Long-Term Impacts of Exposure to High Temperatures on Human Capital and Economic Productivity

Ram Fishman, Paul Carrillo, Jason Russ*

Abstract

Weather anomalies have a range of adverse contemporaneous impacts on health and socio-economic outcomes. This paper tests if temperature anomalies around the time of birth can have *long-term* impacts on individuals' economic productivity. Using unique data sets on historical weather and earnings, place and date of birth of all 1.5 million formal employees in Ecuador, we find that individuals who have experienced in-utero temperatures that are 1°C above average are less educated and earn about 0.7% less as adults. Results are robust to alternative specifications and falsification tests and suggest that warming may have already caused adverse long-term economic impacts.

Keywords: Climate Change, Economic Impacts, Human Capital, Fetal Origins

JEL: O13; O15; J24; Q54; Q56

* Fishman: Dept. of Public Policy, Tel Aviv University and Dept. of Economics, George Washington University. ramf@post.tau.ac.il. Carrillo: Dept. of Economics, George Washington University. pcarrill@gwu.edu. Russ: Water Global Practice, The World Bank. jruss@worldbank.org. We are grateful to the Ecuadorian Tax Authority for their outstanding collaboration, and to the Institute for International Economic Policy at George Washington University for their support. This paper has benefited from comments and suggestions by conference and seminar participants at George Washington University, Aalto University, UC Berkeley, the Hebrew University of Jerusalem, the Washington Area Development Economics Conference, NEUDC 2015, the 3rd World Bank Urbanization and Poverty Reduction Research Conference, and the UNU-Wider 2016 conference. We thank Doug Almond, Maximilian Auffhammer, Britta Ausburg, Antonio Bento, Carmel Chiswick, Solomon Hsiang, Remi Jewab, Arun Malik, Martin Ravallion and Stephen Smith.

1. Introduction

Growing interest in the future impacts of climate change has spurred a burgeoning literature on the economic impacts of high temperatures. 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, *contemporaneous* social, economic and health impacts (see Dell et al., 2012; Deschenes, 2014; Carleton and Hsiang, 2016, for a review, and section 2), including on the health of fetuses and infants (Zivin and Shrader, 2016).

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 Currie, 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 and long-term negative consequences through a number of possible channels, both physiological and economic (In section 2 we summarize some of the existing evidence on the possible channels that can mediate the effect of high temperatures on long-term human capital accumulation.). This, in turn, would suggest that the warming that has already taken place in the past few decades may incur hitherto under-appreciated, long-term economic losses. Despite its importance, to the best of our knowledge, this paper is the first study to formulate and test this hypothesis.

We investigate the effect of high temperature anomalies around the time of birth on formal earnings as an adult. Economic theory suggests that wages provide an accurate indicator of economic productivity and human capital, including physical and cognitive function. A relationship between temperature anomalies in early life and adult earnings would therefore capture economic losses associated with long-term human capital impacts of early-life temperature-derived stress, even if it may not be possible to measure the contribution of each potential channel of causation directly. 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 1979, 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 the 9 months while in-utero, and the 9-month period following birth).

We find that higher temperatures in-utero lead to significantly lower adult earnings, with a 1°C increase in average monthly temperature in-utero leading to about a 0.7% decrease in adult earnings of both men and women, even though the effects on women are somewhat larger(0.9% vs. 0.6%). In contrast, the temperature in the corresponding 9-month period after birth shows no impact on 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. Since these estimates are derived from random, unexpected deviations of monthly temperatures from local, long-term means and trends, we can rule out the possibility that confounding variables are driving the association. Thus, even though the reduced-form analysis does not allow us to identify which of the multiple established negative impacts of high temperatures are driving the association, the random nature of temperature variations over time within a geographical locality facilitates causal inference (Dell et al., 2012).

This paper contributes to a growing literature investigating the implications of exogenous early life weather shocks on children and adults outcomes, pioneered by Maccini and Yang (2009). Most of these papers focus on the impacts of early life rainfall shocks on rural farming populations, and find evidence of impacts on the health, consumption, and education of adult women in Indonesia (Maccini and Yang, 2008), the health and cognitive abilities of Mexican (Aguilar and Vicarelli, 2011) and Nepali (Tiwari et al., 2013) adolescents, among others.

Our findings add to the existing literature in several important ways. First, we are able to estimate long-run impacts on adult economic productivity using administrative earnings data, a first in a developing country setting as far as we are aware.[1] Most papers that have found effects

[1] To be precise, we observe earnings, and so are unable to differentiate impacts on labor supply and labor productivity per se.

[2]First versions of both papers have appeared independently at around the same time. The

on human capital accumulation were unable to map these to reductions in earnings. Second, our sample consists of individuals who are better educated, more urbanized and have higher incomes than in previous studies in developing countries. Indeed, all of the individuals in our sample are employed in the formal sector of a middle-income country, whereas samples in most previous studies consisted mainly of farming households.

Third, while most previous studies are focused on rainfall shocks, this study documents the long-term impacts of high temperature shocks. Our analysis therefore adds a novel result to the growing literature on the economic and welfare impacts of elevated temperatures and climate change, which has thus far mostly focused on short-term impacts. Our results 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 (see section 2). However, we extend these results by directly observing much longer-term economic impacts of high temperatures.

The paper that is most closely related to ours is a recent study in the U.S. that also finds a negative association between high temperatures around the time of birth and earnings at age 30 (Isen et al, 2017).[2] Given the reduced-form nature of both sets of results and the related difficulty of conclusively identifying the mechanism, finding consistent impacts across two such drastically different samples and economic context lends the results with remarkable external validity.

2. Background

There are multiple potential channels through which early life (including in-utero) exposure to high temperatures can affect human capital accumulation. These can be broadly classified into two categories of physiological or income related mechanisms. Physiological mechanisms include the direct effect of exposure to high temperatures, or their biophysical outcomes (e.g. disease burden), on the health of the mother or the fetus, which can in turn carry long-term consequences. They can also potentially include the physiological effects of high temperatures on human behavior, such as aggression, that may, in turn also expose the mother or fetus to stress. Even though there does not appear to be agreement on the physiological

[2]First versions of both papers have appeared independently at around the same time. The working paper version of this paper dates to October 2015.

mechanisms by which heat may affect birth outcomes, several such mechanisms have been proposed as an explanation for repeatedly observed seasonal patterns in birth outcomes, and for the smaller number of studies that directly associate ambient heat with such outcomes (Wells and Cole, 2002; Strand, Barnett and Tong, 2011). Perhaps the most striking evidence of such an association is provided by Deschenes, Greenstone, and Guryan (2009), who find a strong negative association between birth weight and in-utero exposure to high temperatures in the U.S. [3] Low birthweight, in turn, is known to be associated with lower educational attainment and other adult outcomes (Black, Devereux, and Salvanes, 2007; Bharadwaj, Lundborg, and Rooth, 2015). There is also evidence that high temperatures increase mortality, including for infants (Deschênes and Greenstone, 2011), which may also be indicative of non-lethal impacts on fetal or infant health, with potentially long-term outcomes.

High temperatures can also increase the risk of disease (Patz et al., 2005; McMichael, Woodruff, and Hales, 2006). For example, high temperatures increase the incidence of malaria (McCord, 2016), and early life exposure to malaria has been shown to lead to reductions in educational attainment, consumption, and income in multiple studies in the U.S., Brazil, Columbia, Mexico, Sri Lanka and Paruguay (Barreca, 2010; Bleakley, 2010; Cutler, 2010; Lucas, 2010).

Income related mechanisms include all manners in which high temperatures may stress mothers or infants through their effect on household income. There is now a large body of evidence that temperature shocks reduce economic productivity and growth in both agriculture (Deschenes and Greenstone, 2007; Lobell, Schlenker, and Costa-Roberts, 2011; Schlenker and Lobell, 2010; Welch et al., 2010; Guiteras, 2009; Fishman, 2016) and manufacturing (Hsiang, 2010; Dell et al., 2012; Sudarshan and Tewari, 2011; Zivin and Neidel, 2014; Deryugina and Hsiang, 2014, Zhang et al., 2016), and the impacts are not limited to low-income countries. A large literature has shown that such household incomes shocks in early life can carry life-long consequences for human capital accumulation (See Almond and Currie, 2011).

[3] The observed reduced-form relationship could, in principle, also derive from a non-physiological mechanism. For example, similar associations have recently also been observed in the Andes, where our own study is also situated, but the authors hypothesize an income related mechanism (Molina and Saldarriaga, 2017).

