

Long-term effects of weather during gestation on education and labor outcomes: Evidence from Peru

Manuel Barron Sam Heft-Neal Tania Perez

Working Paper No. 134, December 2018

The views expressed in this working paper are those of the author(s) and not those of the Peruvian Economic Association. The association itself takes no institutional policy positions.

Long-term effects of weather during gestation on education and labor outcomes: Evidence from Peru

Manuel Barron

Sam Heft-Neal

Tania Perez

December 2018*

Abstract

Extensive evidence shows that weather conditions during gestation affect birth outcomes and early childhood development in the developing world. Pairing weather data during gestation with education and labor outcomes for more than one million people, we show that in-utero weather has lasting effects through adulthood: temperature during gestation affects schooling attainment, earnings, and access to formal employment among females in Peru, but not among males. We identify maternal anemia as a key driver of these outcomes. Our findings suggest that the persistent negative effects of temperature around birth can be mitigated through improved health services for vulnerable mothers.

JEL codes: I12, I21, J16, O15

Keywords: Climate Change, Human Capital Formation, Labor Markets.

^{*}Barron: Universidad del Pacifico, Department of Economics; Heft-Neal: Standford University, Center on Food Security and the Environment; Perez: Universidad del Pacifico, Research Center. **Acknowledgments**: We have benefited from comments by participants at the Heartland Environmental and Resource Economics Workshop (University of Illinois at Urbana-Champaign), Economics Department Seminar at Universidad del Pacífico, and at the Annual Congress of the European Economic Association (University of Lisbon). We are especially indebted to Erica Myers, Ben Crost, and Juan Castro for invaluable suggestions. Perez is currently at Universidad de Chile. Any errors remain our own.

1 Introduction

A compelling body of evidence shows that weather conditions during the prenatal period affect birth outcomes¹ and early childhood development² across a variety of settings in the developing world. One of the main drivers of these effects is weather shocks that affect maternal nutrition and health-seeking behavior through negative income shocks or food price increases (Hoddinott, 2006; Skoufias, Vinha, and Conroy, 2011; Kim and Lafortune, 2010; Rosales, 2014), increasing the prevalence and severity of maternal anemia. Maternal anemia has been linked to early iron deficiency during brain development (Lozoff and Georgieff, 2006) and even into the first year of life (Allen, 2000; McCann and Ames, 2007). In turn, early iron deficiency hinders cognitive development during adolescence (Lozoff et al., 2006) and has negative effects on adult health (Godfrey and Barker, 2000, 2001).

There is still scarce evidence on the long-term economic effects of weather during the gestational period,³ but the preceding discussion suggests the effects may be severe. In a seminal paper, Maccini and Yang (2009) show that positive rainfall shocks during early life affect health, schooling, and wealth among Indonesian females during adulthood, with no significant effects among males. Millett and Shah (2012) show that children exposed to droughts during gestation in rural India score significantly worse on math and reading tests. In turn, Hu and Li (2016) show that high temperature days during pregnancy reduce schooling and height during adulthood in China. On the other hand, in a sample of Ecuadorian formal sector workers, Fishman, Russ, and Carrillo (2015) find statistically significant but small effects of in-utero temperature on female earnings.

Our paper contributes to this strand of literature by examining the effects of weather

¹See for example Yamauchi (2012); Pereda, Menezes, and Alves (2014); Rocha and Soares (2015); Molina and Saldarriaga (2017); Hu and Li (2016); Andalón et al. (2014); Kudamatsu, Persson, and Strömberg (2012).

²See for example Skoufias and Vinha (2012); Lokshin and Radyakin (2012); Rosales (2014); Kumar, Molitor, and Vollmer (2014); Mendiratta (2015); Aguilar and Vicarelli (2011); Skoufias, Vinha, and Conroy (2011); Rocha and Soares (2015); Rose (1999)

³Other studies analyze long-term effects of early life or prenatal exposure to pollution shocks (e.g. Jayachandran, 2009; Rau, Urzúa, and Reyes, 2015; Bharadwaj et al., 2014; Miller and Vela, 2013), radioactive fallout (Black et al., 2013), Ramadan (Almond, Mazumder, and Ewijk, 2015), well-child visits (Butikofer, Løken, and Salvanes, 2015).

during gestation on human capital accumulation and labor market outcomes in Peru, an especially important setting within the context of global climate impacts since it has been deemed third, after Bangladesh and Honduras, in climate hazard risks by the Tyndall Centre for Climate Change Research. To this end, we combine gridded data on temperature and precipitation from the Climatic Research Unit at the University of East Anglia with household survey data from the 2001-2015 National Household Surveys, aggregating information for over one million individuals born from 1950 onwards. We complement these data sources with the 2004-2015 Demographic and Health Surveys, which provide rich information on maternal health status and health-seeking behavior.

