Long-Term Impacts of High Temperatures on Economic Productivity

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High temperature anomalies have recently been shown to have adverse impacts on multiple health and socio-economic outcomes. A well established literature on the impacts of early life stress on life-long human capital accumulation has led us to hypothesize that high temperature anomalies can have long-term impacts on economic productivity. Using data on historical weather and the earnings, place and date of birth of all 1.5 million formal employees in Ecuador, we find that women who have experienced a 1°C increase in average temperature while in-utero earn 1.1%-1.7% less as adults. The results are highly robust and suggest warming may already have caused adverse long-term economic losses "in the pipeline" that have not been appreciated to date.

Keywords: Climate Change, Economic Impacts, Fetal Origins

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Growing interest in the future impacts of climate change has spurred a burgeoning literature on the economic impacts of high temperatures (see Dell et al, 2012, for a review). Multiple analyses of historical weather and socio-economic data have now produced a substantial body of robust evidence that high temperature anomalies lead to a range of adverse social and economic impacts, including reductions in economic productivity and growth in both the agricultural and non-agricultural sectors (Deschenes and Greenstone, 2007; Lobell, Schlenker, and Costa-Roberts, 2011; Schlenker and Lobell, 2010; Guiteras, 2009; Fishman, 2011; Hsiang, 2010; Dell et al, 2012; Sudarshan and Tewari, 2011; Zivin and Neidel, 2014; Deryugina and Hsiang, 2014), increases in morbidity (Burgess et al, 2011; Patz et al, 2005; McMichael, Woodruff, and Hales, 2006), crime and conflict (Hsiang, Burke and Miguel 2013; Ranson 2012; Blakeslee and Fishman 2013).

Another, independent body of evidence establishes the long-term impacts of early life stress on adult socio-economic indicators, health and well-being. In particular, the *fetal origins hypothesis* posits that in-utero circumstances can have substantial long-term impacts on human development. Numerous studies have provided evidence in support of this hypothesis, finding that economic, environmental or disease-related stress in infancy or in-utero lead to long-term impacts on physical and cognitive health, educational attainment and wages (Almond and Curie, 2011). When combined with the evidence on the multiple socio-economic and health related impacts of high temperature anomalies, this suggests that individuals who are exposed to high ambient temperatures in-utero or in infancy may experience life-long negative consequences through a number of possible channels, both physiological and economic (for example, declines in income or economic hardship can reduce consumption of crucial nutritional inputs by pregnant women). This, in turn, would suggest that the warming that has already taken places in the past few decades may incur hitherto under-appreciated, long-term economic losses. To the best of our knowledge, this paper provides the first body of empirical evidence on this possible important long-term linkage.

In this paper, we investigate the effect of high temperature anomalies around the time of birth on formal earnings as an adult. Economic theory suggests that in well functioning markets, wages provide an accurate indicator of economic productivity and human capital, including physical and cognitive function. A relationship between temperature anomalies in-utero and adult earnings would therefore measure the total economic losses associated with long-term human capital losses resulting from stress in-utero, even if the contribution of each potential channel of causation may not be possible to measure directly (figure 1).

Our analysis makes use of a unique data set on the 2010 earnings of all 1.5 million formal sector workers in Ecuador, born between 1950 and 1989, that was merged with civil registry data to identify the place and time of birth of these individuals, and then merged with historical weather data sets to identify temperature and precipitation levels around the time of birth (including in-utero). A regression analysis of the relationship between adult earnings and temporal temperature anomalies revealed that higher temperatures in-utero lead to significantly lower adult earnings for women, with a 1°C increase in average monthly temperature in-utero leading to a 1.1%-1.7% decrease in adult earnings. These results are highly robust to the inclusion of fine geographic controls, localized annual cycles and time trends, and to various falsification tests. Even though the reduced-form analysis does not allow us to identify which of the established negative impacts of high temperatures is driving the association, the random nature of temperature variations over time within a geographical locality facilitates causal inference (Dell et al, 2012).

Several previous studies have used a similar methodology to find long-term impacts of drought or floods at the year of birth on the welfare, physical and cognitive health of farming households in low-income countries (Maccini and Yang, 2008; Aguilar and Vicarelli, 2011; Tiwari et al, 2013). We believe this study to be the first to focus on temperature anomalies, or to relate weather anomalies to administrative formal earning data. In addition, our sample consists of adults born in both urban and rural areas that are employed in the formal sector of a middle-income economy, and therefore have higher earnings and education levels than the samples studied in previous studies. Our findings are consistent with a small number of other studies that have found detrimental short-term impacts of high temperatures in-utero on post-birth health outcomes. For example, birthweight in the U.S. is found to be negatively correlated with in-utero exposure to high temperatures (Deschens, Greenstone and Guryan, 2009). However, we extend these results by observing much longer-term, economic impacts.

Materials and Methods

Data: Ecuador is a relatively small, middle-income country in South America with a population of about 16 million residents. Over the time period in which our sample was born, GDP per capita has increased significantly, and at the same time, infant mortality has fallen precipitously (Figure S1). Despite its small size, Ecuador's weather patterns display a large degree of spatial and temporal variation (Figure S2).

Earnings data were obtained from the Ecuadorian Tax Authority. This dataset contains the 2010 annual earnings of all Ecuadorians working in the formal sector, i.e. all workers employed in firms that report corporate tax returns to the Tax Authority. The Tax Authority complemented their earnings data with information from the National Civil Registry, which includes several demographic characteristics of workers including their gender, year and month of birth, place of birth (at the level of a canton, a small political administrative unit of which there are 218 in Ecuador, and educational attainment. Our sample includes individuals born between the year 1950 and 1989, implying that all individuals in our dataset are between 21 and 60 years old at the time their earnings are reported. Unfortunately, the data does not allow us to group individuals by family unit.

Precipitation and Temperature data is based on the 1900-2010 Gridded Monthly Time Series on Terrestrial Air Temperature, and the 1900-2010 Gridded Monthly Time Series on Terrestrial Precipitation from the University of Delaware (Willmott and Matsuura, 2001). The gridded data was used to calculate monthly temperature and precipitation in each of Ecuador's 218 Cantons through spatial averaging (see the SI section and figure S3). Summary statistics for the earnings and weather data are given in Table S1.

Regression Analysis: We employ regression analysis to investigate the correlation between in-utero weather and adult earnings. Regressing adult earnings on weather patterns *across* geographical locations of birth can generate biased estimates because of potential unobservable confounding variables. We therefore follow previous studies (Dell et al, 2012) and base our estimates on local temporal deviations of weather from the local long-term mean in each locality. Such deviations are likely to be random and therefore orthogonal to any possible confounders, facilitating causal inference. To isolate these *localized* temporal fluctuations in weather, we include location (canton) fixed effects and year fixed effects in the regressions (the latter flexibly control for annual variation in weather that affects the entire country such as ENSO). Similarly, given the long time span over which individuals in our earnings data are born, it is also important to control for time-trends in the regression. Otherwise, unrelated trends in weather (such as warming), socio-economic circumstances (due to economic growth) and 2010 earnings (due to age effects) can result in spurious correlations. To adequately capture these potentially confounding trends in observable and unobservable variables, our regressions include highly flexible, localized time trends which we allow to vary from linear to quartic in each of Ecuador's 24 provinces. In the same vein, we include fixed-effects for every combination of canton and month (1-12) of birth in order to ensure estimates are not driven by potentially biased correlations between the month of birth and local seasonal patterns that can also lead to spurious correlations. The inclusion of this rich set of controls assures that regression estimates are based solely on temporal random fluctuations in monthly temperature within each locale. Our main model specification therefore takes the following form:

$$ln(y_{icmy}) = \alpha_1 + \alpha_2 T^l_{cmy} + \alpha_3 T^f_{cmy} + \alpha_4 R^l_{cmy} + \alpha_5 R^f_{cmy} + f_p(t) + \gamma_{mc} + \theta_y + \varepsilon_i \quad (1)$$

where is (log) income of individual i, born in canton c, in month m of year y; T^f_{cmy} and T^l_{cmy} are the average temperature (in degrees Celsius) in the canton of birth for the 9 months before birth, and the 9 months after birth, respectively, and R^l_{cmy} and R^f_{cmy} are the average monthly precipitation (cm) in the canton of birth for the 9 months before birth, and the 9 months after birth, respectively; $f_p(t)$ is a province specific time trend (ranging from linear to quartic specifications); γ_{mc} are month-canton fixed effects that capture any unobserved characteristics of every combination of a canton and month of year, such as location specific seasonal cycles; and θ_y are year fixed effects. To account for possible serial or spatial correlations amongst observations, we cluster our main results at several different levels: canton, province-year, region-year[1] and province, but find little impact on the significance of our estimates. Subsequent results have errors conservatively clustered at the province level.

[1] Provinces are Ecuador's largest political unit. There are 24 provinces in Ecuador, including the Galapagos province, which is excluded from our study, leaving 23 provinces. Cantons are the second largest political unit. Our dataset consists of births from 218 cantons. Regions are

Data limitations restrict the analysis to consider average monthly temperature anomalies, even though some of the impacts of high temperature may occur as a result of extreme days. The occurrence of extremes is likely to be correlated with high monthly averages, however, and any associated measurement error is likely to bias estimates downwards. The use of a linear form of temperature and precipitation in the regressions is justified by a non-parametric analysis that reveals an approximately linear relationship between Log earnings and in-utero temperatures (figure S4).

In addition to estimating impacts of weather anomalies on earnings, we also estimate their effect on the size of a cohort of individuals born in the same canton, year and month, and on the size of a cohort of formal sector workers born in the same canton, year and month. These impacts represent the effect of weather anomalies on the probability of live births and survival to adulthood and on the probability of being employed in the formal sector as adults. To do this, we match individuals in the formal sector income dataset with data from Ecuador's civil registry, which lists all working age Ecuadorians. The civil registry data contains 8.2 million individuals, that are approximately half females (so that 14.2%, and 25.9% of females and males, respectively, earned formal sector income in 2010). We then estimate similar regressions to (1) except that the dependent variable is the logarithm of the size of a cohort or a formal sector cohort (and each observation in the sample represents a cohort).