The most likely channels for these effects are reductions in food consumption and health expenditures of both mothers and infants, which are likely to adversely affect infant nutrition and health outcomes. In some cases, direct evidence of these linkages are also observed. For example, Burgess et al. (2011) show that temperature driven agricultural income shocks lead to large increases in mortality in India, for both adults and infants, which suggests similar impacts on morbidity (for which data is absent) are also occurring. Such health shocks are, once again, known to have potential life-long consequences (Almond and Currie, 2011). Finally, there is also a growing body of evidence that high temperatures increase inter-personal conflict, including large scale civil conflict and personal crime, in both high and low-income settings (see Hsiang, Burke and Miguel, 2013, for a comprehensive review), although the relative importance of income-related and physiological channels (increased aggression) remains imperfectly understood in low-income settings (Blakeslee and Fishman 2013). There is also evidence that exposure to violence in early life reduces human capital accumulation (e.g. Leon, 2013) and birth weight (Camacho, 2008).

3. Data and Empirical Strategy

3.1 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 2).

Data on earnings 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 analysis is focused on individuals who are between 30 and 60 years of age at the time of observation, i.e. born between 1950 and 1980. The age group

20-29 is dropped because the earnings of younger individuals is likely to be a noisier measure (e.g. because of part time employment while studying) and may fail to accurately reflect their permanent income potential or educational attainment. However, we carry out robustness tests of our main results that include the full sample (individuals born between 1950 and 1989) and find consistent results. Unfortunately, the data does not allow us to group individuals by family unit, or to observe the characteristics of parents or the current place of residence.

Precipitation and temperature data are 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, with weights proportional to the fraction of area falling within the canton's administrative boundaries (Figure 3). Overall, our combined earnings and weather sample consists of 67,151 cohorts (combinations of year, month and canton). Summary statistics for the earnings and weather data are given in Tables 1 and 2, respectively.

3.2 Empirical Strategy

We employ regression analysis to investigate the correlation between weather conditions around the time of birth and adult earnings. Existing evidence on the physiological effects of in-utero stress leads us to focus on the 9-month periods preceding and following the month of birth. 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 weather that would be expected based on the long-term mean in each locality and calendar month, as well as, in some specifications, the long-term trends in each locality. These deviations are likely to be random and unexpected, and therefore orthogonal to any possible confounders, facilitating causal inference. To isolate these *localized* and unexpected temporal fluctuations in weather, our basic regression model incorporates location fixed effects (for each of Ecuador's 218 cantons) that are interacted with fixed effects for each calendar month, in order to capture the long-term, month specific expected weather, as well as location specific flexible time trends (year fixed effects). To assuage concerns about dynamic treatment effects (Wolfers, 2006) we test the robustness of our results to the use of global, region-specific or province-specific year fixed effects[4], with the latter being the most demanding model. 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 from the long-term mean and trend. The mean magnitude of these anomalies in the sample is about 0.65°C.

The regressions we estimate take the form:

$$ln(y_{icmy}) = \alpha_1 + \alpha_2 T^l_{cmy} + \alpha_3 T^f_{cmy} + \alpha_4 R^l_{cmy} + \alpha_5 R^f_{cmy} + \gamma_{m,c} + \theta_{a,y} + \varepsilon_i \quad (1)$$

where y_{icmy} is the 2010 earnings of individual i, born in canton c, in month m of year y; T^l_{cmy} *and* T^f_{cmy} are the average temperatures (in degrees Celsius) in the canton of birth in the 9 months before birth, and the 9 months after birth, respectively; R^l_{cmy} and R^f_{cmy} are the average monthly precipitation (cm) in the canton of birth in the 9 months before birth, and the 9 months after birth, respectively; $\gamma_{m,c}$ 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 $\theta_{a,y}$ are year fixed effects at each location a: –either the entire country, each of the country's three geographical regions, or each of its e 24 provinces (the most demanding specification). To account for possible serial or spatial correlations amongst observations, we allow for errors to display arbitrary correlations across time within each canton as well as across each of Ecuador's three geographical regions within each year. .

We estimate regression (1) for the combined sample (while controlling for gender) as well as separately by gender, since, first, the male and female formal sector samples differ in attributes, and second, since some previous studies of in-utero stress find impacts that vary by gender (see below).

4. Results

4.1 The Impacts of Early Life Weather on Adult Earning

[4] Ecuador consists of three geographical regions: *Costa*, *Sierra* and Oriente. These are further divided into provinces, Ecuador's largest political units, of which there are 24 (including the Galapagos province, which is excluded from our study). Cantons are the second largest political unit. Our dataset consists of births from 218 cantons.

4.1.1 Basic Results

Estimates of regression (1) are reported in Table 3. Columns 1-3 report results for the full sample obtained from increasingly demanding models that include global (Column 1), region-specific (Column 2) and province-specific (Column 3) year fixed effects. Columns 4 and 5 report separate results for females and males obtained in the most demanding model (with province-year fixed effects). These estimates are also summarized in the left panel of Figure 3.

The results indicate that an increase in 1°C in average temperature during the in-utero period leads to a 0.7%-1.2% reduction in adult earnings, which amounts to a 0.4%-0.7% reduction per typical within canton standard deviation (net of all fixed effects included in the regression) of in-utero temperature (0.6°). The estimated impact is somewhat larger for females (0.86%) than for males (0.59%) though the difference is not statistically significant.

Temperature anomalies during the nine-month period following birth display smaller and statistically insignificant effects on both females and males, which is supportive our focus on the hypothesized in-utero impacts.

To further investigate impacts during the in-utero period, we also estimate a model identical to that reported in Column 3 except that it uses the mean temperatures in six 3-month windows preceding and following the month of birth as explanatory variables (12 such periods in totals). The resulting estimates are reported in Figure 4. The periods labeled as -3,-2,-1 correspond to the first, second and third trimester, respectively.

We find negative and statistically significant impacts in the third trimester, as well as in the first trimester and in the preceding period (i.e. period -4). Note that since we do not observe the exact date, but only the month of birth, the actual 1^{st} month of the gestation period may actually occur in period -4. As above, none of the post-birth periods display statistically significant impacts. Reassuringly, we do not find evidence of impacts from periods -5 and -6. It is interesting to compare these results with those of Deschênes, Greenstone, and Guryan (2009), who find that high temperatures in each trimester reduce birth weight, with the largest effects occurring in the third trimester; and those of Barreca, Deschenes, and Guldi (2015), who find that high temperatures in months 1 and 9 of the gestation period reduce birth weight.

In Appendix Table A1.1 we report similar regressions to model (1) in which the outcome variable is the z-score of each individual's 2010 earnings within the cohort of individuals born in the same year and province or in the same year and region. This specification yields negative impacts that are nevertheless less precisely estimated. Appendix Table A1.2 reports similar results except that the outcome variables are binary indicators of being in the upper or lower portion (defined as the z-score being above 0.5 or below -0.5) of the earnings distribution within the region-year cohort. It shows that higher temperatures in-utero significantly increase the probability of being in the lower portion (for the combined sample, as well as for males and females separately) and decrease the probability of being in the upper portion (albeit mostly for females).

In Figure 5 we compare the distributions of (log) earnings for cohorts exposed to in-utero local temperature shocks above one standard deviation and those that are not. To generate this plot, we calculate residuals from a regression of (log) earnings on the same set of fixed effects included as in Equation (1), and then plot the residuals for two different sub-samples: those individuals whose in-utero mean temperature was up to one standard deviation above the local average, and those whose in-utero average temperature was more than one standard deviation above the local average.[5] The plot suggests that the effect of temperature shocks does not seem to be primarily driven by either the low or high-income tails of the earnings distribution. A Kolmogorov-Smirnov test rejects equality of the two distributions ($p<0.01$).

4.2 Robustness Tests

4.2.1 Controlling for Lags and Leads

In Figure 6 we report estimates of a model like regression (1) that also controls for the mean temperature in 5 annual lags and leads of the in-utero period (we use the most demanding specification that includes province-year fixed effects and maximize statistical power by using the combined sample of both genders). The in-utero period is labeled as period 0. Unfortunately,

---

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

the resulting estimates are not precise enough to allow us to statistically distinguish between the effects of in-utero temperatures to that of other periods. However, while there is also one other significant impact of third forward lag, the in-utero period reassuringly continues to display a statistically significant negative effect of magnitude that is almost identical to the estimate obtained without controlling the other lags and leads (Column 3 in Table 3), indicated by the grey dashed line.

4.2.2 Including Young Cohorts

The earnings of relatively younger individuals are likely to be noisier and to less accurately reflect their long-term earning potential (and human capital accumulation) than those of older individuals. For example, younger individuals may still be studying, even if part-time, into their 20s. We therefore do not include individuals below the age of 30 in our main estimates. However, for completeness, in Appendix Table A2 we also report estimates obtained by including these individuals. These estimates are similar in magnitude to our main estimates, although they are somewhat less precisely estimated (especially for males).

