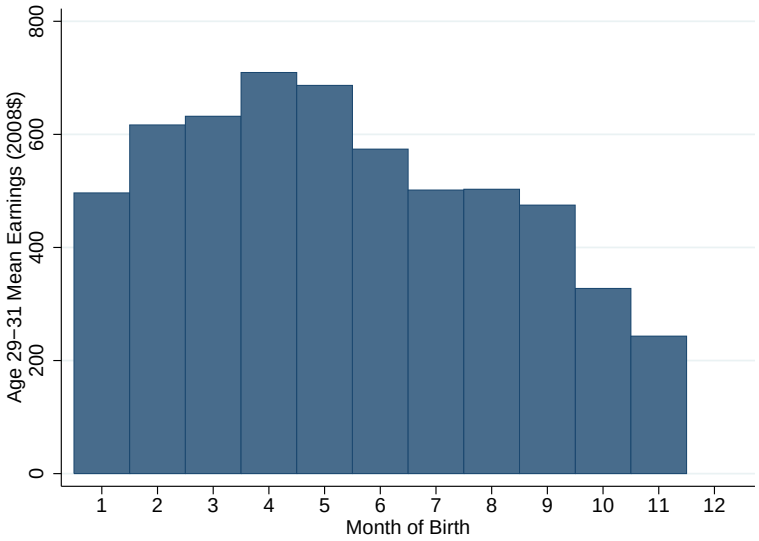
	# Days <0°C (1a)	# Days 24-28°C (1b)	# Days 28-32°C (1c)	# Days 32+°C (1d)
1st Trimester	5.868	-4.656	-0.468	-35.916
	(6.360)	(8.252)	(16.689)	(24.479)
2nd Trimester	2.636	-0.966	-13.349	-91.510***
	(5.714)	(7.285)	(26.160)	(20.016)
3rd Trimester	0.024	-7.610	-29.642	-154.542***
	(5.437)	(7.923)	(22.911)	(19.080)
0-3 Months	6.910	-1.677	-40.950***	-77.629
	(5.034)	(7.881)	(15.716)	(78.866)
3-6 Months	3.674	-7.876	-35.760	-114.715***
	(6.788)	(6.143)	(23.603)	(38.096)
6-12 Months	3.379	-14.113***	-27.231***	-209.608
	(3.877)	(3.434)	(5.215)	(130.045)
1st Trimester×Air Conditioning	-14.971	4.832	-4.793	-10.764
	(19.483)	(13.344)	(23.911)	(54.368)
2nd Trimester×Air Conditioning	-1.439	-3.897	12.602	114.381***
	(15.792)	(11.412)	(40.092)	(39.718)
3rd Trimester×Air Conditioning	-5.040	12.141	36.235	175.721***
	(20.158)	(14.213)	(31.405)	(21.455)
0-3 Months×Air Conditioning	-25.357*	-3.862	50.652**	64.674
	(13.998)	(11.112)	(24.636)	(99.836)
3-6 Months×Air Conditioning	-21.154	10.919	44.654	110.598*
	(13.409)	(10.462)	(28.763)	(61.083)
6-12 Months×Air Conditioning	-19.555***	26.163***	42.902***	248.809
	(6.371)	(6.605)	(8.044)	(170.089)

NOTE: This table reports the results from a single regression corresponding to a version of Equation (2) in the text. The regression augments Equation (1) by including an additional set of temperature response coefficients, now interacted with the fraction of households in a county that have household air conditioning. The dependent variable in the regression is the mean annual earnings between ages 29-31 in real 2008$. Each cell corresponds to a separate regression coefficient, reporting the marginal effect of an increase in the number of days for which average temperature fell in one of the respective temperature bins during a period indicated in the row headings. The regression controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. The regression also includes the baseline air conditioning variable which varies by county×year. The regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