Results

Impacts on Earnings. Estimates of regression (1) are summarized in figure 2 (for females) and reported in Tables S2a and S2b for females and males, respectively. Both the figure and the regression tables report estimates from regressions in which province-specific time trends are allowed to enter into the regression in linear, quadratic, cubic, and quartic form (columns 1-4).

Regression results reveal that females born in cantons which are 1°C warmer than average during the 9 months before birth tend to earn 1.09%-1.69% less as adults. In

geographic based groupings of provinces. See section II for a description of Ecuador's three regions which are included in this paper (the Galapagos region is Ecuador's 4th region, which is omitted).

comparison, temperature anomalies during the 9 month period following birth have smaller and statistically insignificant impacts, in line with other studies that find strongest effect of stress occurring in-utero. Rainfall anomalies in-utero also have positive and statistically significant effect, in agreement with previous studies, with a 100 mm increase in rainfall leading to a 1.03%-1.45% increase in adult earning for women. As with temperature, rainfall anomalies in the 9 months following birth have no statistically significant effect on income.

The corresponding estimates for males, reported in in Table S2b, while of similar sign, are smaller, less precise and less robust to the specification of time trends, and the difference between the impacts of temperature and precipitation anomalies on males and females is statistically significant (p=0.04). Similar gender differences were found in previous studies (see discussion section). The remainder of the analysis is therefore focused on the female sample.

A similar analysis for the impact of in-utero temperature anomalies on educational attainment did not reveal statistically significant patterns (see SI section and tables S4a-S4c), potentially because the educational data available to us is limited to rather rough indicators of high school and college completion.

Cohort Size and Selection. The effect of weather anomalies on cohort size and on formal sector cohort size represent the impacts on the probability of survival to adulthood and on the probability of being employed in the formal sector. In addition to being of interest in themselves, such effects can potentially bias the results of the earnings regressions, since they point to selection effects into the sample (Almond and Currie, 2011).

Regression results indicate that cohorts that experience a 1ºC increase in in-utero temperature tend to be smaller by 2.6%. The effects are somewhat larger for males (3.0%) than for women (2.2%) and are statistically significant (table S5a). Similar effects are found on the sizes of formal sector workers, with male formal sector cohorts declining by 2.7% and female formal sector cohorts declining by 2.1% (table S5c). The similar magnitudes of these impacts suggests the probably of being employed in the formal sector, conditional on survival to adulthood, is unaffected by in-utero weather, and indeed, a regression of the ratio of formal cohort and total cohort sizes (table S5d), or (at the individual level) of this probability on in-utero temperature fails to find a statistically significant relationship (table S5e). We discuss the implications of these results below.

Falsification Tests. In order to examine the possibility that these results are driven by spurious patterns in the earnings or weather data, we subjected them to a number of falsification tests. The first test involved re-estimating regression (1) while replacing each individual's in-utero weather conditions with weather conditions that occurred at the location of birth up to 10 years before or after birth. The resulting coefficient estimates are plotted in figure 3 against the "shift", measured in years. As would be expected, all "shifted" coefficients are smaller than the "true" coefficient, plotted at zero, and other than the immediate lag and lead, are all statistically insignificant. The parallel results for rainfall are displayed in figure S5.

The second falsification test involved re-estimating equation (1) repeatedly on 10,000 "placebo" data sets in which all weather data was randomly re-shuffled between cohorts, either across space, across time or both. As would be expected, histograms of all resulting "placebo" coefficient estimates are centered around zero (figure S6), and the coefficient estimated using the "real" data set lies at the extreme left end of the distribution (and is smaller than 99% of the placebo estimates, whether re-shuffling occurred across space, time, or both). Together, these tests indicate that the likelihood that the results found have occurred by chance is very low.

Discussion

The results of the "reduced-form" statistical analysis, while robust and causally interpretable, do not allow us to isolate the mechanism(s) at play. However, the large literature on the range of adverse impacts of high-temperature anomalies provides several possible mechanisms, some of which, like increases in Malaria incidence (McCord, 2015) can be directly relevant for Ecuador.

However, exploring heterogeneity in impacts across areas with varying rates of urbanization can help shed light on the degree to which agricultural income declines may be driving the observed temperature-earning relationship. A regression that included an interaction between in-utero temperature anomalies and the degree of urbanization of each canton (in the 1990s) revealed that while precipitation anomalies tend to only occur in rural areas, in agreement with the hypothesized central role of agricultural production shocks in channeling the impacts of precipitation, no such effect was found for temperature anomalies, suggesting that non-agricultural channels may have a central role in mediating the impacts of high temperatures (see SI section and table S6 for details).

The appearance of larger and more statistically significant impacts of in-utero weather on women relative to that on men is similar to the results of other studies that show that in poor households, negative household shocks often tend to affect girls more than boys, presumably because of gender bias in intra-household resource allocation in times of economic stress. For example, Jayachandran (2005) find that infant mortality due to poor air quality was higher amongst females than males. Maccini and Yang (2008) find that early life rainfall effects the future incomes, health, and schooling of only females. Baird, Friedman and Schady (2011) find that in developing countries, the infant mortality rate of females is much more sensitive to economic shocks than the infant mortality rate of males

Our results, however, suggest that the impacts of high temperatures occur in-utero, when an infant's gender is likely to be unknown to parents. One possible interpretation is that corrective investments can be made after birth to affected infants, and that these are less likely to be provided to girls. A second possible explanation has to do with the well-documented higher mortality rates of male fetuses subjected to in-utero stress in relation to females (Almond and Mezumder, 2011), which is also consistent with the evidence presented above of reductions in cohort sizes exposed to in-utero high temperature anomalies, that are larger for females than for males. Fetal or infant mortality[2] can remove the most vulnerable individuals from the adult sample, leading to under-estimates of the true impact of high temperature in-utero. If mortality is higher for males, this can also explain the lower impacts observed for males over females (Almond and Currie, 2011).

Survival to adulthood is only one of possible selection effects that can potentially bias regression estimates of adult earnings on in-utero weather and need to be carefully assessed. As explained above, selection through survival to adulthood, which is well recognized in the fetal origins literature, and for which we find some evidence, is likely to downward bias regression estimates (Almond and Currie, 2011). This suggests the true effects are larger than our estimates.

[2] Note that because our data from the civil registry only includes living people and not all births, we cannot distinguish between cohorts that are smaller because of additional fetal deaths, or additional infant, or even later in life mortality.

Similarly, if adverse weather reduces the probability of entering the formal sector (possibly through the same mechanism which reduces future income), then our income regression results would be biased downwards, again leading us to under-estimate the true effect. However, we find no evidence of this type of selection (SI section, tables S5a-e).

Another form of selection that can explain the reduced cohort sizes could occur if pregnant women tend to migrate away from regions with adverse weather before giving birth. Weather induced migration has been documented in both developing and industrialized countries (Feng et al, 2010; Feng et al 2012; Bohra-Mishra et al, 2014). If such weather migrants are more likely to belong to the wealthier part of the income distribution (Fishman et al, 2014), this could lead to a mechanical negative effect on the adult income of cohorts exposed to adverse weather in-utero that is not actually driven by the impacts of high temperatures on human capital. Migration by wealthier pregnant women could therefore results in over-estimates of the true effect on earnings. However, the divergent impacts on male and female earnings is suggestive against this potential explanation, since gender is in all likelihood unobservable before birth in the period of our study, so for migration to explain the observed patterns the female earnings distribution would need to decline more steeply at the high income tail than the male distribution. However, the two distributions are nearly identical, and if anything, the male distribution declines more steeply (figure S7). In addition, to the extent that migration tend to be relatively localized and occurs largely within the same province, then total province-wide cohort size should not decline. However, cohort size regressions estimated at the province level result in very similar estimates to those estimated at the canton level (table S5b as compared to table S5a). We conclude that the sum of the evidence seems to suggest our estimates of the effect of in-utero weather on adult female earnings may be biased downward, if at all.

Conclusion

We document a robust, economically meaningful detrimental influence of hotter in-utero temperatures on female formal sector earnings in Ecuador. We find a similar, but less robust relationship with lower in-utero rainfall. .

The external validity of our results to other countries is limited in some dimensions, given Ecuador's small size and the fact that we only observe formal sector earnings. On the other hand, that these impacts are occurring for formal sector workers in a middle-income country is striking. Previous studies have mostly focused on samples that were dominated by rural farming households. Additional studies of similar relationships would be important to conduct in other contexts.

The size of the effect we find is economically meaningful. A simple extrapolation of our estimates suggests that future warming may have additional economic impacts that have not been sufficiently appreciated to date. In fact, our findings suggest that the warming that has already occurred in Ecuador may have already resulted in large and to date unappreciated economic losses. However, such extrapolations must be made with great caution, since, just as for short-term impacts of high temperatures, the long-term impacts of an isolated temperature shock may be quite different than that of a prolonged persistent change in temperature (Dell et al, 2013). Nevertheless, our results may help improve our understanding of the mechanism driving the well established cross-sectional inverse relationship between temperatures and economic income (Nordhaus, 2006).

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Supplementary Material

Data. The 1900-2010 Gridded Monthly Time Series on Terrestrial Air Temperature and Precipitation from the University of Delaware (Willmott and Matsuura, 2001) compile weather station data from several different sources, and interpolate monthly averages to a 0.5 degree by 0.5 degree latitude/longitude grid, with station nodes centered on the 0.25 degree. In order to merge this gridded data with place of birth identifiers in the earnings data, weather values were averaged across all grid cells falling within each canton, with weights proportional to the fraction of area falling within the canton's administrative boundaries (figure S3). Summary statistics for the earnings and weather data are reported in Table S1.