Our main outcome variables are schooling, earnings, and access to formal employment. Our main explanatory variables are average in-utero temperature (temp) and total in-utero precipitation (*precip*). We estimate step functions, which allow for flexibility in the relation between weather variables and the outcomes of interest. Our main outcome variables vary in response to temp, but are largely unaffected by precip. Exposure to temp below 10C reduces schooling by 0.3 years relative to the group exposed to temp between 17.5-20C ("thermal comfort"). The effect decreases monotonically for ranges of *temp* closer to thermal comfort, to 0.1-0.2 years for temp between 10.0 and 17.5C, and is not significant for temp above 20C. The effects on males are smaller in magnitude and not statistically significant for any range of *temp*. These gender differences are consistent with previous findings (Maccini and Yang, 2009; Fishman, Russ, and Carrillo, 2015). Similar patterns arise in the probability of completing primary and secondary school. The negative effects on education reverberate on key labor market outcomes, including earnings and the probability of being formally employed. Exposure to temp below 10C reduces female income during adulthood by 0.1 standard deviations and access to formal employment by 2.6 percentage points. As in the case of schooling, the effects decrease monotonically as *temp* approaches thermal comfort, and are not significant among males.

The key mediating channel we explore, as suggested by the medical literature, is ma-

ternal health, in particular maternal anemia, and health-seeking behavior. As mentioned above, maternal anemia leads to negative birth outcomes with long term consequences for health and cognitive development (for review studies, see Allen, 2000; Steer, 2000; Bhutta et al., 2005). We find that exposure to colder weather during pregnancy increases maternal anemia prevalence, but exclusively among poor women. Our data suggests that this is due to changes in health-seeking behavior, as non-poor pregnant women respond to colder weather by increasing their number of antenatal visits and their intake of iron supplements, while poor pregnant women show no evidence of this behavior.⁴

We offer four main contributions to the literature of long-term effects of in-utero weather fluctuations. First, we explore the role of temperature and precipitation levels, while most existing studies focus on extreme events, like droughts, heat days, or shocks (usually defined as one standard deviation above or below the temperature or precipitation trend). Second, our data includes people aged 0-65, allowing us to measure final educational outcomes and labor market outcomes across the entire lifespan. Third, our data allows us to explore mediating channels suggested by the medical literature. Fourth, average in-utero temperature in our sample has a wide range, from 2.5 to 27.5C, and the large number of observations in our datasets provides support across this range of exposures including areas with cold baseline temperatures. Large variability in the explanatory variable, paired with adequate support, allows us to explore the nature of the relationship between in-utero temperature and our outcome variables and mediating channels closely.

Collectively, our findings indicate that temperature during gestation can have lasting negative impacts on education and labor market outcomes and that health channels contribute to these outcomes. These impacts are borne primarily by vulnerable groups, and hence policies aimed at reducing vulnerability for pregnant women are likely to have lasting

⁴Antenatal visits are important in this context because pregnant women receive iron supplements during these visits. Menendez et al. (1994) Menendez et al (1994) find that adequate iron supplementation can increase birth weight by up to 100 grams. Rasmussen (2001) reviews other studies that do not find a relation between iron supplementation and birth outcomes, but concludes that the possibility of false negatives is high, either because the study population had adequate values for baseline hemoglobin or because the iron provided was insufficient to cure anemia.

impacts on the child's long-term economic outcomes.

2 Data and Study Setting

The three main data sources we rely on are ENAHO (Peru's National Household Survey), ENDES (Peru's Demographic and Health Survey), and CRU's temperature and precipitation data set. ENAHO has been collected annually since the late 1990s by INEI, Peru's Bureau of Statistics. We exploit data from the 2001-2015 surveys, pooling together over one million observations. Importantly for our purpose, the survey includes information on the district and date of birth, together with a wealth of socio-economic outcomes at the time of the survey. District coordinates are also available from INEI, which allows matching household survey (at the district level) and weather data. Peru's DHS, also collected annually by INEI, includes information on maternal health and health-seeking behavior. In particular, starting in 2004 the DHS contains hemoglobin measurements for a random sample of pregnant women. We pool DHS data from 2004 to 2015 and link temperature during pregnancy to maternal health status and health-seeking behavior. It is worth noting that the available data provide information only about pregnancies from the year 2004 onwards, which constitutes an important limitation of our study. The weather data was obtained from the Climatic Research Unit at the University of East Anglia. We extracted monthly weather values from 1950 onward. The data has a resolution of $0.5 \ge 0.5$ degrees (Mitchell and Jones, 2005). Since districts typically cover parts of multiple grid cells, we take the area-weighted average values of the grid cells overlapping the district. Figure 1 plots average weather conditions per district for the 1950-2015 period.

Table 1 shows the main descriptive statistics on schooling and employment. The literacy rate in the sample is 84 percent, and the figure is higher for males (87 percent) than for females (82 percent). Average schooling in the sample is 7.1 years, 7.4 for males and for 6.8 for females. Eight percent of the population has no formal schooling, 59 percent has

completed at least primary school and 33 percent has completed secondary school. Males are more likely to have completed either of these levels than females. Average monthly real income (in *Soles*, using Lima 2015 as base) is S/.858 for males and S/.526 for females (S/.1.00 \approx US\$0.30 in 2015). While 23 percent of males are formally employed, the figure for females is only 12 percent.