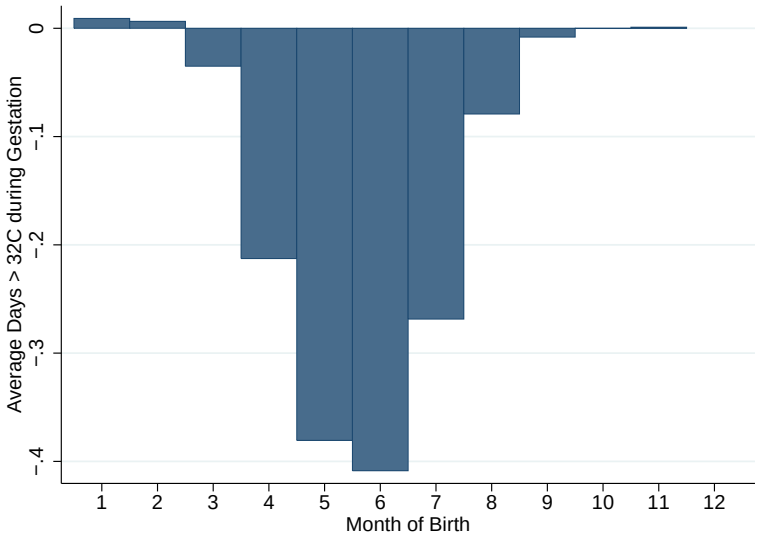
A Appendix Tables and Figures

Figure A1: Conditional Average Earnings and Temperature Exposure by Month of Birth

(a) Average Earnings



(b) Average Days> 32°C during Gestation



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 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. Panel B plots the month of birth coefficients coming from a regression of number of days during gestation for which the daily average temperature exceed 32°Cregressed against county×race×sex fixed effects, year fixed effects, and month fixed effects. An auxiliary regression comparing the 11 observations in Panel A with the 11 observations in Panel B delivers an R-squared of 0.25.

Table A1: Effect of Temperature During Gestation on Age 29-31 Annual Earnings: Model Sensitivity

	(1)	(2)	(3)	(4)	(5)
# Days <0°C	4.980	7.652***	1.473	2.340	1.303
	(13.741)	(0.846)	(1.515)	(5.543)	(5.522)
# Days 24-28°C	-10.966*	-3.325***	0.250	-0.500	-0.534
	(6.361)	(0.932)	(1.390)	(2.360)	(2.094)
# Days 28-32°C	-3.010	-2.217	-0.631	-2.871	-3.434
	(9.852)	(2.589)	(2.458)	(4.445)	(4.269)
# Days 32+°C	-50.206	-13.356***	-11.350***	-25.504*	-28.230*
	(42.071)	(4.247)	(3.702)	(15.242)	(14.998)
Race and Sex FE	X	X	X	X	
Birth County FE		X	X		
Birth Month FE			X		
Birth County×DOY FE				X	
Birth County×DOY×race×sex FE					X

NOTE: This table reports the results from 5 separate regressions, one per column. The reported coefficients correspond to an additional day during gestation for which mean daily temperature fell in the indicated temperature bin. The dependent variable in each regression is the mean annual earnings between ages 29-31 in real 2008$. Each regression model includes a slightly different set of controls as indicated in the table. All regressions control for year fixed effects. Each regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A2: Effect of Temperature During Gestation: Alternative Labor Market Outcomes at Ages 29-31

	(1) Annual Quarters Unemployed	(2) 4-Quarter Earnings	(3) Log Earnings	(4) Log 4-Quarter Earnings
# Days <0°C	-0.000	-1.887	-0.000	-0.000
	(0.000)	(7.047)	(0.000)	(0.000)
# Days 24-28°C	-0.000	-3.549	-0.000	-0.000*
	(0.000)	(4.574)	(0.000)	(0.000)
# Days 28-32°C	0.000	-5.005	0.000	-0.000
	(0.000)	(7.440)	(0.000)	(0.000)
# Days 32+°C	0.002***	-27.913**	-0.001	-0.001
	(0.001)	(13.912)	(0.001)	(0.000)
Dep. Var. Mean	0.86	24,397	9.65	10.34