Non-Parametric Estimation: To test for non-linear effects of in-utero weather, we divided the range of observed precipitation and temperature observations into a series of intervals and defined corresponding binary variables that indicate, for precipitation and temperature separately, which of the intervals a given weather observation falls in. For temperature, we divide the 7^{o}C-29^{o}C range into seven intervals of 3^{o}C width each. For rainfall, we divide the 0-30 cm/month range into 7 intervals, where the first 6 intervals are 4cm/month wide each, and the 7^{th} interval ranges from 24-30cm/month (we did this in lieu of adding an 8^{th} interval because only 8,319 females experienced a value between 28-30cm/month rainfall). We then estimated a semi-parametric version of equation (1) in which the linear weather variables are replaced with these 24 binary variables (7 each for temperature and rainfall, before and after birth, with the indicator of the lowest intervals in each category omitted as a reference value),. The estimated coefficients of these in-utero temperature and rainfall indicators are plotted in figure S4. For both temperature and rainfall, we find that the pattern of the relationship is approximately linear, justifying the use of a linear form in our main regressions. However, we note that for rainfall, coefficients tend to be small and quite imprecise.

Are the Impacts Concentrated in Rural Regions? If the impacts of weather anomalies are mostly occurring through their effect on agricultural production, one would expect them to be concentrated in rural areas. To examine this hypothesis, we estimate a variant of model (1) that also includes interaction terms between each of the four weather variables and a continuous variable measuring the urbanization rate (the fraction of the population residing in urban settlements) of each individual's province of birth in 1990.[3] These interaction terms measure the degree to which impacts of weather anomalies are higher in more urbanized areas. The resulting estimates are reported in Table S6.

Consistently with the hypothesis that rainfall anomalies operate mainly through their impact on agricultural production, which is only a major source of income in rural areas, the estimated interaction term of the in-utero rainfall is statistically significant and has a similar magnitude (0.002) but opposite sign to the un-interacted rainfall coefficient (which measures the impact of in-utero rainfall anomalies in completely rural areas). Thus, the more urbanized a province is, the smaller is the effect of in-utero rainfall on the future earnings of those born there, and the estimates point to a negligible effect of rainfall in completely urbanized locations.

The estimated interaction term between in-utero temperature and urbanization, in contrast, is of very small magnitude (-0.001) in comparison to the un-interacted term (0.01). Thus, we find no evidence to suggest that the effects of temperature differ between rural and urban areas. [4] This can be suggestive of a temperature effect that is not primarily agricultural or rural, which would not be inconsistent with the growing body evidence on the numerous non-agricultural impacts of high temperature anomalies on economic productivity and welfare.

Impacts on Educational Attainment: Much of the literature on the impact of early life weather shocks is focused on human capital accumulation, including indicators of educational attainment. Unfortunately, our data only provides us with rather crude indicators of educational attainment consisting of whether individuals had completed secondary school (84%) or college (29%, Table S4a). In Tables S4b and S4c, we report estimates of regressions parallel to equation (1) in which the dependent variable is a binary indicator of secondary education and higher education, respectively. We find negative, but small and imprecise impact of in-utero temperature exposure on either of these outcomes.

[3] Urban populations rates are only available to us in one time period. The data was obtained from http://www.citypopulation.de/Ecuador-Cities.html
[4] Note, however, that the confidence intervals of the interaction term are quite large. As a result, we are also unable to reject urban temperature effects that are substantially stronger or weaker than those in rural areas.

Impacts on the *Distribution* of Earnings.. In addition to estimating changes in mean cohort earnings, we also examine the impact of temperatures anomalies on the *distribution* of earnings. To do so, we calculate residuals from a regression of (log) earnings on the same fixed effects and (quartic) time trends as in Equation (1), and then plot the residuals for two different sub-samples: those females whose in-utero average temperature was between -0.5 and 0.5 of the local average, and those whose in-utero average temperature was 2°C+ hotter than normal.[5] Histograms of the two sets of residuals are overlaid in figure S8. Perhaps surprisingly, the sample experiencing a 2°C+ hot temperature shock in-utero shows a significant shift in density that mostly occurs in the right-central portion of the income distribution. Even though this is not a conclusive indication, the pattern suggests that the effect does not seem to be primarily driven by the low or high income tails of the earnings distribution.

Selection and Cohort Size: We begin by examining whether birth-cohort size is affected by birth-year weather. To do this, we estimate a regression parallel to equation (1) except that the unit of observation is a cohort rather than an individual and the dependent variable is the logarithm of the cohort size, i.e. the number of individuals born in canton *c*, in month *m* of year *y.* Results for the entire cohort, females only and males only are reported in columns 1-3 of table S5a.,We find that a 1°C increase in in-utero temperature decreases the size of the birth cohort by 2.6%. The point estimate is larger for males (3.0%) than for females (2.2%). As discussed in the text, changes in cohort size could be driven by survival to adulthood or by pre-birth migration by the household. Lower likelihood of survival to adulthood is likely to downward bias the estimated impacts on earnings, whereas selective migration by wealthier household may lead to an upward bias.

In order to partially test whether this cohort size reduction is likely due to migration, we run a similar regression, but re-define cohorts on the basis of province (a larger administrative unit), rather than the canton, of birth. If most migration is relatively local in nature, for instance, from rural areas to the nearest city, than most migration will be inter-provincial, so that, provincial cohort sizes would be less affected by in-utero weather,. Results of the province level

[5] These buckets are used after de-trending the weather data by taking the residuals from the regression of the weather data on the province specific time trends, and the fixed effects used in Equation (1).

regressions, reported in table S5b, are very similar to those reported in table S5a, suggesting against inter-provincial migration as the main driver of the results. As discussed in the main text, migration is also inconsistent with the diverging earnings results found for males and females..

Next, we test if in-utero weather affects one's probability of entering the formal sector. We do so in three different ways. In the first, we test if the count of the number of individuals that earned formal sector income in 2010 in each cohort is affected by birth-year weather. Results are reported in table S5c and indicate that hotter in-utero temperatures do tend to reduce the formal sector cohort size. However, the magnitude of the effect is quite similar to the magnitude of the reduction of the total birth cohort size reported in table S5a, suggesting against additional reduction in the proportion of formal sector workers in a cohort. To test this directly, we replace the dependent variable with the ratio of the number of formal sector cohort size to the total cohort size, i.e. the percentage of individuals in each cohort working in the formal sector. The results, reported in table S5d confirm that birth-year weather does not affect selection into the formal sector, as all coefficients are very small and statistically insignificant. Finally, in the last test for selection, we estimate whether the probability of entering the formal sector is affected by early-life weather by estimating a regression parallel to equation (1) in which the sample consists of all individuals in the civil registry, and the dependent variable is a binary indicator of formal sector employment.[6] We do not find any evidence for selection for either males or females (table S5e).

Falsification Tests. In our first falsification test, we re-estimate Equation (1) while replacing each individual's in-utero weather exposure with weather occurring during "placebo" 9-month periods generated by displacing the actual in-utero period up to 10 years backwards and forward in time. The resulting estimates are plotted in figure 3 (for temperature) and figure S5 (for precipitation) against the number of years by which weather was displaced in time, so that the coefficients of the actual (non-placebo) regressions are plotted at the zero point on the horizontal axis. We note that this falsification test may be too restrictive, in the sense that "placebo" estimates could still be non-zero, for two reasons. First, serial correlation in weather

[6] Note, due to computational restrictions, the regressions are estimated with quadratic province time-trends, rather than the standard quartic time trends.

can create significant correlations between the actual in-utero and placebo weather, and second, it is not implausible that shocks occurring outside of the in-utero period may also affect future earnings. For example, weather shocks occurring before conceptions could still impact household welfare during pregnancy, and post-natal shocks could still be affecting adult outcomes. Nevertheless, one would expect impacts to decline with the level of time displacement. The results, displayed in figure 3, confirm this expectation. All placebo temperature estimates are smaller than the actual one, and other than the first lag and lead, are all statistically insignificant. Figure S5 shows a similar pattern for rainfall, i.e. that only the actual and first lead coefficients statistically significant, with nearly all other point estimates being small in magnitude and statistically insignificant...

In our second falsification test, we repeatedly and randomly “re-shuffle” the weather data across time and space and re-estimate regression (1), in order to test the appropriateness of our statistical model and the likelihood that our results are an artifact of chance or of a systematic error in the data. We conduct three separate such “re-shufflings” (Hsiang and Jina 2014). In the first, we randomly allocate to each birth cohort (individuals born in the same month, year, and canton) the weather values from a different year, but in the same birth month and canton, and then re-estimate Equation (1). We repeat this procedure 10,000 times and plot the distribution of point-estimates (for the impact on in-utero temperature) in figure S6. We find that only 0.52% of these estimates are larger in magnitude (and negative) than the actual coefficient, -0.0109, indicated by the vertical line, implying that it is very unlikely that the estimates we found (table 2) arise by chance. In the second test, we “re-shuffle” weather across space. All individuals born in the same birth cohort are now allocated birth-year weather from their year and month of birth, but from a different canton. Given the granularity of the original weather data, as well as spatial autocorrelation of weather data in general, adjacent cantons may have the same, or very similar weather observations. This increases the likelihood that a birth cohort may be randomly assigned weather data very similar or identical to its actual weather data, making this falsification test highly conservative. Nevertheless, only 0.9% of the estimated coefficients on “in-utero” temperature fall to the left of the actual coefficient. Finally, in the third test, we re-shuffle weather across all cohorts, allocating to each cohort the weather in another, randomly chosen birth month, year, and canton. None of the 10,000 bootstrapped estimates are larger in magnitude than the actual estimate. These results indicate a very low likelihood that our results could have arisen by chance. Also, as expected, the distributions of the "placebos" estimates are centered around zero, providing a degree of validation to our model specification and the data sets we use.

The parallel results for rainfall are similar but less conclusive. Reshuffling across time, we find that 6.27% of placebo estimates to be larger in magnitude (and positive) than the actual coefficient, 0.001. Reshuffling across space, we find 20.86% of placebo estimates to be larger. However, when reshuffling across both space and time, none of the placebo estimates are larger than the actual estimate.

Supplementary Material

Data. The 1900-2010 Gridded Monthly Time Series on Terrestrial Air Temperature and Precipitation from the University of Delaware (Willmott and Matsuura, 2001) compile weather station data from several different sources, and interpolate monthly averages to a 0.5 degree by 0.5 degree latitude/longitude grid, with station nodes centered on the 0.25 degree. In order to merge this gridded data with place of birth identifiers in the earnings data, weather values were averaged across all grid cells falling within each canton, with weights proportional to the fraction of area falling within the canton's administrative boundaries (figure S3). Summary statistics for the earnings and weather data are reported in Table S1.