Table 2 shows descriptive statistics on health status and health seeking behavior of pregnant women, split by poverty status. Twenty-eight percent of pregnant women were found to be anemic. Iron supplements are recommended in all pregnancies (Allen, 2000) because they have been widely shown to reduce anemia prevalence and incidence⁵, but only 77 percent of pregnant women in the sample reported having taken iron supplements at some point during their pregnancy, for an average duration of 55 days. The last panel in Table 2 shows that most pregnant women (96 percent) had at least one antenatal care visit. The figure for poor women is slightly lower than for non-poor women, at 95 and 99 percent, respectively. On average, the first visit took place shortly before the third month of pregnancy, and women averaged 7.8 visits across the duration of their pregnancy, with poor women reporting their first visit 0.6 months later than non-poor women, and 1.5 fewer visits in total.

3 Empirical Approach

Our estimating equations allow for considerable flexibility regarding the nature of the relationship between weather variables and the outcomes of interest. Our main estimating equation is of the form:

$$y_{idbt} = \beta_0 + \sum_j \beta_j \times I(\text{Temp}=j)_{idbt} + \sum_k \delta_k \times I(\text{Precip}=k)_{idbt} + \gamma_d + \gamma_b + \gamma_t + \mu_d \times t + \varepsilon_{ipbt}$$
(1)

⁵Studies reviewed in Bhutta et al. (2005).

where y is the outcome of interest for individual *i* born in district *d* on date b,⁶ and surveyed in year *t*. Temperature is measured in degrees Celsius, and precipitation in millimeters. Temperature is binned at 2.5C intervals. We use the bin that includes 18C (\approx 65F) which is usually deemed as "thermal comfort", as a comparison category. Precipitation, on the other hand, is binned in 50mm intervals. There is no natural comparison category, but we use 0-50mm. Hence, the comparison category is people exposed to average in-utero temperature of 17.5-20C, and with less than 50mm of rain.

The specification includes fixed effects for district of birth, date of birth, and year of the survey. In words, we compare outcomes across individuals born in the same district, controlling for economy-wide shocks at the time of their birth, and the year they were surveyed. In addition we include district-specific linear time trends to account for changes in outcomes from 1950 to 2015. After controlling for fixed effects as described above, if monthly variations around the trend are exogenous to the individual, OLS provides consistent and unbiased estimates for β and δ . Thus, our identification assumption, similar to Schlenker and Roberts (2009), is that controlling for all other district characteristics and time trends, weather is as good as randomly assigned. To account for spatial correlation of weather, standard errors are clustered at the province level.⁷

We explore maternal health and health-seeking behavior during pregnancy as main mediating channels. To that end, we use the DHS data on iron intake, anemia prevalence, number of antenatal visits, and month of first antenatal visit. The equation is of the form:

$$y_{idbt} = \beta_0 + \sum_j \beta_j \times I(\text{pregtemp}=j)_{idbt} + \sum_k \delta_k \times I(\text{pregprecip}=k)_{idbt} + \gamma_d + \gamma_b + \gamma_t + \mu_d \times t + \varepsilon_{ipbt}$$
(2)

, where y_{idbt} denotes the outcome of interest for pregnancy *i*, in district *d*, with delivery on date *b*, and surveyed in year *t*. The variables *pregtem* and *pregprecip* denote the 9-month

⁶Date of birth is month and year of birth, e.g. May 1979

⁷There are 196 provinces in the country, which group approximately 10 districts each.

temperature and precipitation averages leading to the delivery. We include the same fixed effects and trends as in equation (1), and cluster the standard errors at the province level.

4 Results

4.1 Schooling

Table 3 and Figure 2 report the main results in the paper. The dependent variable is years of schooling. Column 1 shows the results for the whole sample, while columns 2 and 3 split the sample by gender. Our main finding, and a result that comes up recurrently in the following analysis, is that average in-utero temperature (temp) affects female outcomes but not male outcomes.⁸ Column 2 shows that lower average in-utero temperature (temp) reduces female schooling compared with the comparison category (17.5-20C). The difference is largest at the lowest values of temp (below 10C), at 0.32-0.36 years. This difference decreases monotonically as the temperature increases towards the comparison category, to 0.18 for $10 < temp \leq 12.5$, 0.13 for $12.5 < temp \leq 15$, and 0.11 for $15 < temp \leq 17.5$. There are no statistically significant effects for females with temp > 20, although the confidence intervals do not allow to conclude null effects.

In Table 4 we analyze if *temp* affects the probability of graduating from primary and secondary school. This analysis also allows exploring whether the effects of *temp* happen at the higher or lower end of the schooling distribution. Consistently with the previous table, the effects on males are close to zero and have no statistical significance, but lower values of *temp* decrease the likelihood that females finish primary and secondary school, with magnitudes that follow the same pattern as Table 3. Relative to the comparison category, values of *temp* below 10C reduce the probability of finishing primary by 4-5 percentage points, and the probability of finishing secondary by 3-4 percentage points. These effects

 $^{^{8}}$ In these and the following tables, the coefficients on *precip* result not statistically significant and thus are not discussed in the main text.

decrease monotonically as *temp* approaches the comparison category, and with no significant effects for *temp* above it.