NOTE: This table reports the results from 4 separate regressions, one per column. The reported coefficients correspond to an additional day during gestation for which mean daily temperature fell in the indicated temperature bin. The dependent variable in each regression is indicated in the column headings and changes across columns. All dollar values are reported in real 2008$. All regressions controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. Each regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A3: 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 <0°C	-0.086	-0.007	0.017	0.047*	0.025	0.005	0.019	-0.007	-0.015	
	(0.090)	(0.045)	(0.023)	(0.028)	(0.043)	(0.040)	(0.049)	(0.020)	(0.012)	
# Days 24-28°C	-0.003	-0.001	-0.010	-0.003	0.015	0.021	-0.026	0.006	0.001	
	(0.041)	(0.011)	(0.011)	(0.014)	(0.018)	(0.020)	(0.016)	(0.010)	(0.009)	
# Days 28-32°C	-0.016	-0.040	-0.001	0.014	0.071	0.006	-0.026	0.003	-0.005	
	(0.060)	(0.040)	(0.021)	(0.026)	(0.046)	(0.032)	(0.042)	(0.019)	(0.013)	
# Days 32+°C	0.390	-0.032	0.071*	0.226***	0.019	-0.338**	-0.245***	-0.037	-0.022	
	(0.439)	(0.085)	(0.039)	(0.082)	(0.173)	(0.142)	(0.065)	(0.043)	(0.064)	
Dep. Var. Mean	0.013	0.044	0.053	0.151	0.240	0.240	0.146	0.051	0.046	0.015

NOTE: This table reports the results from 10 separate regressions, one per column. The reported coefficients correspond to an additional day during gestation for which mean daily temperature fell in the indicated temperature bin. 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 32°Cduring gestation. All regressions controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. Each regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A4: 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 <0°C	1.862	2.532	1.882	1.226	2.442	1.303
	(7.928)	(7.770)	(5.193)	(4.034)	(5.082)	(5.522)
# Days 24-28°C	1.187	-0.314	-0.814	-0.630	-0.501	-0.534
	(2.297)	(2.804)	(2.219)	(2.078)	(2.769)	(2.094)
# Days 28-32°C	5.200	2.730	-2.592	-7.789**	-20.959**	-3.434
	(5.322)	(5.179)	(4.465)	(3.608)	(8.801)	(4.269)
# Days 32+°C	-37.747	-26.518	-27.253*	-27.647***	-61.154***	-28.230*
	(23.227)	(17.770)	(13.935)	(9.439)	(22.440)	(14.998)

NOTE: This table reports the results from 6 separate regressions, one per column. The reported coefficients correspond to an additional day during gestation for which mean daily temperature fell in the indicated temperature bin. The dependent variable in each regression is the mean annual earnings at ages indicated in the column headings in real 2008$. All regressions controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. Each regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A5: Baseline Estimates without Population Weighted Temperature

	# Days <0°C	# Days 24-28°C	# Days 28-32°C	# Days 32+°C	# Days <0°C	# Days 24-28°C	# Days 28-32°C	# Days 32+°C
	Panel A: Independent Effect				Panel B: Joint Estimation			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Gestation	1.302	-0.081	-3.243	-33.288*	—	—	—	—
	(5.479)	(2.013)	(4.618)	(18.848)	—	—	—	—
1st Trimester	2.054	-0.218	-3.032	-31.615**	0.981	-1.392	-4.114	-25.658*
	(5.639)	(2.466)	(4.816)	(14.841)	(5.914)	(3.014)	(3.897)	(13.505)
2nd Trimester	3.259	0.269	0.746	-18.839	2.170	-2.383	-3.083	-16.750
	(5.099)	(2.362)	(6.021)	(20.901)	(5.405)	(3.680)	(6.205)	(18.933)
3rd Trimester	-0.715	1.050	-5.365	-45.988**	-1.093	-0.809	-8.235	-43.586**
	(5.085)	(2.419)	(5.284)	(19.742)	(5.472)	(3.341)	(5.257)	(19.812)
0-3 Months	-0.995	-2.072	-6.752	-39.496**	-1.676	-2.875	-7.400	-40.410*
	(2.980)	(2.605)	(4.467)	(19.592)	(4.386)	(3.698)	(4.586)	(20.621)
3-6 Months	-2.613	-1.060	-6.741	-36.020**	-3.733	-2.129	-7.788	-40.095**
	(3.500)	(2.969)	(7.523)	(17.913)	(3.963)	(4.074)	(7.431)	(16.389)
6-12 Months	-2.906	-1.760	-3.463	-47.668**	-3.409	-2.424	-3.656	-44.198**
	(2.809)	(1.477)	(2.345)	(22.478)	(2.715)	(2.645)	(2.789)	(17.574)