4.2.3 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 falsification test that involves repeatedly and randomly “re-shuffling” the weather data across time and space (i.e. precipitation and temperature in the 9-month post and pre-birth periods) and re-estimating regression (1). Inspections of the resulting distribution of point estimates can help test the appropriateness of our statistical model and the likelihood that our results are an artifact of chance or of a systematic structure in the data. We conduct three separate forms of “re-shuffling” (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 canton, but in the same birth month and year, and then re-estimate Equation (1). We repeat this procedure 1,000 times and plot the distribution of point-estimates (for the impact on in-utero temperature) in Figure 7 (rightmost panel). Spatial autocorrelation of the weather data leads adjacent cantons to tend to have similar weather observations, which increases the likelihood that a birth cohort may be randomly assigned weather realizations that is similar to its actual weather, and makes this falsification test quite conservative. Nevertheless, we find that only 2% of these estimates are larger in magnitude (and negative) than the actual coefficient. In the second test, we "re-shuffle" weather realizations across years, keeping the canton and month of birth unaffected. Less than 1% of these estimates fall to the left of the actual coefficient (Figure 7, middle panel). 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 1,000 bootstrapped estimates are larger in magnitude than the actual estimate (Figure 7, leftmost panels). Also, as expected, the distributions of these "placebo" estimates are centered around zero, providing a degree of validation to our model specification and the data sets we use.

4.4 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. Our data only provides us with rather coarse binary indicators of educational attainment consisting of at least secondary (84% in the overall sample) or higher (29% in the overall sample) education (Table 4). In Table 5 (and the middle and right panels of Figure 3) we report estimates of regressions parallel to equation (1), employing our most demanding model with province-year fixed effects, in which the dependent variables consist of these two binary indicators of educational attainment (top and bottom panels). The results indicate that a 1^{0}C in-utero temperature shock has a negative, but marginally insignificant 0.2% reduction in the probability of attaining secondary education (the impacts on both males and females are negative and similar in magnitude, but imprecisely estimated), as well as a statistically significant 0.5% reduction in the probability that females attain higher education.

4.5 Potential Selection Mechanisms

Selection into the sample can potentially bias our estimates if inclusion in the sample of formal sector employees is affected by early life weather shocks in ways that are correlated with factors that are predictive of future earnings (Almond and Currie, 2011). In our context, inclusion in the sample is a product of survival to adulthood (including a live birth), remaining in Ecuador, and being employed in the formal sector.

5.2.1 Selection through Survival

To test for selection, we begin by examining whether the size of a birth-cohort is affected by weather anomalies around the time of birth. We use data from Ecuador's civil registry, which lists all working age Ecuadorians, and consists of 8.2 million individuals that are approximately half females, to calculate each birth cohort's size. We then 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 obtained using our preferred specification (province-year fixed effects) are reported in the top panel of Table 6 and indicate that a 1°C increase in in-utero temperature decreases the size of a birth cohort by a statistically significant 3.9%, with statistically significant effects on cohorts of both genders that are somewhat larger for males (4.0% vs. 3.4%). These estimates represent the combined effect of weather anomalies on the probability of live birth, survival to adulthood and remaining in Ecuador. [6] In the bottom panel of Table 6, we repeat the same estimation except that the dependent variable is the formal sector cohort size. The results are qualitatively similar, if somewhat smaller (at about 3%).

Selection through survival to adulthood, which is well recognized in the fetal origins literature, is likely to downward bias regression estimates, since it is reasonable to assume that individuals who would have survived or become employed in the formal sector would exhibit lower earnings (Maccini and Yang, 2008; Almond and Currie, 2011). If the reductions in cohort size are driven by survival, this would suggest our estimates of the impacts on earnings may be conservative. It is, however, less straightforward to predict potential biases associated with selection through potential emigration by individuals or households away from Ecuador post-birth, and our data does not allow us to differentiate between emigration and survival as driving the cohort size results.

5.2.2 Selection through Formal Sector Employment

---

[6] Cohort size is not the sole indicator of selection, but lack of data on pre-birth attributes of individuals in our sample or their household prevents us from testing effects on cohort composition.

Next, we test if early life temperature anomalies affect one's probability of entering the formal sector. To do this, we match individuals in the formal sector sample with civil registry data. Overall, 14.2% and 25.9% of the females and males, respectively, in the civil registry data earned formal sector income in 2010 (i.e. are also identified in the formal sector sample). We then test whether the probability of entering the formal sector is affected by early-life weather anomalies 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. We do not find evidence of sizable or statistically significant effects on formal sector participation for either gender (Table 7).

Estimating the impacts of high temperatures on the size of the birth cohort or formal sector cohort only help to test for average selection effects. It does not help reject heterogeneous selection effects that can disproportionally affect survival into the sample for certain sub-populations in ways that have little or negative influence on overall cohort size but do affect its composition. Our data does not allow us to test for such effects because we do not observe parents' properties. For example, Barreca, Deschenes, and Guldi (2015) show that high temperatures reduce fertility in the U.S. If the effect were larger for higher income parents, it could lead to a composition-driven impact on the outcomes of individuals born to the said cohort.

5.2.3 Selection through Pre-Birth Behavior

Another form of selection that can potentially drive both the reduced cohort size and impacts on earnings (as well as education and formal sector employment) 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 outcomes of cohorts exposed to adverse weather in-utero that is not actually driven by the impacts of high temperatures. Migration by wealthier pregnant women could therefore results in over-estimates of the true effect on earnings.

While we cannot fully rule out this possibility, two stylized considerations are suggestive against it. First, a simple calculation of the impacts on earnings that would occur by removing the top earners from cohorts experiences high temperatures in-utero suggests very similar impacts on males and females, in contrast to the differences in impacts we discuss above. [7] Second, if most distress migration is relatively local in nature, such as from rural areas to the provincial urban centers, than most migration will be inter-provincial, and provincial cohort sizes might be expected to be less affected by weather anomalies. In order to assess this possibility, we compare the estimated impact of in-utero temperature shocks on the size of a birth-cohort size defined either at the level of a canton or a province (a larger administrative unit). The two sets of estimates, reported side-by-side in Appendix Table A3, are very similar, suggesting against inter-provincial migration as a driver of the results. [8]

5. Conclusion

We document a robust, economically meaningful detrimental influence of hotter in-utero temperatures on female formal sector earnings in Ecuador. 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).

[7] To be precise, we remove the 3%-5% from the earning distribution of both males and females in cohorts experiencing an in-utero temperature anomaly exceeding 1 standard deviation (see the explanation of Figure 5). We remove the same percent of earners from the distribution of both genders because pre-birth behavior is unlikely to differ by the likely unobservable gender of the fetus.

[8] We estimate these models with region-year, rather than province-year fixed effects in order to allow for sufficient variation in temperature when cohorts are defined at the province level.

References

1. Aguilar, Arturo, and Marta Vicarelli. "El Nino and Mexican children: medium-term effects of early-life weather shocks on cognitive and health outcomes." Cambridge, United States: Harvard University, Department of Economics. Manuscript (2011).

2. Almond, Douglas, and Bhashkar Mazumder. "Health capital and the prenatal environment: the effect of Ramadan observance during pregnancy." *American Economic Journal: Applied Economics* (2011): 56-85.

3. Almond, Douglas, and Janet Currie. "Killing me softly: The fetal origins hypothesis." The Journal of Economic Perspectives (2011): 153-172.

4. Barreca, Alan I. "The long-term economic impact of in utero and postnatal exposure to malaria." *Journal of Human resources* 45.4 (2010): 865-892.

5. Barreca, Alan, Olivier Deschenes, and Melanie Guldi. *Maybe next month? Temperature shocks, climate change, and dynamic adjustments in birth rates*. No. w21681. National Bureau of Economic Research, 2015.

6. Bharadwaj, Prashant, Petter Lundborg, and Dan-Olof Rooth. *Birth Weight in the Long Run*. No. w21354. National Bureau of Economic Research, 2015.

7. Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. "From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes*." *The Quarterly journal of economics* 122.1 (2007): 409-439.

8. Blakeslee, David, and Ram Fishman. "Weather Shocks, Crime and Agriculture: Evidence from India." Unpublished Manuscript (2013).

9. Bleakley, Hoyt. "Malaria eradication in the Americas: A retrospective analysis of childhood exposure." *American Economic Journal: Applied Economics* 2.2 (2010): 1-45.

10. Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang. "Nonlinear permanent migration response to climatic variations but minimal response to disasters." *Proceedings of the National Academy of Sciences*(2014): 201317166.

11. Burgess, Robin, et al.. "Weather and death in India." Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript (2011).