4.2 Labor Market Outcomes

Table 5 and Figure 3 show that the schooling effects reported in the previous section have sizable repercussions in standardized earnings. Following the pattern found in education, while *temp* does not affect male earnings during adulthood, females born in the lowest bins of *temp* have significantly lower earnings during adulthood than the comparison category. Being exposed to *temp* below 10C reduces earnings by 0.09-0.10 standard deviations. As in the case of schooling, the effect decreases monotonically for observations closer to the comparison category. The difference with the comparison category is 0.05 standard deviations in the 10.0-12.5 *temp* bin, and about 0.03 standard deviations for *temp* between 12.5 and 17.5C. Marginal effects for males are smaller in magnitude and, with two exceptions, not statistically significant. As a robustness check we constructed real income (in Soles of 2015 Lima), with similar results.

To complement the findings on earnings we examine access to formal employment. In Peru, as in most developing countries, formal employment is a good indicator of job quality, as the informal sector, which accounts for a large fraction of jobs, offers low, unsteady wages, no pension plans or other benefits. Thus, these variable is also an indicator for having a pension plan. Results, reported in Table 6, show the same pattern as all the previously reported outcomes: colder temperatures during gestation reduce the probability of being formally employed for females but not for males. Being exposed to *temp* below 10C reduces the probability of having formal employment during adulthood by 3 percentage points relative to the comparison category. The point estimates decrease to 1-2 percentage points for bins closer to the comparison category. Only 12 percent of females are formally employed, so these effects are sizable. As in previous outcomes, variations in *temp* have no effect on access to formal employment among males.

4.3 Mechanisms

The main mediating channel we examine is maternal health and health-seeking behavior. In this and the following tables, the explanatory variable is average temperature during pregnancy, *pregtemp*. Table 7 and Figures 4- 6, report results on the prevalence of maternal anemia and iron intake by poverty status. In this and the following tables we present the results of equation (3). Columns (1) and (2) show that maternal anemia prevalence increases in response to higher *pregtemp*, but only among women from poor households. The effects are largest for the lowest values of *pregtemp*, with a 1C increase in *pregtemp* increasing maternal anemia prevalence by 60-80 percentage points in bins below 7.5C, by 40-50 percentage points in the 7.5-12.5C bins, and 30 percentage points in the 12.5-15C bin. The effect becomes non significant for *pregtemp* above 15C. There is extensive evidence that iron supplementation reduces maternal anemia (Bhutta et al., 2005). Columns (3) and (4) show that, while poor women do not change iron intake in response to variations in *pregtemp*, non-poor women with *pregtemp* up to 17.5C increase iron intake in response to higher *pregtemp*, possibly explaining why anemia prevalence in this group does not respond to changes in temperature during pregnancy.

Among non-poor women exposed to *pregtem* below 10C, the share of pregnant women taking iron supplements increases in response to 1C higher *pregtemp* by 25-35 percentage points. The effect reduces monotonically for values of *pregtemp* closer to thermal comfort, from 17 percentage points in the 10.0-12.5C bin, to 4 percentage points in the 15-17.5C bin. Furthermore, columns (5) and (6) show an increase in the number of days taking iron, from 30 additional days in *pregtemp* below 10C, to 21 days for *pregtemp* between 10.0 and 12.5C. On the other hand, women from poor households do not exhibit this behavior, with a couple of exceptions.⁹

In Table 8 and Figure 7 we analyze the effects of *preqtemp* on antenatal care. Changes in

⁹Poor pregnant women in the 15-17.5C *pregtemp* bin increase the percentage taking iron supplements by 6 percentage points, and poor pregnant women with *pregtemp* between 12.5 and 17.5C increase the number of days taking iron supplements by 18-21 days for pregnancies with *pregtemp* between 12.5 and 17.5C.

pregtemp do not statistically affect the probability of having at least one antenatal care visit among poor women. The likelihood of having at least one visit increases by 2 percentage points among non-poor women in the 7.5-10C and 12.5-15.0C pregtemp bins, and by 1-2 percentage points in the pregtemp bins above 20C. However, temperature does not affect the timing of the first visit, with the exception of the 12.5-15.0C pregtemp bin among nonpoor women, who have their first visit roughly a week earlier than the comparison category. Despite the effects are not statistically significant among poor women, the coefficients are too large to conclude a null effect. Fluctuations in pregtemp also have an effect on the number of antenatal visits. Non-poor women from cold areas respond to higher temperatures by increasing the number of antenatal visits. Females in the 7.5-10 and 10-12.5C pregtemp bins have 1.3 and 1 additional visits, respectively, than the comparison category. The number of visits among poor women, on the other hand, does not change. The marginal effects are not significant (with one exception, at the 10% of confidence) and the point estimates in the coldest bins (up to 12.5C) are negative.