Non-Parametric Estimation: To test for non-linear effects of in-utero weather, we divided the range of observed precipitation and temperature observations into a series of intervals and defined corresponding binary variables that indicate, for precipitation and temperature separately, which of the intervals a given weather observation falls in. For temperature, we divide the 7^{0}C-29^{0}C range into seven intervals of 3^{0}C width each. For rainfall, we divide the 0-30 cm/month range into 7 intervals, where the first 6 intervals are 4cm/month wide each, and the 7^{th} interval ranges from 24-30cm/month (we did this in lieu of adding an 8^{th} interval because only 8,319 females experienced a value between 28-30cm/month rainfall). We then estimated a semi-parametric version of equation (1) in which the linear weather variables are replaced with these 24 binary variables (7 each for temperature and rainfall, before and after birth, with the indicator of the lowest intervals in each category omitted as a reference value),. The estimated coefficients of these in-utero temperature and rainfall indicators are plotted in figure S4. For both temperature and rainfall, we find that the pattern of the relationship is approximately linear, justifying the use of a linear form in our main regressions. However, we note that for rainfall, coefficients tend to be small and quite imprecise.

Are the Impacts Concentrated in Rural Regions? If the impacts of weather anomalies are mostly occurring through their effect on agricultural production, one would expect them to be concentrated in rural areas. To examine this hypothesis, we estimate a variant of model (1) that also includes interaction terms between each of the four weather variables and a continuous variable measuring the urbanization rate (the fraction of the population residing in urban settlements) of each individual's province of birth in 1990.[3] These interaction terms measure the degree to which impacts of weather anomalies are higher in more urbanized areas. The resulting estimates are reported in Table S6.

Consistently with the hypothesis that rainfall anomalies operate mainly through their impact on agricultural production, which is only a major source of income in rural areas, the estimated interaction term of the in-utero rainfall is statistically significant and has a similar magnitude (0.002) but opposite sign to the un-interacted rainfall coefficient (which measures the impact of in-utero rainfall anomalies in completely rural areas). Thus, the more urbanized a province is, the smaller is the effect of in-utero rainfall on the future earnings of those born there, and the estimates point to a negligible effect of rainfall in completely urbanized locations.

The estimated interaction term between in-utero temperature and urbanization, in contrast, is of very small magnitude (-0.001) in comparison to the un-interacted term (0.01). Thus, we find no evidence to suggest that the effects of temperature differ between rural and urban areas. [4] This can be suggestive of a temperature effect that is not primarily agricultural or rural, which would not be inconsistent with the growing body evidence on the numerous non-agricultural impacts of high temperature anomalies on economic productivity and welfare.

Impacts on Educational Attainment: Much of the literature on the impact of early life weather shocks is focused on human capital accumulation, including indicators of educational attainment. Unfortunately, our data only provides us with rather crude indicators of educational attainment consisting of whether individuals had completed secondary school (84%) or college (29%, Table S4a). In Tables S4b and S4c, we report estimates of regressions parallel to equation (1) in which the dependent variable is a binary indicator of secondary education and higher education, respectively. We find negative, but small and imprecise impact of in-utero temperature exposure on either of these outcomes.

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[3] Urban populations rates are only available to us in one time period. The data was obtained from http://www.citypopulation.de/Ecuador-Cities.html

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Table S1: Income data (2010), summary statistics

Formal Sector Earnings

	Obs	Mean	Median	St. Dev	Min	Max
Males	1,058,277	$6,787.3	$4,661.8	$6,508.60	$84.33	$41,136.10
Females	580,659	$6,681.7	$4,604.1	$6,063.20	$84.36	$41,135.04

Notes: Formal sector earnings data is obtained from the Ecuadorian Tax Authority. They indicate earnings for all individuals who earned formal sector income in Ecuador in 2010. Figures are given in US$. Top 1% of earners are excluded.

Table S2: Average Monthly Weather

Province	Temperature (^{0}C)					Rainfall (cm/month)				
	Mean	Median	St Dev	Min	Max	Mean	Median	St Dev	Min	Max
Azuay	14.2	14.1	0.85	11.4	17.1	7.88	6.31	5.07	0.08	40.37
Bolivar	21.1	21.2	0.95	17.8	23.6	13.18	7.23	12.88	0.0	73.27
Carchi	17.9	17.9	0.73	15.5	20.6	13.93	13.50	4.65	4.39	35.91
Cañar	14.3	14.3	0.92	11.1	18.2	10.35	7.45	7.67	0.64	50.63
Chimborazo	11.6	11.7	0.82	8.7	13.8	7.73	6.50	5.13	0.98	51.51
Cotopaxi	13.5	13.6	0.81	10.7	16.1	12.01	10.05	7.75	0.26	51.51
El Oro	24.4	24.4	1.14	21.2	27.8	7.94	3.80	8.61	0.04	52.16
Esmeraldas	24.4	24.4	0.74	21.8	27.1	18.86	16.78	9.94	1.05	57.75
Guayas	24.6	24.6	1.22	20.2	27.4	10.93	3.62	13.53	0.02	79.99
Imbabura	18.1	18.0	0.92	14.6	23.4	9.73	9.21	5.56	0.47	34.82
Loja	20.4	20.4	1.00	17.2	23.9	7.74	4.53	7.66	0.13	50.07
Los Rios	24.3	24.4	1.00	20.6	27.0	15.75	8.06	16.43	0.0	88.65
Manabi	24.4	24.4	1.15	20.0	27.3	10.83	5.70	11.25	0.0	55.73
Morona Santiago	22.7	22.7	0.89	19.6	25.0	19.55	18.84	4.90	5.13	40.34
Napo	18.2	18.2	0.72	15.5	20.6	24.41	23.94	6.28	5.93	56.95
Orellana	25.3	25.3	0.81	22.3	27.9	26.04	24.73	7.40	5.26	48.23
Pastaza	25.6	25.7	0.78	22.6	27.8	29.27	29.04	6.23	8.55	55.21
Pichincha	15.2	15.2	0.70	12.1	17.5	14.36	12.69	8.83	1.03	43.30
Santa Elena	23.4	23.3	1.79	17.8	27.3	5.13	0.86	8.28	0.0	65.53
Santo Domingo	21.6	21.6	0.96	19.1	24.4	22.57	14.56	19.48	0.04	88.08
Sucumbios	23.9	23.9	0.83	21.1	26.7	21.48	21.34	6.50	4.02	53.68
Tungurahua	12.2	12.3	0.94	8.9	14.6	12.86	12.75	4.57	1.03	39.95
Zamora Chinchipe	20.9	21.0	0.92	17.8	24.1	12.30	11.11	4.86	0.84	43.14

Notes: Raw weather data is obtained from Willmott and Matsuura (2001), and is in the form of gridded monthly averages. Province averages are calculated by taking the spatially weighted average of all grids falling within a province. Annual averages are calculated by averaging the average monthly temperature for each month in a given year.

Table S3a: Effects of birth-year weather on future income, females only

Dependent Variable: log income (2010)	(1)	(2)	(3)	(4)
Average Temperature, 9 months before birth (°C)	-0.0169 (0.0045)*** (0.0070)** (0.0045)*** (0.0048)***	-0.0130 (0.0026)*** (0.0035)*** (0.0037)*** (0.0044)***	-0.0112 (0.0023)*** (0.0028)*** (0.0035)*** (0.0041)***	-0.0109 (0.0024)*** (0.0029)*** (0.0035)*** (0.0041)***
Average Temperature, 9 months after birth (°C)	-0.0058 (0.0044) (0.0050) (0.0040) (0.0038)	-0.0015 (0.0029) (0.0049) (0.0031) (0.0032)	-0.0007 (0.0026) (0.0050) (0.0029) (0.0030)	-0.0009 (0.0025) (0.0046) (0.0029) (0.0031)
Average Rainfall, 9 months before birth (cm/month)	0.0015 (0.0005)*** (0.0006)** (0.0008)* (0.0008)*	0.0015 (0.0006)** (0.0006)** (0.0007)** (0.0007)**	0.0010 (0.0004)** (0.0005)** (0.0006) (0.0006)*	0.0010 (0.0004)** (0.0005)** (0.0006)* (0.0005)**
Average Rainfall, 9 months after birth (cm/month)	0.0008 (0.0006) (0.0005) (0.0006) (0.0006)	0.0007 (0.0005) (0.0005) (0.0005) (0.0006)	0.0003 (0.0006) (0.0006) (0.0005) (0.0005)	0.0004 (0.0006) (0.0006) (0.0005) (0.0005)
Province-Specific Time Trends	Linear	Quadratic	Cubic	Quartic
Year Fixed Effects	Y	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y	Y
Observations	580,134	580,134	580,134	580,134
R-squared	0.1735	0.1743	0.1746	0.1746

Notes: Sample includes females born between 1950 and 1989 who earned formal sector income in the year 2010. Each column presents coefficients and four sets of standard errors from a separate regression estimated using OLS. Standard errors in parentheses are, in order from top to bottom: clustered at the province level, clustered at canton level, clustered at province/year level, and clustered at region/year level. Stars indicate confidence levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table S3b: Effects of birth-year weather on future income, males only

Dependent Variable: log income (2010)	(1)	(2)	(3)	(4)
Average Temperature, 9 months before birth (°C)	-0.0111 (0.0075) (0.0078) (0.0042)*** (0.0039)***	-0.0060 (0.0038) (0.0035)* (0.0026)** (0.0029)**	-0.0040 (0.0032) (0.0028) (0.0023)* (0.0027)	-0.0037 (0.0032) (0.0028) (0.0023) (0.0026)
Average Temperature, 9 months after birth (°C)	-0.0102 (0.0060) (0.0051)** (0.0047)** (0.0045)**	-0.0051 (0.0031) (0.0030)* (0.0031)* (0.0033)	-0.0036 (0.0026) (0.0036) (0.0028) (0.0030)	-0.0035 (0.0026) (0.0029) (0.0029) (0.0030)
Average Rainfall, 9 months before birth (cm/month)	-0.0001 (0.0005) (0.0005) (0.0006) (0.0007)	-0.0002 (0.0005) (0.0004) (0.0005) (0.0005)	-0.0005 (0.0005) (0.0004) (0.0004) (0.0004)	-0.0004 (0.0004) (0.0004) (0.0004) (0.0004)
Average Rainfall, 9 months after birth (cm/month)	0.0007 (0.0006) (0.0006) (0.0006) (0.0007)	0.0006 (0.0005) (0.0006) (0.0005) (0.0006)	0.0003 (0.0004) (0.0006) (0.0005) (0.0005)	0.0004 (0.0004) (0.0006) (0.0005) (0.0005)
Province-Specific Time Trends	Linear	Quadratic	Cubic	Quartic
Year Fixed Effects	Y	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y	Y
Observations	1,057,446	1,057,446	1,057,446	1,057,446
R-squared	0.1421	0.1430	0.1431	0.1432