12. Camacho, Adriana. "Stress and birth weight: evidence from terrorist attacks." *The American Economic Review* 98.2 (2008): 511-515

13. Cutler, David, et al. "Early-life malaria exposure and adult outcomes: Evidence from malaria eradication in India." *American Economic Journal: Applied Economics* 2.2 (2010): 72-94

14. Carleton, Tamma A., and Solomon M. Hsiang. "Social and economic impacts of climate." *Science* 353.6304 (2016): aad9837

15. Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. "Temperature shocks and economic growth: Evidence from the last half century." American Economic Journal: Macroeconomics 4.3 (2012): 66-95.

16. Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. "What Do We Learn from the Weather? The New Climate–Economy Literature." *Journal of Economic Literature* 52.3 (2014): 740-798.

17. Deryugina, Tatyana, and Solomon M. Hsiang. *Does the environment still matter? Daily temperature and income in the United States*. No. w20750. National Bureau of Economic Research, 2014.

18. Deschenes, Olivier. "Temperature, human health, and adaptation: A review of the empirical literature." *Energy Economics* 46 (2014): 606-619.

19. Deschenes, Olivier, and Michael Greenstone. "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather." The American Economic Review (2007): 354-385.

20. Deschênes, Olivier, and Michael Greenstone. "Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US." *American Economic Journal: Applied Economics* 3.4 (2011): 152-185.

21. Deschênes, Olivier, Michael Greenstone, and Jonathan Guryan. "Climate change and birth weight." The American Economic Review (2009): 211-217.

22. Feng, Shuaizhang, Alan B. Krueger, and Michael Oppenheimer. "Linkages among climate change, crop yields and Mexico–US cross-border migration."*Proceedings of the National Academy of Sciences* 107.32 (2010): 14257-14262.

23. Feng, Shuaizhang, Michael Oppenheimer, and Wolfram Schlenker. *Climate change, crop yields, and internal migration in the United States*. No. w17734. National Bureau of Economic Research, 2012.

24. Fishman, Ram, Meha Jain, and Avinash Kishore. "Groundwater Depletion, Adaptation and Migration: Evidence from Gujarat, India." (2013).

25. Fishman, Ram. "More uneven distributions overturn benefits of higher precipitation for crop yields." *Environmental Research Letters* 11.2 (2016): 024004.

26. Guiteras, Raymond. "The impact of climate change on Indian agriculture." Manuscript, Department of Economics, University of Maryland, College Park, Maryland (2009).

27. Hsiang, Solomon M. "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America." Proceedings of the National Academy of Sciences 107.35 (2010): 15367-15372.

28. Hsiang, Solomon M., and Amir S. Jina. *The causal effect of environmental catastrophe on long-run economic growth: evidence from 6,700 cyclones*. No. w20352. National Bureau of Economic Research, 2014.

29. Hsiang, Solomon M., Marshall Burke, and Edward Miguel. "Quantifying the influence of climate on human conflict." Science 341.6151 (2013): 1235367.

30. Isen, Adam, Maya Rossin-Slater, and Reed Walker. "Relationship between season of birth, temperature exposure, and later life wellbeing." *Proceedings of the National Academy of Sciences* 114, no. 51 (2017): 13447-13452.

31. Leon, Gianmarco. "Civil conflict and human capital accumulation the long-term effects of political violence in perú." *Journal of Human Resources* 47.4 (2012): 991-1022.

32. Lobell, David B., Wolfram Schlenker, and Justin Costa-Roberts. "Climate trends and global crop production since 1980." Science 333.6042 (2011): 616-620.

33. Lucas, Adrienne M. "Malaria eradication and educational attainment: evidence from Paraguay and Sri Lanka." *American Economic Journal: Applied Economics* 2.2 (2010): 46-71.

34. Maccini, Sharon, and Dean Yang. "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall." American Economic Review 99.3 (2009): 1006-26.

35. McCord, G. C. "Malaria ecology and climate change." *The European Physical Journal Special Topics* 225.3 (2016): 459-470.

36. McCord, Gordon. "Malaria Ecology and Climate Change". Forthcoming, European Physics Journal.

37. McMichael, Anthony J., Rosalie E. Woodruff, and Simon Hales. "Climate change and human health: present and future risks." *The Lancet* 367.9513 (2006): 859-869.

38. McMichael, Anthony J., Rosalie E. Woodruff, and Simon Hales. "Climate change and human health: present and future risks." *The Lancet* 367.9513 (2006): 859-869.

39. Molina, Oswaldo, and Victor Saldarriaga. "The perils of climate change: In utero exposure to temperature variability and birth outcomes in the Andean region." *Economics & Human Biology* 24 (2017): 111-124.

40. Nordhaus, William D. "Geography and macroeconomics: New data and new findings." *Proceedings of the National Academy of Sciences of the United States of America* 103.10 (2006): 3510-3517.

41. Patz, Jonathan A., et al.. "Impact of regional climate change on human health." *Nature* 438.7066 (2005): 310-317.

42. Ranson, Matthew. "Crime, weather, and climate change." *Journal of environmental economics and management* 67.3 (2014): 274-302.

43. Schlenker, Wolfram, and David B. Lobell. "Robust negative impacts of climate change on African agriculture." Environmental Research Letters 5.1 (2010): 014010.

44. Strand, Linn B., Adrian G. Barnett, and Shilu Tong. "The influence of season and ambient temperature on birth outcomes: a review of the epidemiological literature." Environmental Research 111.3 (2011): 451-462

45. Sudarshan, Anant, and Meenu Tewari. The economic impacts of temperature on industrial productivity: Evidence from indian manufacturing. Working Paper, 2013.

46. Tiwari, Sailesh, Hanan G. Jacoby, and Emmanuel Skoufias. "Monsoon babies: rainfall shocks and child nutrition in Nepal." World Bank Policy Research Working Paper 6395 (2013).

47. Welch, Jarrod R., Jeffrey R. Vincent, Maximilian Auffhammer, Piedad F. Moya, Achim Dobermann, and David Dawe. "Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures." *Proceedings of the National Academy of Sciences* 107, no. 33 (2010): 14562-14567.

48. Wells, Jonathan CK, and Tim J. Cole. "Birth weight and environmental heat load: A between‐population analysis." *American journal of physical anthropology* 119.3 (2002): 276-282.

49. Willmott, C. J. and K. Matsuura (2001) Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series (V 3.01), http://climate.geog.udel.edu/~climate/html_pages/Global2011/README.GlobalTsT2011.html

50. Willmott, C. J. and K. Matsuura (2001) Terrestrial Precipitation: 1900-2010 Gridded Monthly Time Series (V 3.01), http://climate.geog.udel.edu/~climate/html_pages/Global2011/README.GlobalTsP2011.html

51. Wolfers, Justin. "Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results." American Economic Review, 96.5. (2006): 1802-1820.

52. Zhang, Peng, Junjie Zhang, Olivier Deschênes, and Kyle Meng. *Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants*. Working paper, 2016.

53. Zivin, Joshua Graff, and Matthew Neidell. "Temperature and the allocation of time: Implications for climate change." *Journal of Labor Economics* 32.1 (2014): 1-26.

54. Zivin, Joshua Graff, and Jeffrey Shrader. "Temperature extremes, health, and human capital." *The Future of Children*26, no. 1 (2016): 31-50.