Summing up, the evidence in Tables 7 and 8 collectively suggests that non-poor women are able to, at least partially, mitigate the effects of colder temperature. Their intake of iron pills is increased, reducing anemia prevalence, as well as the number of antenatal visits. However, their counterparts from poor households do not exhibit these behaviors, and in consequence anemia prevalence is higher than the comparison category.

5 Conclusions

This paper shows that temperature during gestation has sizable effects on human capital accumulation among females in Peru. The effects on males are smaller in magnitude and not statistically significant. Females exposed to average in-utero temperature under 10C lose 0.3 years of schooling relative to the comparison category (*temp* between 17.5-20C). Consistent with previous studies, temperature during gestation plays a more important role

than precipitation, which has no significant effects on the variables under analysis.

The large effects on schooling we document are reflected in labor market outcomes. Females exposed to *temp* below 10C report average labor income 0.10 standard deviations lower than the comparison category, and their probability of being formally employed is 25% lower (3 percentage point reduction, off of a mean of 12 percent).

Maternal health and health-seeking behavior during pregnancy seem to be an important mediating channel for these outcomes. Maternal anemia prevalence is higher among women who had pregnancies in cold temperatures in than in the comparison category, but only among poor women. Non-poor women, on the other hand, adjust their behavior in response to cold weather and mitigate the effects of temperature on maternal anemia, for instance, by increasing iron supplement intake and the number of antenatal visits. As a result, the prevalence of maternal anemia is unaltered by temperature for this group.

Unlike the patterns that appear for females, the effects of *temp* on male education and labor outcomes are small and not statistically significant. This suggests households take measures to mitigate the effects of *temp* on their sons' development. Furthermore, since weather shocks increase maternal anemia among poor women but apparently not the development of their sons, our findings suggest that even poor households put in place mitigation mechanisms to allow their sons to catch up. Further research is necessary to corroborate this corollary, and to understand the underlying causes behind it.

Our study has two important caveats. First, the available data on the mediating channels starts only in 2004, not in 1950 like the data on schooling attainment and employment. Second, our data does not allow to identify whether the changes in maternal health and health-seeking behavior are due to supply or demand bottlenecks. A further caveat of our study is that the effects of high *temp* are indeterminate. Despite some coefficients are positive, the confidence intervals are too wide to rule out negative effects. This is due to two facts: (i) There are fewer clusters in the right tail of the *temp* distribution, and (ii) the sample does not include extremely high values of *temp*.

However, a clear policy implication stems from our findings: efforts to promote iron intake among pregnant women should be boosted, especially in cold regions. Besides our findings, other literature suggests that investments during gestation offer the highest payoffs, because their benefits are larger, are enjoyed for longer, and increase the return to investment (Doyle et al., 2009) as early investment raises the productivity of later investment (Heckman, 2006).

References

- Aguilar, Arturo and Marta Vicarelli. 2011. "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*.
- Allen, Lindsay H. 2000. "Anemia and iron deficiency: effects on pregnancy outcome." *The American journal of clinical nutrition* 71 (5):1280s–1284s.
- Almond, Douglas, Bhashkar Mazumder, and Reyn Ewijk. 2015. "In utero Ramadan exposure and children's academic performance." *The Economic Journal* 125 (589):1501–1533.
- Andalón, Mabel, Carlos Rodriguez-Castelan, Viviane Sanfelice, Joao Pedro Azevedo, and Daniel Valderrama. 2014. "Weather shocks and health at birth in Colombia." World Bank Policy Research Working Paper (7081).
- Bharadwaj, Prashant, Matthew Gibson, Joshua Graff Zivin, and Christopher A. Neilson. 2014. "Gray Matters: Fetal Pollution Exposure and Human Capital Formation." Working Paper 20662, National Bureau of Economic Research. URL http://www.nber.org/papers/w20662.
- Bhutta, Zulfiqar A, Gary L Darmstadt, Babar S Hasan, and Rachel A Haws. 2005. "Community-based interventions for improving perinatal and neonatal health outcomes in developing countries: a review of the evidence." *Pediatrics* 115 (Supplement 2):519–617.
- Black, Sandra E, Aline Bütikofer, Paul J Devereux, and Kjell G Salvanes. 2013. "This is only a test? long-run impacts of prenatal exposure to radioactive fallout." Tech. rep., National Bureau of Economic Research.
- Butikofer, Aline, Katrine Vellesen Løken, and Kjell G Salvanes. 2015. "Long-term consequences of access to well-child visits." .
- Doyle, Orla, Colm P Harmon, James J Heckman, and Richard E Tremblay. 2009. "Investing in early human development: timing and economic efficiency." *Economics & Human Biology* 7 (1):1–6.
- Fishman, Ram, Jason Russ, and Paul Carrillo. 2015. "Long-Term Impacts of High Temperatures on Economic Productivity." .
- Godfrey, Keith M and David JP Barker. 2000. "Fetal nutrition and adult disease." The American journal of clinical nutrition 71 (5):1344s-1352s.
- ———. 2001. "Fetal programming and adult health." Public health nutrition 4 (2b):611–624.
- Heckman, James J. 2006. "Skill formation and the economics of investing in disadvantaged children." *Science* 312 (5782):1900–1902.
- Hoddinott, John. 2006. "Shocks and their consequences across and within households in rural Zimbabwe." The Journal of Development Studies 42 (2):301–321.