Notes: Sample includes males born between 1950 and 1989 who earned formal sector income in the year 2010. Each column presents coefficients and four sets of standard errors from a separate regression estimated using OLS. Standard errors in parentheses are, in order from top to bottom: clustered at the province level, clustered at canton level, clustered at province/year level, and clustered at region/year level. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S4a: Summary Statistics: Educational Attainment

Educational Attainment	Percent completed, females	Percent completed, males	Average Income, females	Average Income, males
Less than Secondary School	16.25%	33.70%	$3,225	$3,999
At least Secondary School	83.75%	66.30%	$7,352	$8,204
At least College	29.43%	15.81%	$9,832	$12,316

Notes: Sample includes females born between 1950 and 1989 who earned formal sector income in the year 2010. Educational attainment data is obtained from the National Civil Registry and is merged with earnings data from the Ecuadorian tax authority. Data is from 2010.

Table S4b: Effect of birth-year weather on Secondary School Completion, females only

Dependent Variable: =1 if highest educational attainment at least secondary school	(1)	(2)	(3)	(4)
Average Temperature, 9 months before birth (°C)	-0.0019 (0.0025)	-0.0017 (0.0018)	-0.0014 (0.0015)	-0.0015 (0.0016)
Average Temperature, 9 months after birth (°C)	-0.0011 (0.0010)	-0.0013 (0.0009)	-0.0011 (0.0009)	-0.0012 (0.0008)
Average Rainfall, 9 months before birth (cm/month)	0.0002 (0.0003)	0.0002 (0.0003)	-0.00004 (0.0003)	0.00005 (0.0003)
Average Rainfall, 9 months after birth (cm/month)	0.0004 (0.0002)	0.0004* (0.0002)	0.0003 (0.0002)	0.0004 (0.0002)
Province-Specific Time Trends	Linear	Quadratic	Cubic	Quartic
Year Fixed Effects	Y	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y	Y
Observations	580,134	580,134	580,134	580,134
R-squared	0.0910	0.0924	0.0928	0.0930

Notes: Sample includes females born between 1950 and 1989 who earned formal sector income in the year 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S4c: Effect of birth-year weather on College Completion, females only

Dependent Variable: =1 if highest educational attainment at least college	(1)	(2)	(3)	(4)
Average Temperature, 9 months before birth (ºC)	-0.0059 (0.0043)	-0.0047* (0.0023)	-0.0034 (0.0023)	-0.0033 (0.0023)
Average Temperature, 9 months after birth (ºC)	-0.0046 (0.0028)	-0.0036** (0.0016)	-0.0020* (0.0011)	-0.0017* (0.0010)
Average Rainfall, 9 months before birth (cm/month)	0.0008** (0.0003)	0.0008*** (0.0003)	0.0006*** (0.0002)	0.0005** (0.0002)
Average Rainfall, 9 months after birth (cm/month)	0.0007* (0.0004)	0.0008** (0.0003)	0.0007** (0.0003)	0.0006** (0.0002)
Province-Specific Time Trends	Linear	Quadratic	Cubic	Quartic
Year Fixed Effects	Y	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y	Y
Observations	580,134	580,134	580,134	580,134
R-squared	0.0798	0.0796	0.0805	0.0806

Notes: Sample includes females born between 1950 and 1989 who earned formal sector income in the year 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S5a: Effect of birth-year weather on birth cohort size, canton level

Dependent Variable: (Log) number of individuals born in each month, year, and canton cohort	(1) Full Sample	(2) Females Only	(3) Males Only
Average Temperature, 9 months before birth (ºC)	-0.0264** (0.0121)	-0.0221* (0.0119)	-0.0300** (0.0110)
Average Temperature, 9 months after birth (ºC)	-0.0154 (0.0110)	-0.0162 (0.00987)	-0.0103 (0.0113)
Average Rainfall, 9 months before birth (cm/month)	-0.00109 (0.00142)	-0.000901 (0.00134)	-0.00134 (0.00153)
Average Rainfall, 9 months after birth (cm/month)	-0.00144 (0.00127)	-0.00155 (0.00133)	-0.00120 (0.00113)
Province-Specific Time Trends	Quartic	Quartic	Quartic
Year Fixed Effects	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y
Observations	67,157	65,994	65,799
R-Squared	0.912	0.904	0.903

Notes: Sample includes individuals born between 1950 and 1989 who were in the Ecuadorian civil registry in 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Column (1) includes the full population, while columns (2) and (3) only include females and males, respectively. Each observation is a month, year, and canton cohort in which at least one individual in the civil registry was born. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S5b: Effect of birth-year weather on birth cohort size, province level

Dependent Variable: (Log) Number of individuals born in each month, year, and province cohort	(1) Full Sample	(2) Females Only	(3) Males Only
Average Temperature, 9 months before birth (ºC)	-0.0188*** (0.005)	-0.0152** (0.007)	-0.0221*** (0.007)
Average Rainfall, 9 months before birth (cm/month)	0.00812 (0.007)	0.000833 (0.009)	0.0145** (0.006)
Average Temperature, 9 months before birth (ºC)	-0.00140* (0.001)	-0.00207*** (0.001)	-0.000982 (0.001)
Average Rainfall, 9 months before birth (cm/month)	-0.00261** (0.001)	-0.00214** (0.001)	-0.00295** (0.001)
Province-Specific Time Trends	Quartic	Quartic	Quartic
Year Fixed Effects	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y
Observations	11318	11312	11310
R-Squared	0.992	0.988	0.986

Notes: Sample includes individuals born between 1950 and 1989 who were in the Ecuadorian civil registry in 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Column (1) includes the full population, while columns (2) and (3) only include females and males, respectively. Each observation is a month, year, and province cohort in which at least one individual in the civil registry was born. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S5c: Effect of birth-year weather on formal sector cohort size

Dependent Variable: (Log) Number of individuals earning formal sector income in 2010 that were born in each month, year, and canton cohort	(1) Full Sample	(2) Females Only	(3) Males Only
Average Temperature, 9 months before birth (ºC)	-0.027** (0.011)	-0.021** (0.009)	-0.027** (0.011)
Average Temperature, 9 months after birth (ºC)	-0.0082 (0.007)	-0.003 (0.005)	-0.003 (0.007)
Average Rainfall, 9 months before birth (cm/month)	-0.002 (0.001)	-0.002 (0.001)	-0.001 (0.001)
Average Rainfall, 9 months after birth (cm/month)	-0.0003 (0.001)	-0.0006 (0.009)	-0.0004 (0.001)
Province-Specific Time Trends	Quartic	Quartic	Quartic
Year Fixed Effects	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y
Observations	60,090	48,996	57,126
R-Squared	0.894	0.858	0.878

Notes: Sample includes individuals born between 1950 and 1989 who earned formal sector income in the year 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Column (1) includes the full population, while columns (2) and (3) only include females and males, respectively. Each observation is a month, year, and canton cohort in which at least one individual that earned 2010 formal sector income was born. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S5d: Effect of birth-year weather on formal sector cohort to birth cohort ratio

Dependent Variable: Ratio of formal sector cohort size and birth cohort size	(1) Full Sample	(2) Females Only	(3) Males Only
Average Temperature, 9 months before birth (ºC)	-0.0011 (0.0013)	-0.00005 (0.00110)	-0.002 (0.0021)
Average Temperature, 9 months after birth (ºC)	-0.0011 (0.001)	-0.0012 (0.0013)	-0.0017 (0.0016)
Average Rainfall, 9 months before birth (cm/month)	0.0002 (0.0002)	-0.00002 (0.0002)	0.0003 (0.0003)
Average Rainfall, 9 months after birth (cm/month)	0.0003* (0.0002)	0.0001 (0.0001)	0.0003 (0.0002)
Province-Specific Time Trends	Quartic	Quartic	Quartic
Year Fixed Effects	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y
Observations	67,157	65,994	65,799
R-Squared	0.285	0.194	0.256

Notes: Sample includes individuals born between 1950 and 1989 who earned formal sector income in the year 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Column (1) includes the full population, while columns (2) and (3) only include females and males, respectively. Each observation is a month, year, and canton cohort in which at least one individual in the civil registry was born. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S5e: Effect of birth-year weather on formal sector selection

Dependent Variable: =1 if earned formal sector income, 2010	(1) Full Population	(2) Females Only	(3) Males Only
Average Temperature, 9 months before birth (ºC)	-0.00059 (0.00055)	-0.00065 (0.00055)	-0.00055 (0.00085)
Average Temperature, 9 months after birth (ºC)	0.000148 (0.000615)	0.000839 (0.000879)	-0.000629 (0.000481)
Average Rainfall, 9 months before birth (cm/month)	0.000158 (0.000104)	0.000109 (0.000093)	0.000203 (0.000128)
Average Rainfall, 9 months after birth (cm/month)	0.000171* (0.000085)	0.000166* (0.000082)	0.000162 (0.000118)
Province-Specific Time Trends	Quadratic	Quadratic	Quadratic
Year Fixed Effects	Y	Y	Y
Month-Province Fixed Effects	Y	Y	Y
Observations	8,159,284	4,078,650	4,080,634
R-squared	0.034	0.04	0.037

Notes: Sample includes individuals born between 1950 and 1989 who were registered with the Ecuadorian Civil Registry in 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Column (1) includes the full population, while columns (2) and (3) only include females and males, respectively. Each observation is an individual who was registered with the Ecuadorian Civil Registry in 2010. The dependent variable is equal to 1 if the individual earned any formal sector income in 2010, and 0 otherwise. Stars indicate confidence levels: * p<0.1, ** p<0.05, *** p<0.01