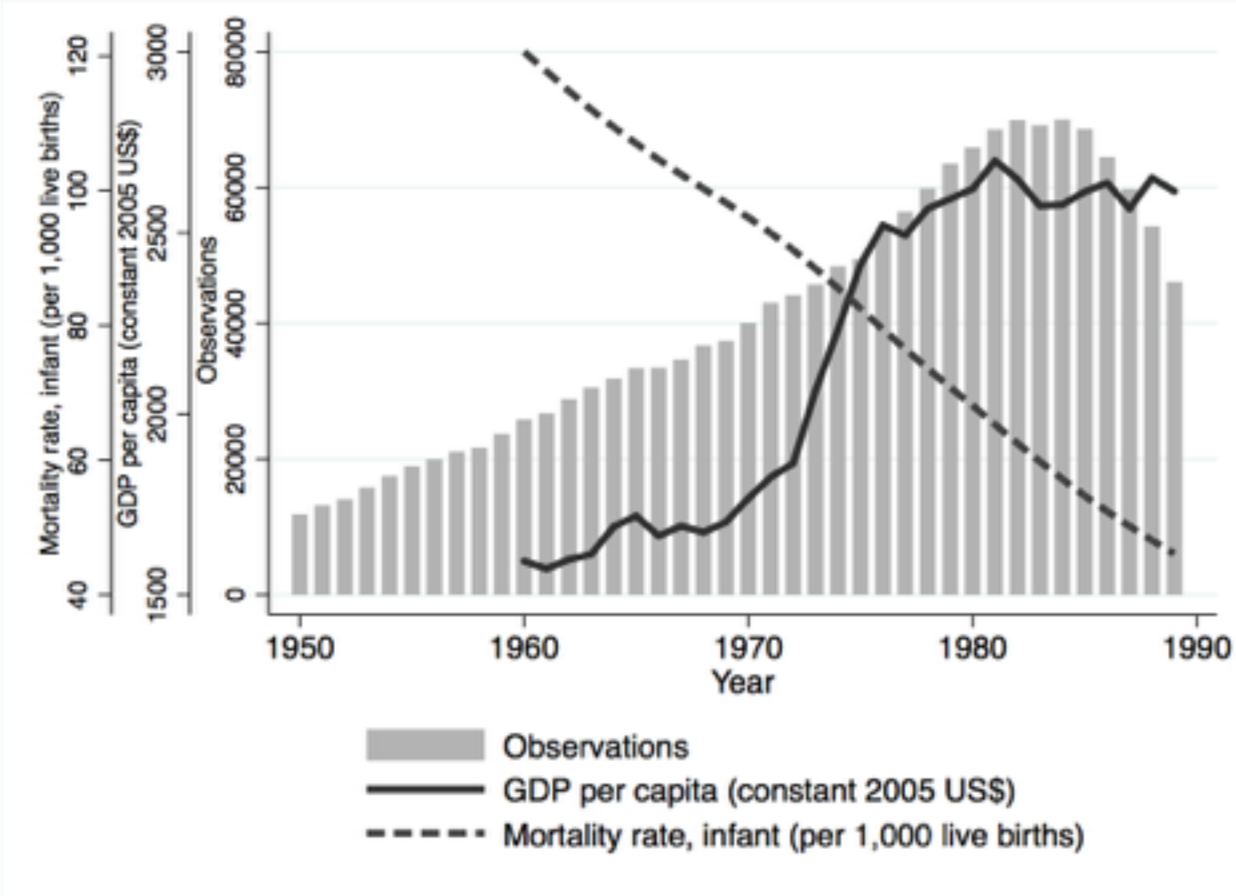


Figure 1: Economic growth and the infant mortality rate during the birth period of the sample. Bars (inner left axis) indicate the number of individuals in the sample that were born in each year. GDP per capita (center left axis, solid line), and infant mortality rate (outer left axis, dotted line) are also plotted (source: World Bank Development Indicators).

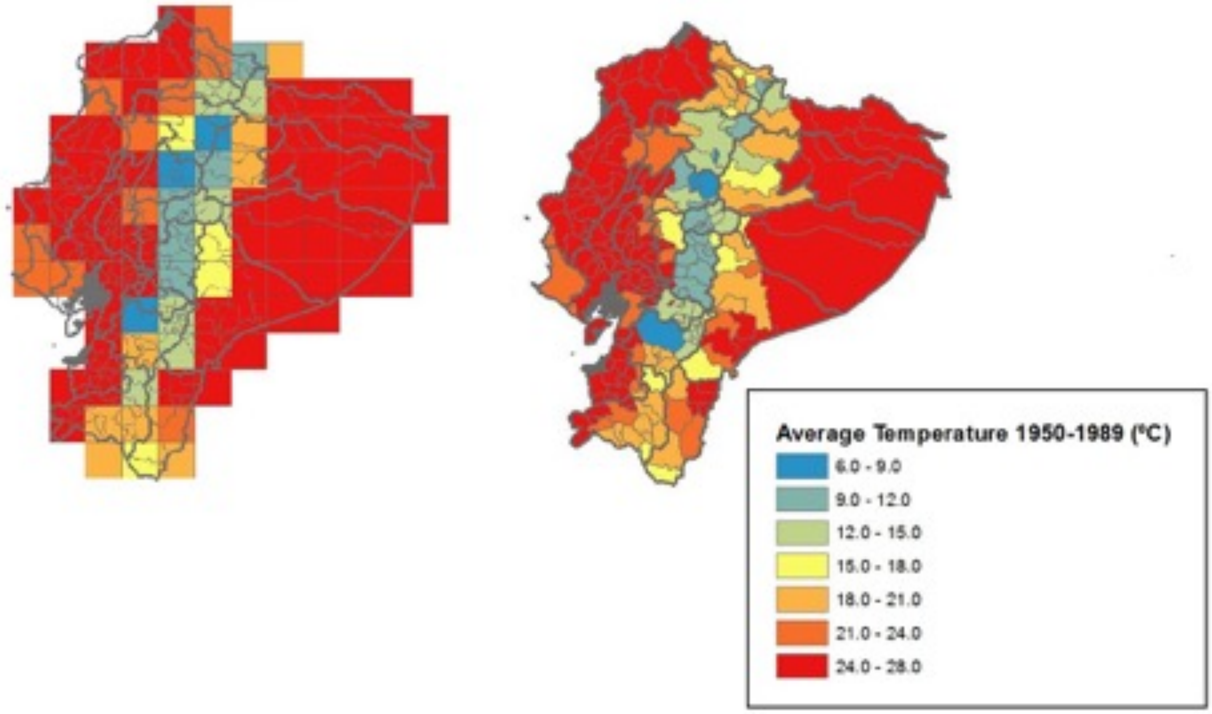


Figure 2 : An overlay of average temperature (1950-1989) calculated from the gridded weather data of Willmott and Matsuura (2001) on a map of Ecuador's administrative boundaries. The left panel displays average temperatures from the raw gridded data and the right panel displays the result of spatial averaging of the gridded data within each administrative unit (canton).

Figure 3: Summary of main findings. Estimated impacts of in-utero mean temperature anomalies on (Log) earning (left), the probability of completing secondary education (middle) and higher education (right) for the entire sample (blue), females (red) and males (green). Each point estimate is from a separate regression that includes province-year and canton-month fixed effects. Error bars indicate 95% confidence intervals.

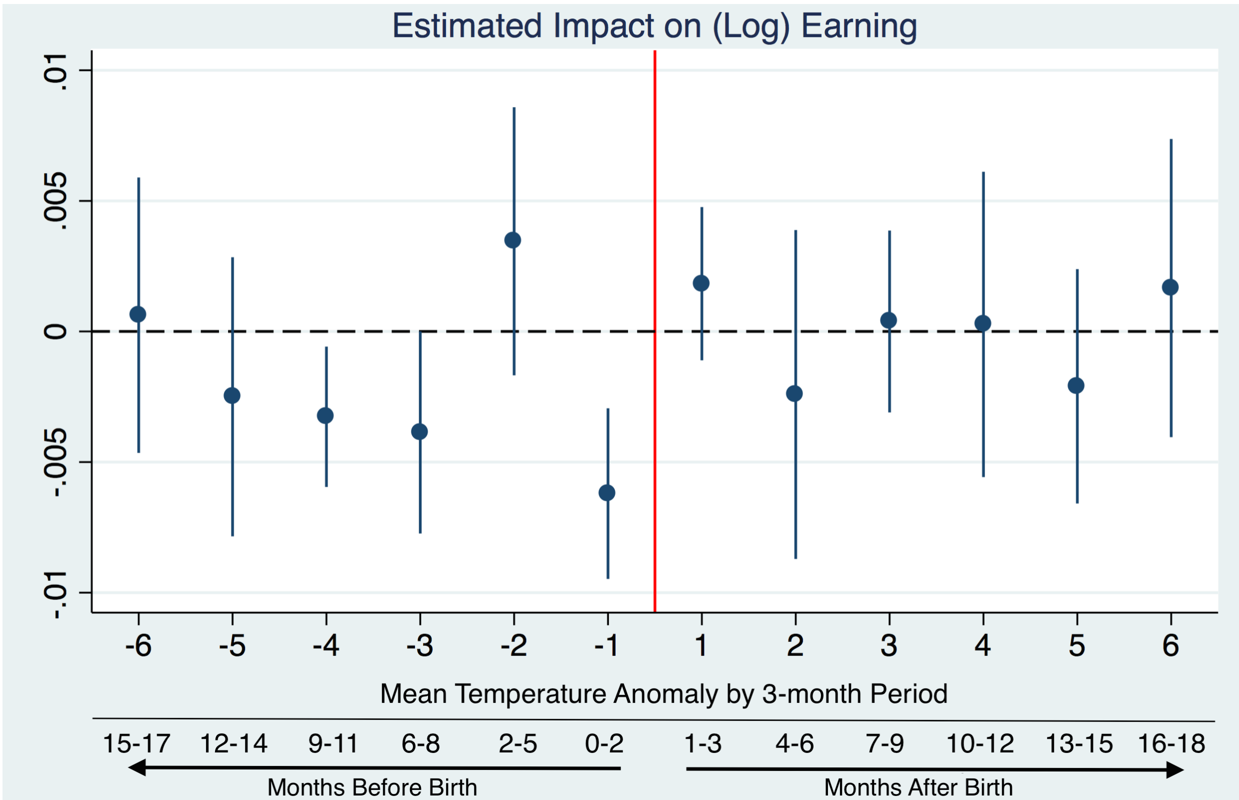


Figure 4: Estimated impacts on (Log) earning of the mean temperature anomaly in six 3-month periods preceding and following the month of birth. All estimates are derived from a single regression as in equation 1, that includes province-year and month-cantons fixed effects. Sample includes all individuals (males and females) born between 1950 and 1979 who earned formal sector income in the year 2010. Error bars indicate 95% confidence intervals.