NOTE: This table reports the exact same specifications as reported in Table 2 except that the temperature variables are constructed without weighting the grid cells by Census Block 2000 population counts. Panel A reports regression coefficients from 7 separate regressions, and Panel B reports coefficients from a single regression, each corresponding to a version of Equation (1) in the text. The dependent variable in each regression is the mean annual earnings between ages 29-31 in real 2008$. Each cell in each panel corresponds to a separate regression coefficient, reporting the marginal effect of an increase in the number of days for which average temperature fell in one of the respective temperature bins during a period indicated in the row headings. Panel A estimates the marginal effect of an increase in temperatures for each critical period separately (i.e. 7 separate regressions). Panel B reports estimates from the combined model. All regressions controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. Each regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A6: Leads in Temperature Do Not Predict Later-Life Outcomes

	# Days <0°C (1a)	# Days 24-28°C (1b)	# Days 28-32°C (1c)	# Days 32+°C (1d)
1st Trimester (t-2)	4.971	-7.471*	-9.306***	-6.053
	(4.806)	(4.106)	(3.504)	(13.918)
2nd Trimester (t-2)	6.933	-5.248	-7.748***	9.321
	(4.825)	(4.691)	(2.483)	(13.391)
3rd Trimester (t-2)	4.665	-8.853**	-5.203*	-9.073
	(3.648)	(3.656)	(3.021)	(9.677)
0-3 Months (t-2)	2.703	-4.762*	-3.833	2.540
	(6.806)	(2.749)	(3.299)	(15.390)
3-6 Months (t-2)	0.484	-2.155	-4.477	-8.601
	(5.021)	(4.221)	(5.043)	(8.433)
6-12 Months (t-2)	-2.616	-0.807	-0.098	-16.145
	(3.647)	(3.120)	(3.004)	(10.300)
1st Trimester	2.357	-1.267	-5.126	-44.090*
	(5.964)	(3.884)	(3.882)	(23.900)
2nd Trimester	3.743	-2.523	-2.949	-6.844
	(5.181)	(4.070)	(4.862)	(16.194)
3rd Trimester	-1.126	-1.075	-7.265*	-27.558**
	(5.081)	(3.516)	(4.235)	(11.753)
0-3 Months	-2.940	-2.865	-8.031**	-25.878
	(4.361)	(3.722)	(4.020)	(18.958)
3-6 Months	-4.654	-2.749	-8.598	-34.787***
	(4.274)	(4.589)	(7.230)	(13.299)
6-12 Months	-3.321	-3.235	-5.739*	-33.280
	(3.107)	(3.167)	(3.154)	(22.582)

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 lags in the temperature response variables for temperatures experienced two years prior to birth. The dependent variable in the regression is the mean annual earnings between ages 29-31 in real 2008$. Each cell corresponds to a separate regression coefficient, reporting the marginal effect of an increase in the number of days for which average temperature fell in one of the respective temperature bins during a period indicated in the row headings. The regression controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. The regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A7: The Long-Run Effect of Early-Life Temperature Exposure, Controlling for Temperature×Agricultural Economic Shocks