Table S6: Heterogenous Impacts by Urbanization Status

Dependent Variable: log income (2010)	(1)	(2)	(3)	(4)
Average Temperature, 9 months before birth	-0.0131 (0.00786)	-0.0129** (0.00618)	-0.0116** (0.00541)	-0.0101* (0.00505)
Average Temperature, 9 months before birth X Urbanization Rate	-0.00710 (0.0101)	0.0000259 (0.00852)	0.00109 (0.00760)	-0.00131 (0.00729)
Average Temperature, 9 months after birth	-0.00448 (0.00993)	-0.00620 (0.00806)	-0.00500 (0.00791)	-0.00313 (0.00755)
Average Temperature, 9 months after birth X Urbanization Rate	-0.00256 (0.0127)	0.00865 (0.0102)	0.00797 (0.0103)	0.00418 (0.0101)
Average Rainfall, 9 months before birth	0.00195** (0.000924)	0.00226** (0.000991)	0.00235** (0.00104)	0.00237** (0.00105)
Average Rainfall, 9 months before birth X Urbanization Rate	-0.000661 (0.00111)	-0.00132 (0.00123)	-0.00229* (0.00119)	-0.00216* (0.00119)
Average Rainfall, 9 months after birth	-0.00218 (0.00129)	-0.00126 (0.00117)	-0.000822 (0.00121)	-0.000860 (0.00121)
Average Rainfall, 9 months after birth X Urbanization Rate	0.00491*** (0.00174)	0.00309* (0.00157)	0.00180 (0.00186)	0.00208 (0.00182)
Province-Specific Time Trends	Quartic	Quartic	Quartic	Quartic
Year Fixed Effects	Y	Y	Y	Y
Month-Canton Fixed Effects	Y	Y	Y	Y
Observations	570,941	570,941	570,941	570,941
R-squared	0.173	0.174	0.175	0.175

Notes: Sample includes females born between 1950 and 1989 who were registered with the Ecuadorian Civil Registry in 2010. Each column presents coefficients (standard errors) from a separate regression estimated using OLS. Standard errors in parentheses are clustered at the province level. Stars indicate confidence levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

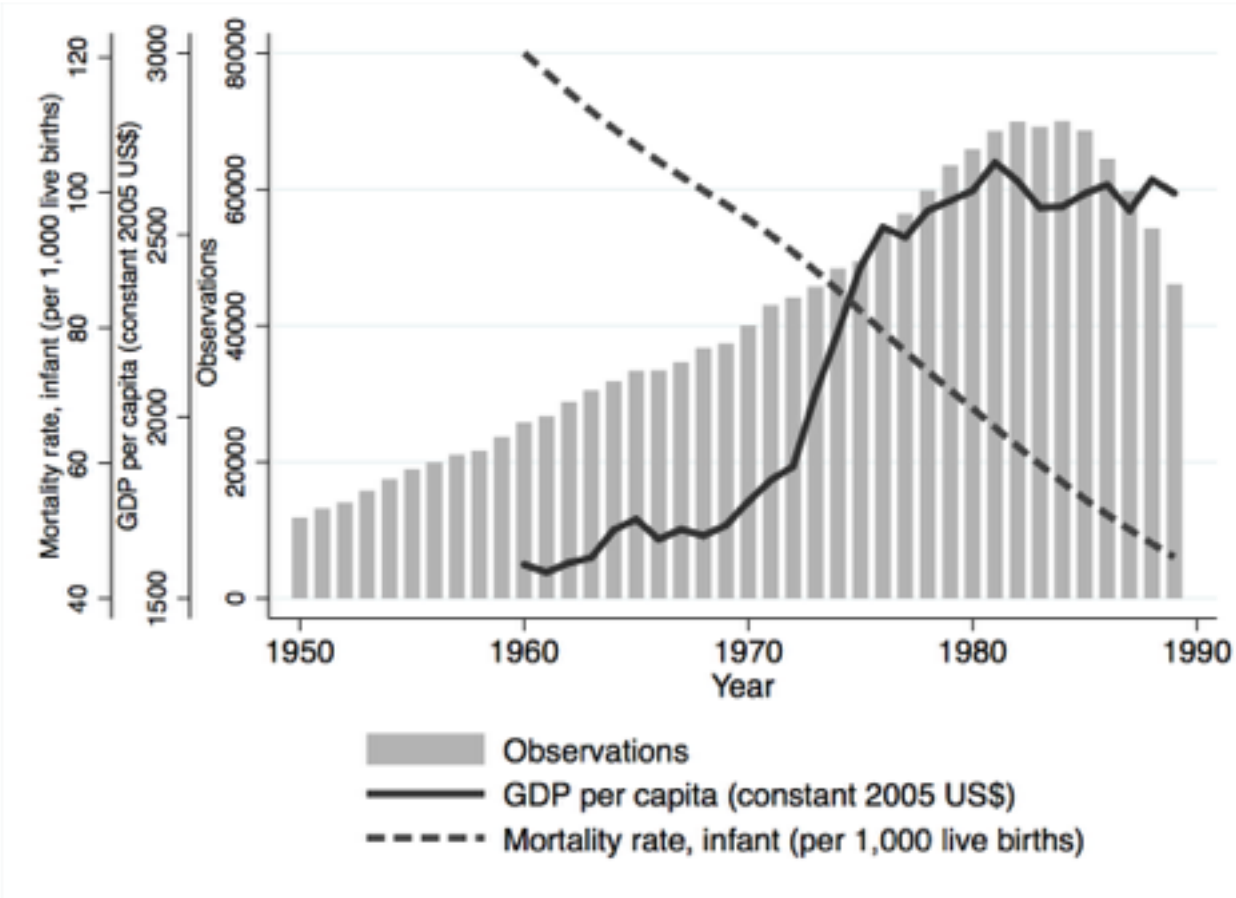
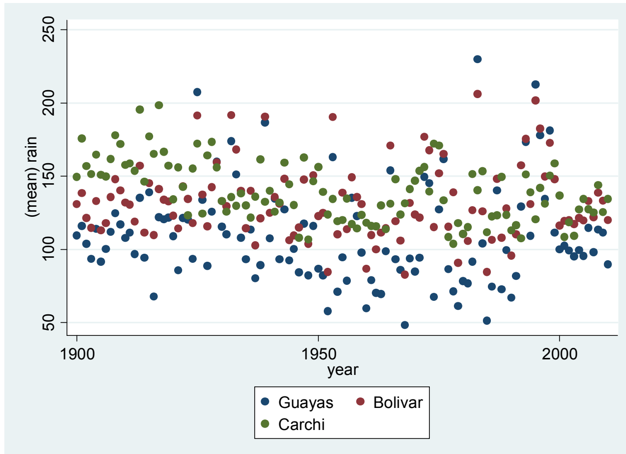


Figure S1: Economic growth and infant mortality rate during sample birth period. Bars (inner left axis) indicate the number of individuals in the sample that were born in each year. GDP per capita (center left axis, solid line), and infant mortality rate (outer left axis, dotted line) are also plotted (source: World Bank Development Indicators).



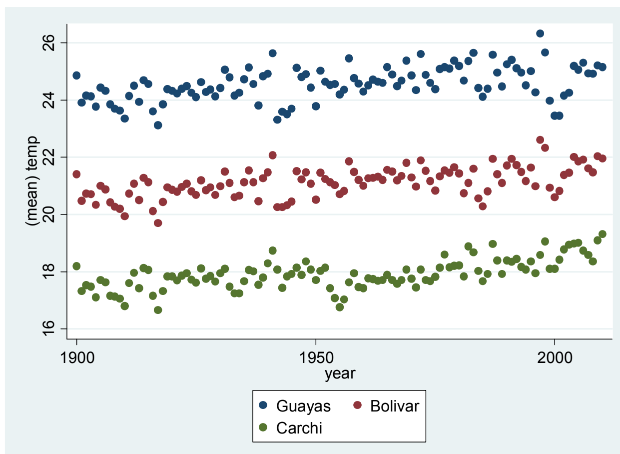


Figure S2: Time series of average annual temperature (^{0}C, top panel) and precipitation (mm/month, bottom panel) for the provinces of Guayas, Bolivar, and Carchi between 1900 and 2010. Source: Authirs' calculations based on Willmott and Matsuura (2001).