- Hu, Zihan and Teng Li. 2016. "Too hot to hold: the effects of high temperatures during pregnancy on birth weight and adult welfare outcomes." .
- Jayachandran, Seema. 2009. "Air quality and early-life mortality evidence from Indonesias wildfires." Journal of Human Resources 44 (4):916–954.
- Kim, Yeon Soo and Jeanne Lafortune. 2010. "The Impact of Rainfall on Early Child Health."
- Kudamatsu, Masayuki, Torsten Persson, and David Strömberg. 2012. "Weather and infant mortality in Africa." .
- Kumar, Santosh, Ramona Molitor, and Sebastian Vollmer. 2014. "Children of drought: Rainfall shocks and early child health in rural India." *Available at SSRN 2478107*.
- Lokshin, Michael and Sergiy Radyakin. 2012. "Month of Birth and Children's Health in India." Journal of Human Resources 47 (1):174 203. URL http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=70502424& lang=es&site=ehost-live&scope=site.
- Lozoff, Betsy, John Beard, James Connor, Barbara Felt, Michael Georgieff, and Timothy Schallert. 2006. "Long-lasting neural and behavioral effects of iron deficiency in infancy." *Nutrition reviews* 64 (suppl_2):S34–S43.
- Lozoff, Betsy and Michael K Georgieff. 2006. "Iron deficiency and brain development." In Seminars in pediatric neurology, vol. 13. Elsevier, 158–165.
- Maccini, Sharon and Dean Yang. 2009. "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall." American Economic Review 99 (3):1006-26. URL http://www.aeaweb.org/articles?id=10.1257/aer.99.3.1006.
- McCann, Joyce C and Bruce N Ames. 2007. "An overview of evidence for a causal relation between iron deficiency during development and deficits in cognitive or behavioral function." The American journal of clinical nutrition 85 (4):931–945.
- Mendiratta, Vibhuti. 2015. "Impact of Rainfall Shocks on Child Health: Evidence from India." .
- Menendez, Clara, James Todd, Pedro L Alonso, N Francis, S Lulat, S Ceesay, B M'boge, and BM Greenwood. 1994. "The effects of iron supplementation during pregnancy, given by traditional birth attendants, on the prevalence of anaemia and malaria." *Transactions* of the Royal Society of Tropical Medicine and Hygiene 88 (5):590–593.
- Miller, Sebastian and Mauricio A Vela. 2013. "The Effects of Air Pollution on Educational Outcomes: Evidence from Chile." .
- Millett, Bryce and Manisha Shah. 2012. "The Effects of In-Utero Shocks on Cognitive Test Scores: Evidence from Droughts in India." .

- Mitchell, Timothy D and Philip D Jones. 2005. "An improved method of constructing a database of monthly climate observations and associated high-resolution grids." *International journal of climatology* 25 (6):693–712.
- Molina, Oswaldo and Victor Saldarriaga. 2017. "The perils of climate change: In utero exposure to temperature variability and birth outcomes in the Andean region." *Economics & Human Biology* 24:111–124.
- Pereda, Paula Carvalho, Tatiane Menezes, and Denisard CO Alves. 2014. "Climate Change Impacts on Birth Outcomes in Brazil." Tech. rep., IDB Working Paper Series.
- Rasmussen, Kathleen M. 2001. "Is there a causal relationship between iron deficiency or iron-deficiency anemia and weight at birth, length of gestation and perinatal mortality?" *The Journal of nutrition* 131 (2):590S–603S.
- Rau, Tomás, Sergio Urzúa, and Loreto Reyes. 2015. "Early Exposure to Hazardous Waste and Academic Achievement: Evidence from a Case of Environmental Negligence." *Journal* of the Association of Environmental and Resource Economists 2 (4):527–563.
- Rocha, Rudi and Rodrigo R. Soares. 2015. "Water scarcity and birth outcomes in the Brazilian semiarid." Journal of Development Economics 112:72 - 91. URL http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN= 99793506&lang=es&site=ehost-live&scope=site.
- Rosales, María Fernanda. 2014. "Impact of Early Life Shocks on Human Capital Formation: El Nino Floods in Ecuador." .
- Rose, Elaina. 1999. "Consumption smoothing and excess female mortality in rural India." *Review of Economics and statistics* 81 (1):41–49.
- Schlenker, Wolfram and Michael J Roberts. 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." Proceedings of the National Academy of sciences 106 (37):15594–15598.
- Skoufias, Emmanuel and Katja Vinha. 2012. "Climate variability and child height in rural Mexico." Economics & Human Biology 10 (1):54–73.
- Skoufias, Emmanuel, Katja Vinha, and Hector V Conroy. 2011. "The impacts of climate variability on welfare in rural Mexico." World Bank Policy Research Working Paper Series, Vol.
- Steer, Philip J. 2000. "Maternal hemoglobin concentration and birth weight." The American journal of clinical nutrition 71 (5):1285s–1287s.
- Yamauchi, Futoshi. 2012. "Prenatal Seasonality, Child Growth, and Schooling Investments: Evidence from Rural Indonesia." Journal of Development Studies 48 (9):1323 - 1341. URL http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN= 80232027&lang=es&site=ehost-live&scope=site.