	# Days <0°C (1a)	# Days 24-28°C (1b)	# Days 28-32°C (1c)	# Days 32+°C (1d)
1st Trimester	-1.199	-1.720	-3.624	-34.692
	(6.707)	(3.487)	(3.719)	(27.977)
2nd Trimester	1.779	-3.524	-0.936	15.679
	(6.689)	(3.616)	(6.141)	(14.161)
3rd Trimester	-3.945	-2.759	-6.392	-26.650*
	(6.869)	(3.446)	(4.656)	(14.815)
0-3 Months	-3.643	-2.184	-2.413	-20.508
	(4.532)	(3.572)	(4.322)	(17.835)
3-6 Months	-5.779	-1.832	-3.278	-16.645
	(4.304)	(3.850)	(7.162)	(14.040)
6-12 Months	-4.181	-2.316	-2.629	-18.977
	(2.927)	(2.933)	(2.900)	(24.320)

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 interactions between temperature and the fraction of county employment engaged in agricultural production. The dependent variable in the regression is the mean annual earnings between ages 29-31 in real 2008$. Each cell corresponds to a separate regression coefficient, reporting the marginal effect of an increase in the number of days for which average temperature fell in one of the respective temperature bins during a period indicated in the row headings. The regression controls for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. The regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A8: The Conditional Relationship Between Temperatures and Predicted Earnings

	# Days <0°C (1a)	# Days 24-28°C (1b)	# Days 28-32°C (1c)	# Days 32+°C (1d)
1st Trimester	-1.225*	-0.246	-0.642	5.212*
	(0.725)	(0.550)	(0.676)	(2.687)
2nd Trimester	-0.100	-0.058	-2.547**	-4.905***
	(0.698)	(0.836)	(1.068)	(1.600)
3rd Trimester	-1.238*	-1.001*	-3.304***	-6.438*
	(0.735)	(0.547)	(1.246)	(3.355)
0-3 Months	-0.811	-0.536	-1.894**	-3.189**
	(0.523)	(0.649)	(0.896)	(1.270)
3-6 Months	-0.697	-0.105	-0.754	-2.748**
	(0.571)	(0.645)	(1.004)	(1.353)
6-12 Months	0.451	0.549**	-0.299	1.326
	(0.586)	(0.268)	(0.534)	(2.926)

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. Each cell corresponds to a separate regression coefficient, reporting the marginal effect of an increase in the number of days for which average temperature fell in one of the respective temperature bins during a period indicated in the row headings. The regression controls for birth-county×day-of-year fixed effects, year fixed effects, and a cubic polynomial in precipitation. The regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

Table A9: The Relationship Between 1970-1980 Changes in County Level Household AC Adoption and Changes in Population/Income

	(1)	(2)	(3)
ΔPopulation	-0.577		-0.196
	(1.441)		(1.559)
ΔIncome Per Capita		-1.844	-1.783
		(1.901)	(2.047)
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.

Table A10: Adaptation Mechanisms: Air Conditioning Exposure, State-Level AC and Income Controls