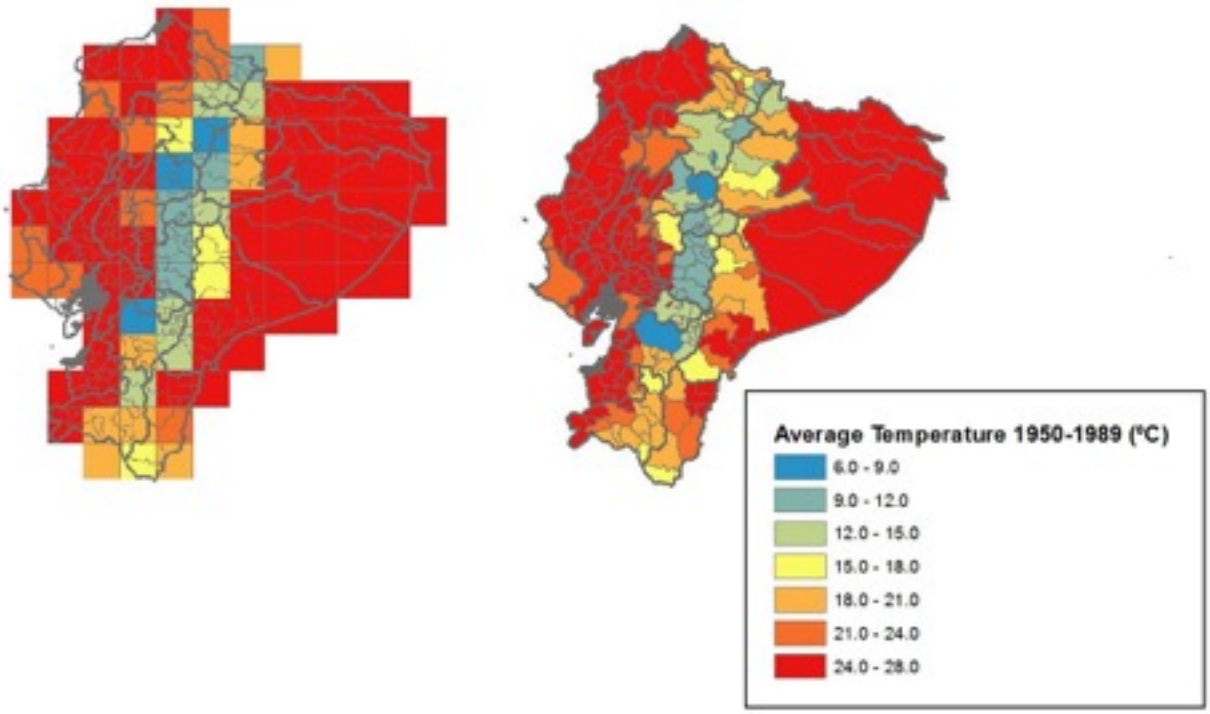
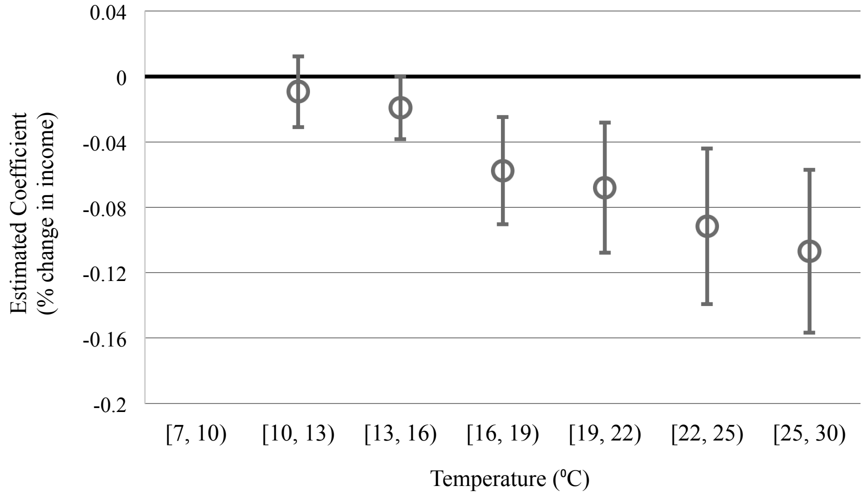


Figure S3 : An overlay of average temperature (1950-1989) calculated from the gridded weather data of Willmott and Matsuura (2001) on a map of Ecuador's administrative boundaries. The felt panel displays average temperatures from the raw gridded data and the right panel displays the result of spatial averaging of the gridded data within each administrative unit (canton).



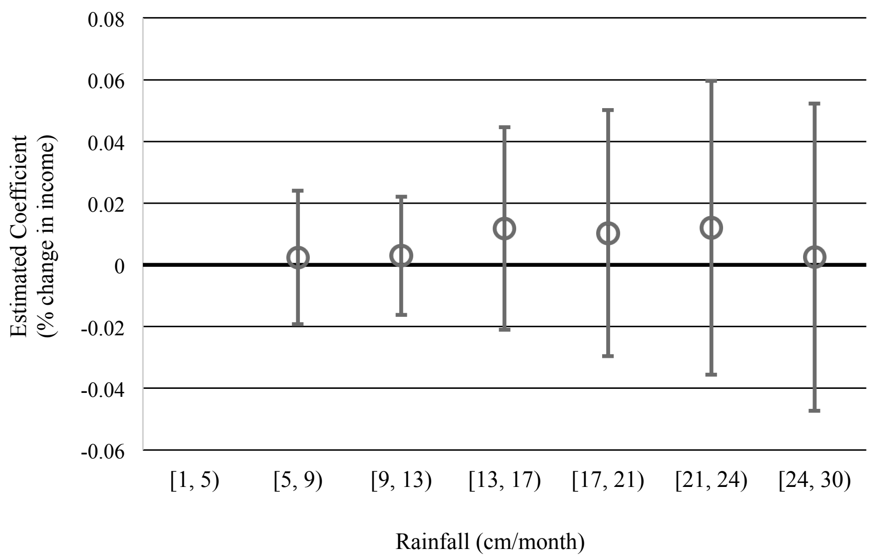


Figure S4: Semi-parametric estimates of the weather-earning relationship. The graph reports coefficients from a regression of log earnings (2010, females only) similar to model (1) except that linear expressions in rainfall and temperatures are replaced with a group of binary indicators for whether temperature and precipitation fall in specific rages indicated in the horizontal axis. Temperature coefficients are displayed in the top panel and rainfall coefficients are displayed in the bottom panel. Error bars indicate 95% confidence intervals.

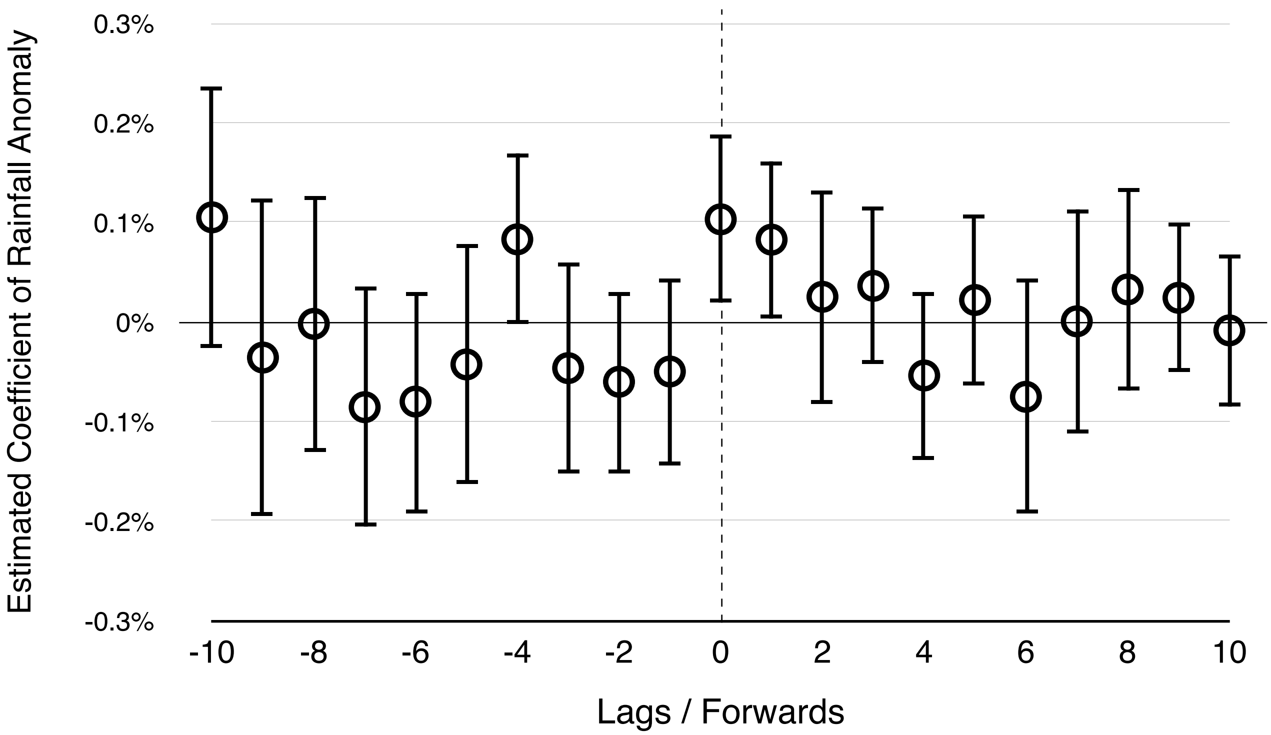


Figure S5: Estimated coefficients from variants of regression (1) for females, in which the period of rainfall exposure is shifted by -10 to 10 years (horizontal axis) from the real in-utero period. Each marker's vertical position therefore measures the estimated impact of 1 cm/month higher average rainfall at the appropriate period of exposure. For example, the marker at the dotted line (no lag) represents the impact of actual in-utero temperatures discussed in the text. Other markers represent the impact of "placebo" rainfall exposures. Error bars represent 95% confidence intervals.