Figure 1: Average weather conditions, 1950-2015

Notes: Dots represent each district's centroid. Source: Climatic Research Unit.



Figure 2: Marginal effect of in-utero temperature on schooling attainment

Notes: These figures illustrate the results of Table 3, columns (2) and (3). The vertical axis measures the marginal effect of a 1C increase in average in-utero temperature on schooling attainment. The comparison category is 17.5-20C. Dashed lines represent the 95% confidence bands (standard errors clustered at the province level). Sources: National Household Surveys, 2001-2015, and Climatic Research Unit.



Figure 3: Marginal effect of in-utero temperature on earnings during adulthood

Notes: These figures illustrate the results of Table 5, columns (2) and (3). The vertical axis measures the marginal effect of a 1C increase in average in-utero temperature on earnings during adulthood. The comparison category is 17.5-20C. Dashed lines represent the 95% confidence bands (standard errors clustered at the province level). Sources: National Household Surveys, 2001-2015, and Climatic Research Unit.

Figure 4: Marginal effect average temperature during pregnancy on prevalence of maternal anemia



(a) Poor

Notes: These figures illustrate the results of Table 7, columns (1) and (2). The vertical axis measures the marginal effect of a 1C increase in average temperature during pregnancy on anemia prevalence. The comparison category is 17.5-20C. Dashed lines represent the 95% confidence bands (standard errors clustered at the province level). Sources: Demographic and Health Surveys 2004-2015, and Climatic Research Unit.

Figure 5: Marginal effect of average temperature during pregnancy on probability of consuming iron supplements



(a) Poor

Notes: These figures illustrate the results of Table 7, columns (3) and (4). The vertical axis measures the marginal effect of a 1C increase in average temperature during pregnancy on the percentage of pregnant women that take iron supplements. The comparison category is 17.5-20C. Dashed lines represent the 95% confidence bands (standard errors clustered at the province level). Sources: Demographic and Health Surveys 2004-2015, and Climatic Research Unit.

Figure 6: Marginal effect of average temperature during pregnancy on consumption of iron supplements (days)



(a) Poor

Notes: These figures illustrate the results of Table 7, columns (5) and (6). The vertical axis measures the marginal effect of a 1C increase in average temperature during pregnancy on the number of days pregnant women took iron supplements. The comparison category is 17.5-20C. Dashed lines represent the 95% confidence bands (standard errors clustered at the province level). Sources: Demographic and Health Surveys 2004-2015, and Climatic Research Unit.

Figure 7: Marginal effect of average temperature during pregnancy on number of prenatal care visits



(a) Poor

Notes: These figures illustrate the results of Table 8, columns (5) and (6). The vertical axis measures the marginal effect of a 1C increase in average temperature during pregnancy on the number of prenatal care visits. The comparison category is 17.5-20C. Dashed lines represent the 95% confidence bands (standard errors clustered at the province level). Sources: Demographic and Health Surveys 2004-2015, and Climatic Research Unit.

	All	Female	Male
Education			
Years of Schooling	7.12	6.80	7.44
	(4.84)	(4.92)	(4.73)
Literacy rate	0.84	0.82	0.87
	(0.36)	(0.39)	(0.34)
No schooling $(\%)$	0.08	0.10	0.07
	(0.28)	(0.30)	(0.25)
Complete primary (%)	0.59	0.56	0.63
、 、 ,	(0.49)	(0.50)	(0.48)
Complete secondary (%)	0.33	0.31	0.35
- • • • • • • •	(0.47)	(0.46)	(0.48)
Labor Market			
Monthly income	710.6	526.9	857.7
v	(1165.83)	(888.18)	(1329.43)
Formal employment (%)	0.18	0.12	0.23
	(0.38)	(0.33)	(0.42)

Table 1: Descriptive statistics: Schooling and employment

Source: National Household Surveys, 2001-2015

	All	Poor	Non-Poor
Anemia prevalence (%)	0.283	0.295	0.266
	(0.450)	(0.456)	(0.442)
Iron intake during pregnancy			
Took iron supplements $(\%)$	0.770	0.750	0.796
	(0.421)	(0.433)	(0.403)
Days of iron intake	55.06	50.36	61.30
	(62.15)	(58.51)	(66.15)
Pre-natal care visits			
% With at least one visit	0.964	0.947	0.986
	(0.186)	(0.223)	(0.116)
Month of first visit	2.874	3.122	2.557)
	(1.627)	(1.676)	(1.505)
Number of visits	7.796	7.137	8.670
	(3.335)	(3.251)	(3.241)