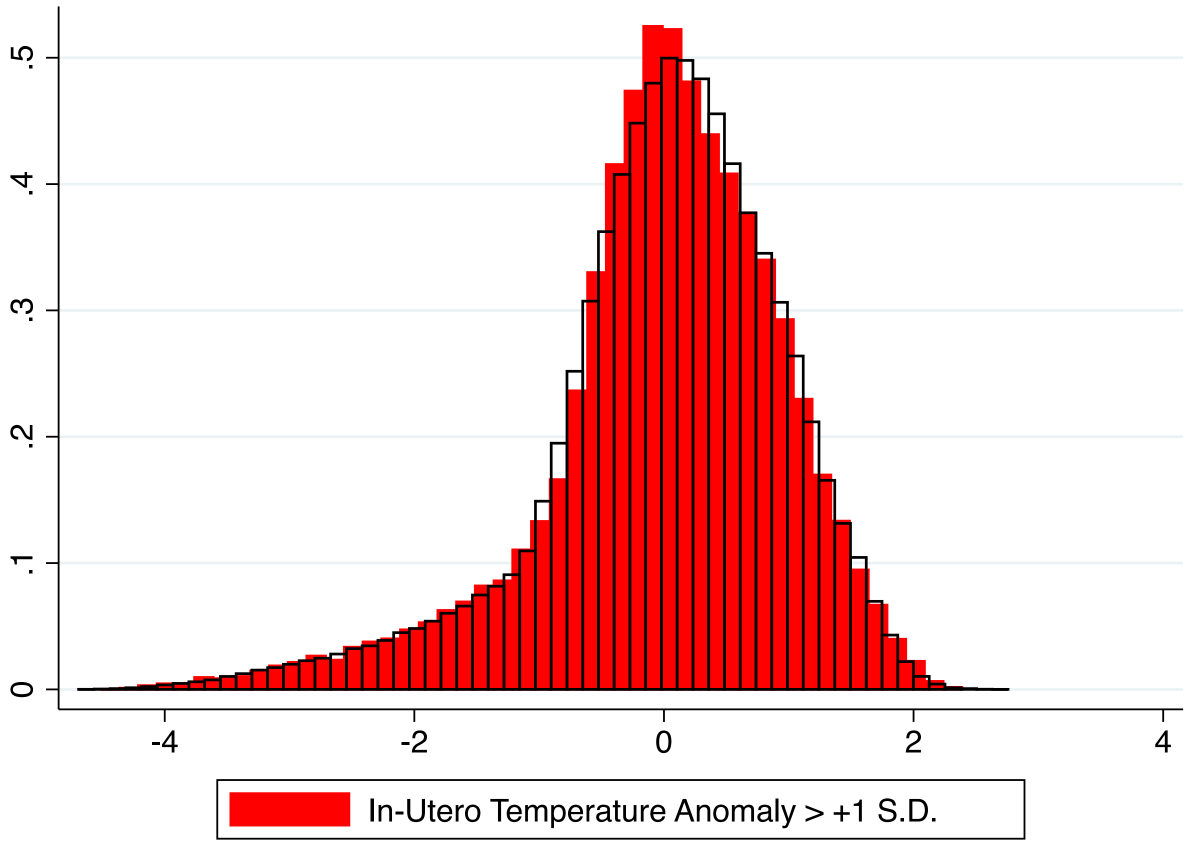


Figure 5: Shifts in the distribution of earnings. Histograms representing the distributions of (Log) earnings (residuals of regressions which include all controls in equation 1 except for the weather variables) for cohorts experiencing mean in-utero temperatures above (red) and below one standard deviation (net of all location and time of birth fixed effects). See text for details.

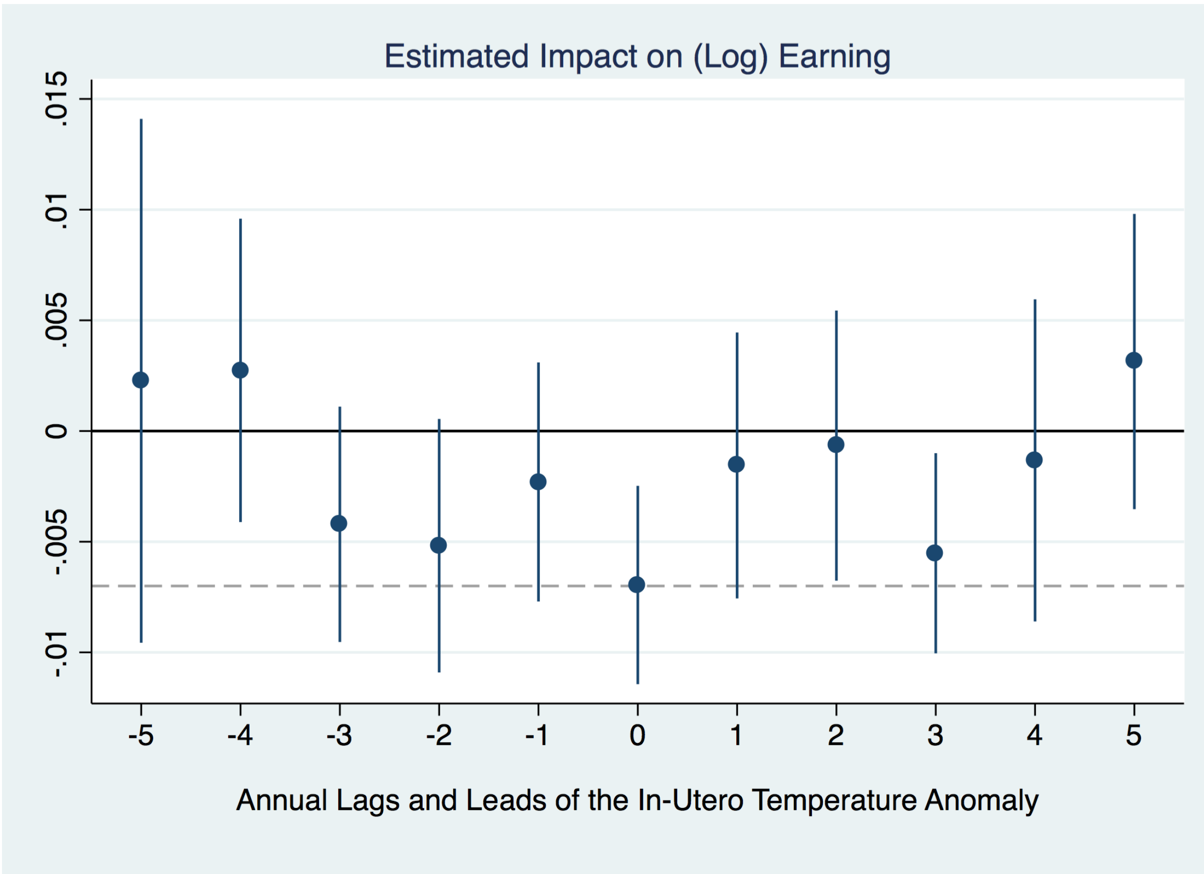


Figure 6: Estimated impacts on (Log) earning of the mean temperature anomaly in the in-utero period (labeled as zero on the horizontal axis) and of five annual lags and leads. All estimates are derived from a single regression as in equation 1 that includes province-year and month-cantons fixed effects. Sample includes all individuals (males and females) born between 1950 and 1979 who earned formal sector income in the year 2010. Error bars indicate 95% confidence intervals.

Figure 7: Falsification Tests. Each histograms displays the distributions of estimates of the impacts of in-utero mean temperature on (Log) earnings obtained from 1,000 regressions (for each plot), each of which is parallel to model (1), estimated over the entire sample (males and females) except that weather data is randomly “re-shuffled” across cantons (right panel), years (middle panel) or both simultaneously (left panel). Red lines indicate the magnitude of the “true” coefficient as estimated from regression (1), i.e. when in-utero temperatures are at their actual levels. P-values indicate the fraction of estimates which exceed the “actual” estimate.