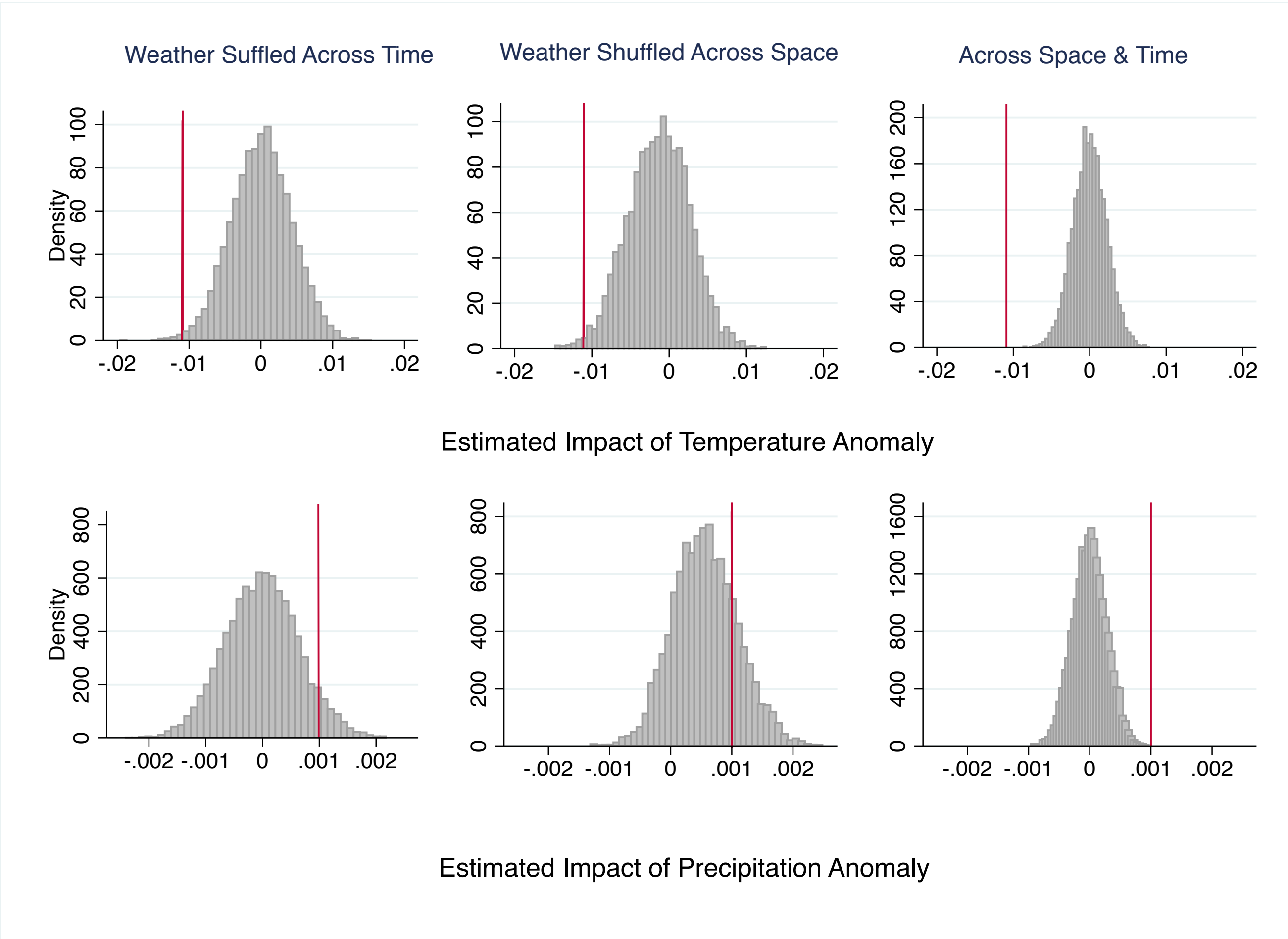


Figure S6: Falsification Tests. Each histograms displays the distributions of estimates of in-utero temperature (top panels) and rainfall (bottom panels) coefficients from 10,000 regressions, each of which is parallel to model (1) except that weather data is randomly "re-shuffled" across time (left panels), administrative units (middle panels) or both (right panels). Red lines indicate the magnitude of the same coefficient as estimated from regression (1), i.e. when in-utero temperature and rainfall exposure are at their "actual" levels.

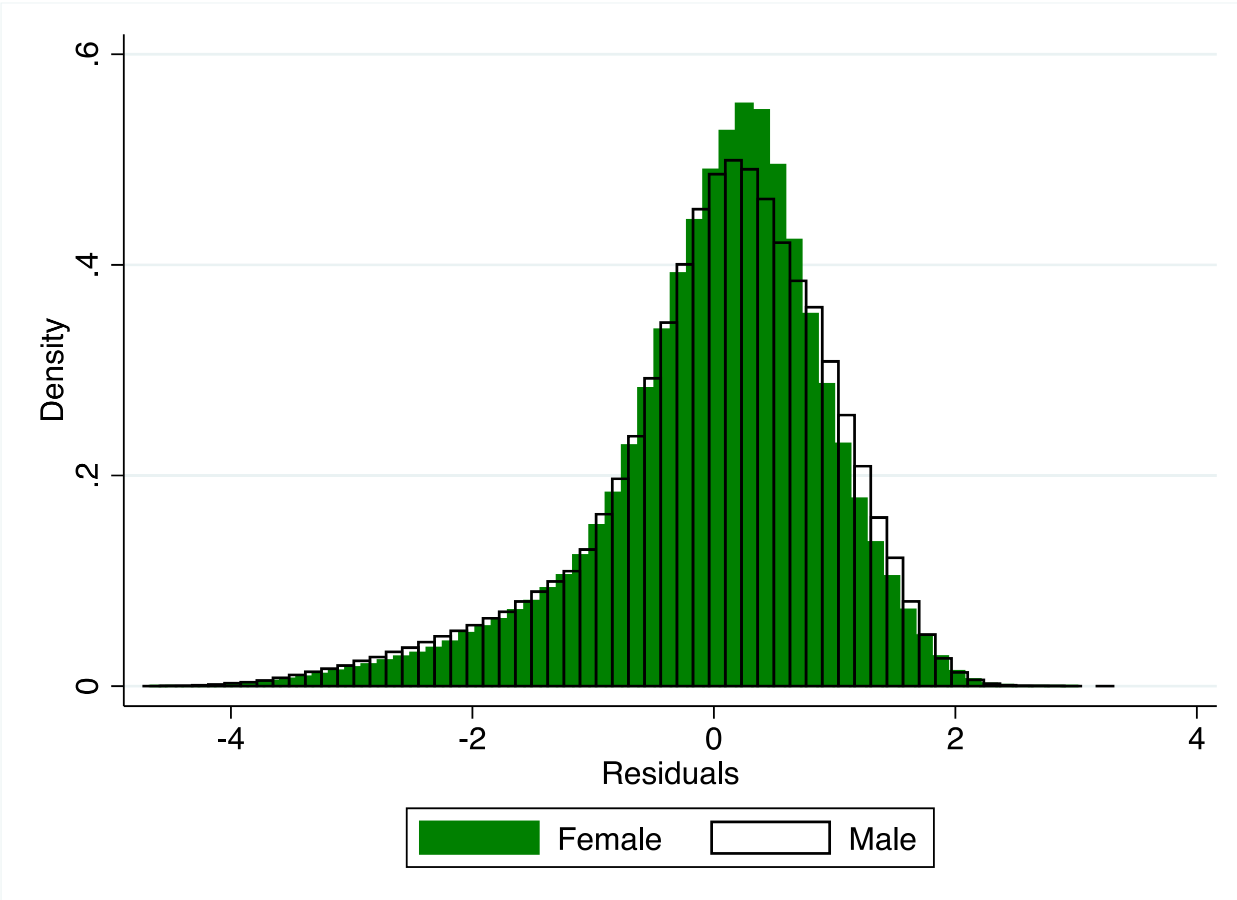


Figure S7: Histograms representing the distribution of (log) earnings (residuals from regressions on all controls included in equation 1 other than weather variables) of males (transparent bars) and females (green shaded bars).

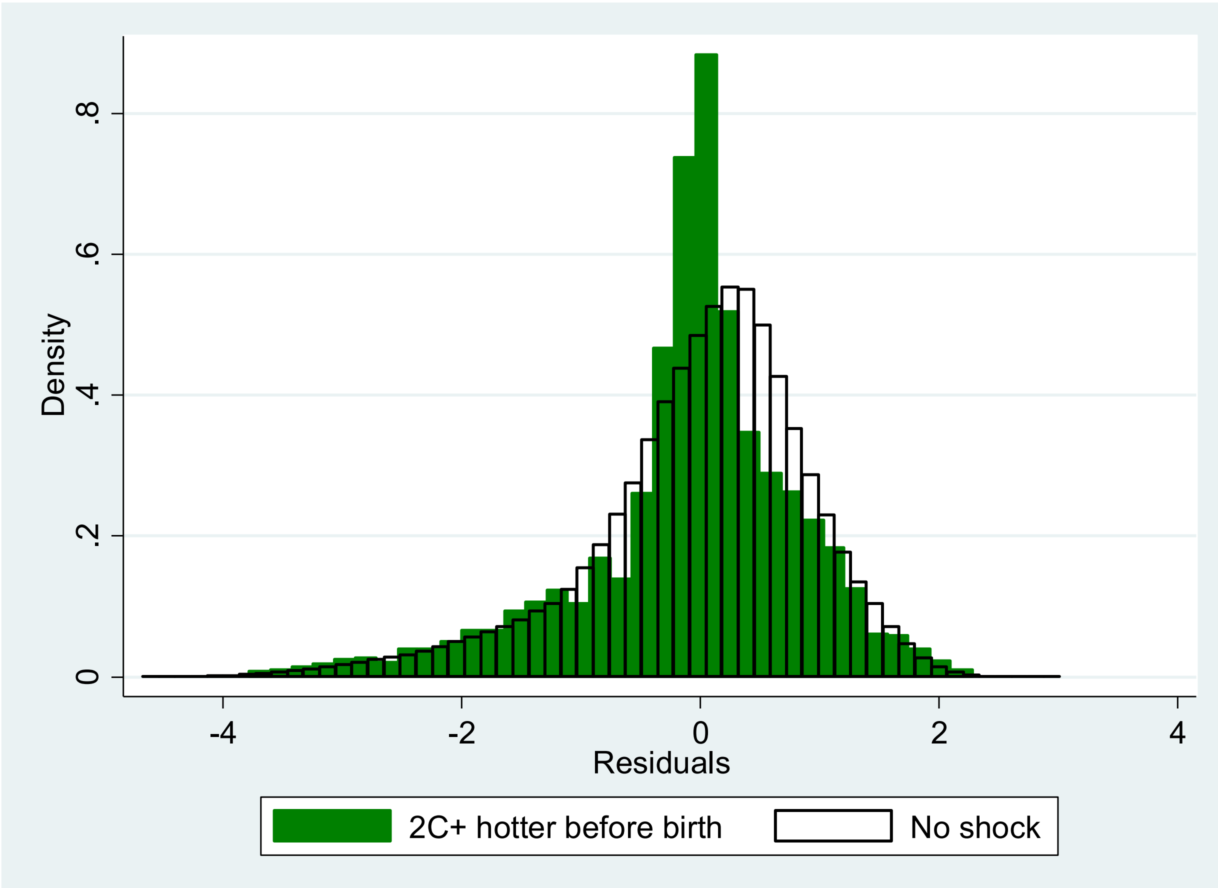


Figure S8: Shifts in the distribution of earnings. Histograms representing the distributions of (Log) earnings (residuals of regressions which include all controls in equation 1 except for the weather variables) for females, for cohorts experiencing low (between -0.5 and +0.5 ^{0}C, empty bars) and high (above 2^{0}C, green bars) in-utero temperature anomalies.