	Panel A: State AC Adoption				Panel B: Income×Temperature Controls			
	# Days <0°C (1a)	# Days 24-28°C (1b)	# Days 28-32°C (1c)	# Days 32+°C (1d)	# Days <0°C (2a)	# Days 24-28°C (2b)	# Days 28-32°C (2c)	# Days 32+°C (2d)
1st Trimester	12.943	-3.980	42.254***	-61.739	12.592	-23.634**	-58.300***	-164.928***
	(10.965)	(9.043)	(14.945)	(61.540)	(10.325)	(9.443)	(8.029)	(58.084)
2nd Trimester	7.871	-16.093*	39.936**	-62.564*	-5.701	2.670	-78.983***	-190.129***
	(9.815)	(8.500)	(16.744)	(33.583)	(12.334)	(8.060)	(16.495)	(41.752)
3rd Trimester	3.143	-7.387	39.318	-64.624***	21.138*	-15.991	-69.035***	-374.810***
	(9.565)	(10.499)	(28.352)	(16.128)	(12.165)	(9.747)	(20.482)	(55.186)
0-3 Months	7.053	-10.907	-22.865	-127.558***	18.010*	-7.698	-67.113***	-535.778***
	(6.346)	(11.003)	(31.180)	(16.181)	(9.400)	(11.661)	(14.126)	(163.991)
3-6 Months	3.355	-18.588*	18.455	-91.941**	1.385	-18.028*	-81.813***	-222.598
	(10.019)	(10.374)	(18.960)	(42.426)	(8.313)	(9.520)	(12.111)	(146.545)
6-12 Months	7.918	-7.951	-42.827***	-123.726***	-3.347	-16.468***	-48.349***	-219.837**
	(5.100)	(7.094)	(12.815)	(21.714)	(8.949)	(5.541)	(5.358)	(93.799)
1st Trimester×AC	-33.041	3.658	-80.418***	47.702	6.103	24.407*	41.476*	336.558*
	(34.991)	(14.967)	(24.011)	(91.528)	(20.836)	(13.704)	(24.219)	(176.039)
2nd Trimester×AC	-13.563	27.161*	-68.662**	106.980*	20.514	5.299	56.511*	177.907*
	(31.319)	(14.461)	(26.817)	(60.701)	(16.392)	(13.093)	(30.358)	(104.866)
3rd Trimester×AC	-13.967	9.473	-79.185*	58.170**	18.554	24.180**	71.565***	381.017***
	(34.466)	(19.443)	(46.798)	(25.784)	(19.590)	(11.741)	(19.665)	(80.600)
0-3 Months×AC	-25.171	16.403	27.057	174.694***	-14.579	-1.069	70.148***	670.744***
	(19.869)	(18.848)	(52.063)	(25.972)	(17.345)	(15.297)	(25.798)	(99.779)
3-6 Months×AC	-19.348	32.565	-40.351	104.725	-12.566	13.029	67.960***	230.036
	(23.873)	(20.846)	(33.819)	(71.010)	(13.827)	(9.346)	(17.248)	(177.066)
6-12 Months×AC	-33.157**	13.576	67.504***	188.514***	-15.161	22.817***	40.263***	270.118*
	(13.203)	(13.133)	(21.412)	(54.690)	(10.619)	(8.147)	(12.446)	(158.684)

NOTE: This table reports the results from two regressions, one per panel, corresponding to a version of Equation (2) in the text. Panel A 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. Panel B reports estimates from the same regression model as outlined in Equation (1) and presented in Table 3 while also including a set of controls for income interacted with the temperature response variables. The dependent variable in each regression is the mean annual earnings between ages 29-31 in real 2008$. Each cell in each panel corresponds to a separate regression coefficient, reporting the marginal effect of an increase in the number of days for which average temperature fell in one of the respective temperature bins during a period indicated in the row headings. The regressions control for birth-county×day-of-year×race×sex fixed effects, year fixed effects, and a cubic polynomial in precipitation. The regression also includes the baseline air conditioning variable which varies by state×year in Panel A and county×year in Panel B. Each regression consists of approximately 12,000,000 observations. Standard errors are clustered by state.

B Data Appendix

Longitudinal Employer Household Dynamics Files

For each individual in our sample, we calculate the year at which they turn 28-32, and we search for their earnings record in the employment history file. We take the combined earnings for a worker in a given year, combining over both employers and states (in the event of multiple job spells within a year). We also calculate the number of quarters for which that worker has positive earnings in a given year. In the event that a worker works in more than one state in a given year, we assign the worker to be working in the state for which he/she has the maximum earnings in that year. If the earnings record is missing for a particular age category (i.e. because the worker is unemployed or has attritted from the data), we do one of two things: we either keep this earnings record as missing or we replace it with a zero. For the workers for which we do not observe an earnings records in "the sample period", we impute the current state of work using the state for which the worker has the most quarterly earnings observations either in future or previous years. In the event that a worker has the same earnings observations in more than one state, we randomly assign the worker to one of these states.[24]

[24] For the purposes of our analysis, it does not particularly matter where an individual ends up. We are primarily focused on place of birth. However, in some econometric specifications, we control for underlying earnings heterogeneity in a particular work-state×year.