Table 1: Summary Statistics, Earnings Data

	Male Earnings		
Age group	Mean	Median	St. Dev.
Full Population (31-60)	$8,110.67	$5,603.33	$7,299.41
31-40	$7,219.91	$5,091.67	$6,515.68
41-50	$8,628.58	$5,972.06	$7,722.52
51-60	$9,757.75	$7,149.74	$8,227.32
	Female Earnings		
Age group	Mean	Median	St. Dev.
Full Population (31-60)	$8,053.77	$6,103.11	$6,658.39
31-40	$6,820.57	$4,803.00	$6,079.69
41-50	$8,472.82	$6,761.09	$6,824.74
51-60	$10,657.46	$10,008.52	$7,010.78

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

Table 2: 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 3: Log Earnings, 2010

	(1)	(2)	(3)	(4)	(5)
	All	All	All	Females	Males
Temperature (9 months pre birth)	-0.01206**	-0.01247***	-0.00730**	-0.00864*	-0.00587*
	(0.00368)	(0.00332)	(0.00233)	(0.00413)	(0.00230)
Temperature (9 months post birth)	-0.00454	-0.00386	-0.00227	0.00008	-0.00258
	(0.00350)	(0.00372)	(0.00338)	(0.00379)	(0.00415)
Rainfall (9 months pre birth)	-0.00004	0.00058	0.00101	0.00217*	0.00054
	(0.00073)	(0.00081)	(0.00061)	(0.00089)	(0.00078)
Rainfall (9 months post birth)	0.00043	0.00090	0.00083	0.00045	0.00101
	(0.00055)	(0.00065)	(0.00048)	(0.00112)	(0.00072)
Observations	1001088	1001088	1001088	355436	645603
R-squared	0.076	0.077	0.078	0.099	0.080
Year Fixed Effects	Yes	No	No	No	No
Region-Year Fixed Effects	No	Yes	No	No	No
Province-Year Fixed Effects	No	No	Yes	Yes	Yes
Month-Canton Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: Log Earnings (2010). Sample includes individuals born between 1950 and 1979 who earned formal sector income in the year 2010. Each column presents coefficients from a separate regression estimated using OLS. Standard errors in parentheses are clustered by canton and province-year. Stars indicate confidence levels:* p<0.05, ** p<0.01, *** p<0.001.

Table 4: Educational Attainment, Summary Statistics

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 1979 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.

Table 5: Educational Attainment

	(1)	(2)	(3)
	All	Females	Males
	Secondary Education		
Temperature (9 months pre birth)	-0.00282	-0.00300	-0.00219
	(0.00153)	(0.00310)	(0.00156)
Temperature (9 months post birth)	-0.00156	-0.00409	0.00107
	(0.00170)	(0.00267)	(0.00191)
Rainfall (9 months pre birth)	0.00024	0.00067	0.00006
	(0.00024)	(0.00044)	(0.00032)
Rainfall (9 months post birth)	0.00061*	0.00090	0.00042
	(0.00029)	(0.00053)	(0.00035)
Observations	1001088	355436	645603
R-squared	0.136	0.094	0.118
	Higher Education		
Temperature (9 months pre birth)	-0.00207	-0.00462**	0.00011
	(0.00113)	(0.00147)	(0.00152)
Temperature (9 months post birth)	-0.00132	-0.00152	-0.00071
	(0.00112)	(0.00158)	(0.00132)
Rainfall (9 months pre birth)	0.00021	0.00059	-0.00000
	(0.00029)	(0.00052)	(0.00029)
Rainfall (9 months post birth)	0.00035	0.00091	0.00013
	(0.00028)	(0.00056)	(0.00028)
Observations	1001088	355436	645603
R-squared	0.094	0.060	0.089

Notes: Independent variable: completion of secondary (top panel) and higher (bottom panel) education. Sample includes individuals born between 1950 and 1979 who earned formal sector income in the year 2010. Each column presents coefficients from a separate regression estimated using OLS that includes province-year fixed effects and month-canton fixed effects. Standard errors in parentheses are clustered by canton and province-year. Stars indicate confidence levels:* p<0.05, ** p<0.01, *** p<0.001.

Table 6: Cohort Size

	(1)	(2)	(3)
	All	Females	Males
	Total Cohort Size		
Temperature (9 months pre birth)	-0.0396*	-0.0339*	-0.0407***
	(0.0159)	(0.0154)	(0.0144)
Temperature (9 months post birth)	-0.0252	-0.0216	-0.0220
	(0.0176)	(0.0161)	(0.0167)
Rainfall (9 months pre birth)	0.00116	0.00135	0.000667
	(0.00380)	(0.00310)	(0.00338)
Rainfall (9 months post birth)	-0.000512	-0.000966	-0.000136
	(0.00266)	(0.00241)	(0.00237)
Observations	49689	48592	48397
R-squared	0.926	0.915	0.914
	Formal Sector Cohort Size		
Temperature (9 months pre birth)	-0.0308**	-0.0287**	-0.0333***
	(0.00960)	(0.00987)	(0.00861)
Temperature (9 months post birth)	-0.0169	-0.00163	-0.0140
	(0.0126)	(0.0134)	(0.0118)
Rainfall (9 months pre birth)	-0.00246	-0.00433*	-0.000319
	(0.00210)	(0.00195)	(0.00201)
Rainfall (9 months post birth)	-0.000785	-0.000640	-0.000419
	(0.00179)	(0.00134)	(0.00176)
Observations	43441	34905	41066
R-squared	0.900	0.863	0.883

Notes: Independent variable: (Log) cohort size in the civil registry (top panel) and formal sector sample (bottom). Sample includes all cohorts born between 1950 and 1979. Each column presents coefficients from a separate regression estimated using OLS that includes province-year fixed effects and month-canton fixed effects. Standard errors in parentheses are clustered by canton and province-year. Stars indicate confidence levels:* p<0.05, ** p<0.01, *** p<0.001.

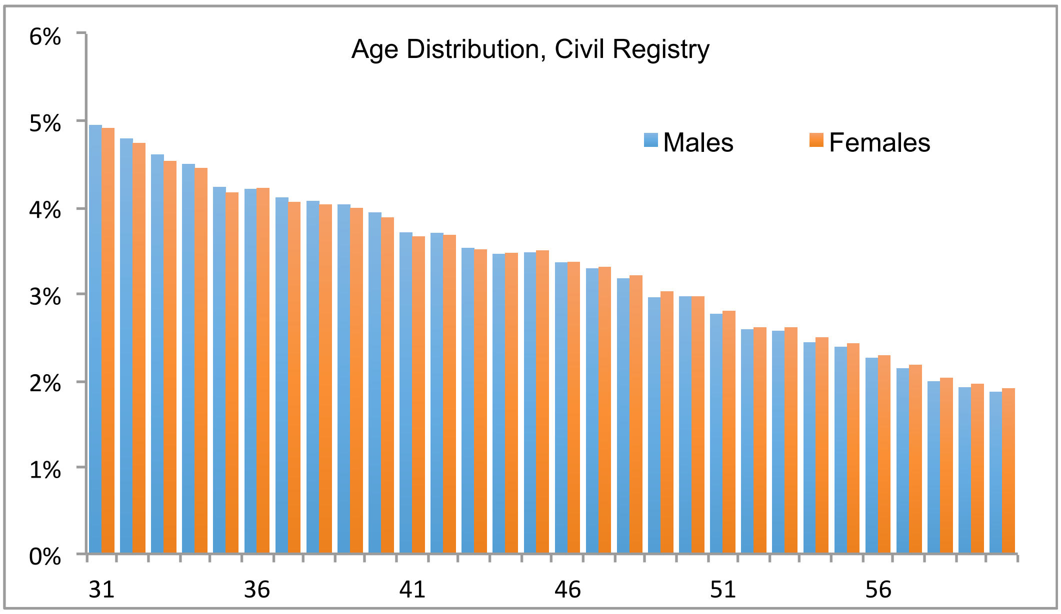
Table 7: Selection into the Formal Sector

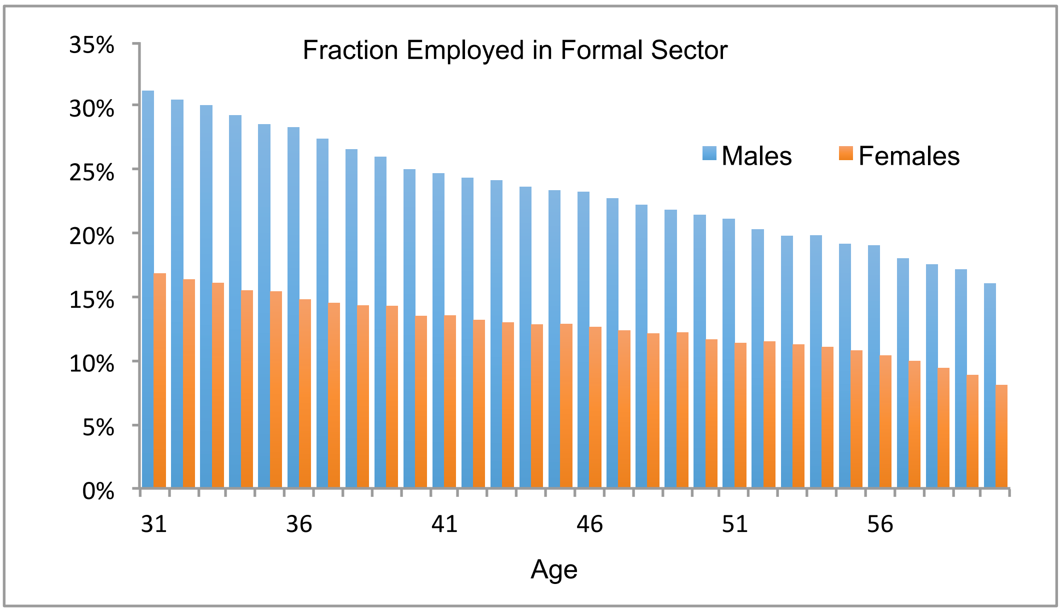
	(1)	(2)	(3)
	All	Females	Males
Temperature (9 months pre birth)	0.00050	0.00026	0.00073
	(0.00104)	(0.00119)	(0.00108)
Temperature (9 months post birth)	0.00094	0.00222**	-0.00033
	(0.00066)	(0.00080)	(0.00082)
Rainfall (9 months pre birth)	0.00005	-0.00005	0.00019
	(0.00016)	(0.00019)	(0.00018)
Rainfall (9 months post birth)	0.00017	0.00018	0.00016
	(0.00012)	(0.00013)	(0.00017)
Observations	5416801	2717137	2699658
R-squared	0.051	0.034	0.035

Notes: Independent variable: a binary indicator of participation in the formal sector. Sample includes all individuals in the civil registry that were born between 1950 and 1979. Each column presents coefficients from a separate regression estimated using OLS (linear probability models) that includes province-year fixed effects and month-canton fixed effects. Standard errors in parentheses are clustered by canton and province-year. Stars indicate confidence levels:* p<0.05, ** p<0.01, *** p<0.001.

Appendix Figures and Tables

Figure A1: Additional Summary Statistics





Top: The age distribution of the civil registry sample for males and females. **Bottom**: The probability, by age and gender, of being employed in the formal sector.

Table A1.1: Standardised Earning Score (Z-score)

	(1)	(2)	(3)	(4)	(5)	(6)
	Combined		Females		Males	
Temperature (9 months pre birth)	-0.00641**	-0.00602**	-0.00908**	-0.00884**	-0.00440	-0.00422
	(0.00235)	(0.00222)	(0.00273)	(0.00275)	(0.00306)	(0.00312)
Temperature (9 months post birth)	-0.00205	-0.00144	0.00150	0.00188	-0.00332	-0.00309
	(0.00266)	(0.00267)	(0.00351)	(0.00384)	(0.00408)	(0.00403)
Rainfall (9 months pre birth)	0.000957	0.00110	0.00196	0.00191	0.000519	0.000765
	(0.000763)	(0.000825)	(0.00121)	(0.00122)	(0.000862)	(0.000957)
Rainfall (9 months post birth)	0.000350	0.000304	0.000474	0.000134	0.000331	0.000451
	(0.000511)	(0.000539)	(0.00111)	(0.00109)	(0.000637)	(0.000703)
Outcome of Z score within:	Region-Year	Province-Year	Region-Year	Province-Year	Region-Year	Province-Year
N	1001088	1001086	355436	355436	645603	645603
R-sq	0.038	0.024	0.040	0.026	0.044	0.028

Notes: Independent variable: the Z-score of earning calculated within region-year cohorts (columns 1,3,5) or province-year cohorts (columns 2,4,6). Sample includes individuals born between 1950 and 1979 who earned formal sector income in the year 2010. Each column presents coefficients from a separate regression estimated using OLS that includes canton-month and province-year fixed effects. Standard errors in parentheses are clustered at the canton and region-year levels. Stars indicate confidence levels: * p<0.05, ** p<0.01, *** p<0.001.

Table A1.2: Standardised Earning Score (Z-score)

	(1)	(2)	(3)	(4)	(5)	(6)
	Belong to Upper Part of the Earning Distribution			Belong to Lower Part of the Earning Distribution		
	All	Females	Males	All	Females	Males
Temperature (9 months pre bi	-0.00207	-0.00359*	-0.00098	0.00387***	0.00403***	0.00353*
	(0.00104)	(0.00137)	(0.00129)	(0.00100)	(0.00106)	(0.00140)
Temperature (9 months post b	-0.00094	0.00127	-0.00189	0.00167	0.00051	0.00174
	(0.00113)	(0.00157)	(0.00185)	(0.00159)	(0.00132)	(0.00201)
Rainfall (9 months pre birth)	0.00040	0.00049	0.00034	-0.00063*	-0.00117**	-0.00046
	(0.00030)	(0.00046)	(0.00041)	(0.00028)	(0.00040)	(0.00037)
Rainfall (9 months post birth)	0.00027	0.00014	0.00034	-0.00037	-0.00032	-0.00046
	(0.00024)	(0.00048)	(0.00032)	(0.00029)	(0.00039)	(0.00036)
Observations	1001088	355436	645603	1001088	355436	645603
R-squared	0.034	0.040	0.040	0.027	0.040	0.030

Notes: Independent variable: Binary indicators of belonging to the upper (Columns 1-3) or lower (Columns 4-6) portions (at least 0.5 standard deviation above or below the mean) of the earning distribution within each region-year. Sample includes individuals born between 1950 and 1979 who earned formal sector income in the year 2010. Each column presents coefficients from a separate regression estimated using OLS that includes canton-month and province-year fixed effects. Standard errors in parentheses are clustered at the canton and region-year levels. Stars indicate confidence levels: * p<0.05, ** p<0.01, *** p<0.001.

Table A2:Inclusion of Young Cohorts

	(1)	(2)	(3)
	All	Females	Males
Temperature (9 months pre birth)	-0.00730*	-0.00919*	-0.00567
	(0.00309)	(0.00431)	(0.00337)
Temperature (9 months post birth)	-0.00392	-0.00092	-0.00514
	(0.00347)	(0.00389)	(0.00407)
Rainfall (9 months pre birth)	0.00127*	0.00234***	0.00072
	(0.00062)	(0.00046)	(0.00075)
Rainfall (9 months post birth)	0.00081	0.00057	0.00087
	(0.00045)	(0.00086)	(0.00072)
Observations	1637571	580112	1057430
R-squared	0.149	0.176	0.144

Notes: Independent Variable: (Log) Earnings in 2010. Sample includes individuals born between 1950 and 1989 who earned formal sector income in the year 2010. Each column presents coefficients from a separate regression estimated using OLS that includes region-year and month-canton fixed effects. Standard errors in parentheses are clustered at the province level. Stars indicate confidence levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A3: Cohort Size by Province and Canton

	(1)	(2)	(3)	(4)
	Males		Females	
	Canton	Province	Canton	Province
Average Temperature, 9 months before birth (C)	-0.0310	-0.0345	-0.0234	-0.0228
	(0.0180)	(0.0251)	(0.0195)	(0.0280)
Average Temperature, 9 months after birth (C)	-0.0103	0.00284	-0.0204	-0.0160
	(0.0234)	(0.0245)	(0.0215)	(0.0219)
Average Rainfall, 9 months before birth (cm/month)	-0.00164	0.00072	-0.00120	0.00000
	(0.00218)	(0.00323)	(0.00210)	(0.00206)
Average Rainfall, 9 months after birth (cm/month)	-0.00113	-0.00297	-0.00162	-0.00191
	(0.00177)	(0.00151)	(0.00195)	(0.00115)
N	48474	8274	48670	8274
R-sq	0.903	0.972	0.905	0.974

Notes: Independent variable: Cohort size, determined at the year and month of birth and the canton (in Columns 1 and 3), or the province level, in (Columns 2 and 4). Sample includes cohorts born between 1950 and 1979. Each column reports estimates from a separate regression that includes region-year fixed effects and month-canton (columns 1,3) or month-province (Columns 2,4) fixed effects. Standard errors in parentheses are clustered at the province level. Stars indicate confidence levels: * p<0.05, ** p<0.01, *** p<0.001.