Table 2: Descriptive statistics: Maternal health

Source: Demographic Health Surveys, 2004-2015

	(1)	(2)	(3)
	Alll	Females	Males
temp ≤ 5.0	-0.111	-0.363*	0.089
	(0.131)	(0.186)	(0.152)
$5.0 < \text{temp} \le 7.5$	-0.082	-0.317**	0.129
	(0.105)	(0.130)	(0.132)
$7.5 < \text{temp} \le 10.0$	-0.095	-0.323***	0.110
	(0.097)	(0.123)	(0.115)
$10.0 < \text{temp} \le 12.5$	-0.024	-0.184*	0.122
	(0.084)	(0.111)	(0.090)
$12.5 < \text{temp} \le 15.0$	-0.044	-0.128	0.038
	(0.063)	(0.079)	(0.069)
$15.0 < \text{temp} \le 17.5$	-0.045	-0.109***	0.031
	(0.032)	(0.039)	(0.038)
$20.0 < \text{temp} \le 22.5$	-0.027	-0.022	-0.042
	(0.029)	(0.041)	(0.041)
$22.5 < \text{temp} \le 25.0$	-0.060	-0.056	-0.063
	(0.045)	(0.053)	(0.060)
temp > 25.0	-0.022	0.037	-0.085
	(0.064)	(0.082)	(0.082)
Mean of Dep Variable:	7.12	6.80	7.44
Number of Observations	1006833	507801	499023
R squared	0.506	0.502	0.549

Table 3: Schooling attainment (years)

Notes: Dependent variable is years of schooling. *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions control for precipitation (binned at 50mm intervals) and include fixed effects for district of birth, date of birth (month and year), year the person was surveyed, and district-level trends, following the specification in equation (1). Standard errors are clustered at the province level. Statistically significant at the 90(*), 95(**) and 99(***) percent of confidence. Source: National Household Surveys, 2001-2015, and CRU database.

	(1)	(2)	(3)	(4)	(5)	(6)
		Primary			Secondary	
	All	Females	Males	All	Females	Males
temp ≤ 5.0	-0.024**	-0.046***	-0.006	-0.009	-0.038**	0.016
	(0.012)	(0.017)	(0.015)	(0.015)	(0.019)	(0.019)
5.0 < temp < 7.5	-0.022**	-0.043***	-0.004	-0.013	-0.038***	0.010
	(0.010)	(0.013)	(0.013)	(0.012)	(0.014)	(0.017)
75 < topp < 100	-0.024**	-0.046***	0.002	-0.015	-0.034***	0.002
$7.5 < \text{temp} \le 10.0$			-0.003			
	(0.010)	(0.012)	(0.012)	(0.011)	(0.013)	(0.014)
$10.0 < \text{temp} \le 12.5$	-0.012	-0.028***	0.003	-0.008	-0.026**	0.008
	(0.009)	(0.011)	(0.011)	(0.010)	(0.012)	(0.013)
$12.5 < \text{temp} \le 15.0$	-0.006	-0.016**	0.005	-0.008	-0.020***	0.005
12.0 < tomp _10.0	(0.007)	(0.008)	(0.008)	(0.006)	(0.007)	(0.009)
	0.000	0.000*	0.004		0.019***	0.000
$15.0 < \text{temp} \le 17.5$	-0.003	-0.009^{*}	0.004	-0.005	-0.013***	0.003
	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)
$20.0 < \text{temp} \le 22.5$	-0.003	-0.004	-0.003	0.000	0.006	-0.006
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
$22.5 < \text{temp} \le 25.0$	-0.006	-0.008	-0.005	-0.001	0.006	-0.008
22.0 (tomp2010	(0.004)	(0.006)	(0.006)	(0.001)	(0.007)	(0.008)
	0.004			0.00	0.010*	0.000
temp > 25.0	-0.004	-0.005	-0.005	0.005	0.018^{*}	-0.008
	(0.006)	(0.009)	(0.008)	(0.009)	(0.011)	(0.011)
Mean of Dep Variable:	0.59	0.56	0.63	0.33	0.31	0.35
Number of Observations	1006833	507801	499023	1006833	507801	499023
R squared	0.419	0.420	0.448	0.332	0.333	0.354

 Table 4: Schooling attainment (level)

Notes: Dependent variable is having completed primary (cols 1-3) or secondary (cols 4-6) education. *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions control for precipitation (binned at 50mm intervals) and include fixed effects for district of birth, date of birth (month and year), year the person was surveyed, and district-level trends, following the specification in equation (1). Standard errors are clustered at the province level. Statistically significant at the 90(*), 95(**), and 99(***) percent of confidence Source: National Household Surveys, 2001-2015, and CRU database.

Table 5: Earnings

	(1)	(2)	(3)
	All	Females	Males
temp ≤ 5.0	-0.042	-0.098***	-0.007
	(0.032)	(0.034)	(0.046)
$5.0 < \text{temp} \le 7.5$	-0.052*	-0.104***	-0.008
	(0.027)	(0.028)	(0.039)
$7.5 < \text{temp} \le 10.0$	-0.034	-0.093***	0.016
	(0.026)	(0.027)	(0.038)
$10.0 < \text{temp} \le 12.5$	-0.008	-0.053**	0.033
	(0.020)	(0.022)	(0.030)
$12.5 < \text{temp} \le 15.0$	-0.004	-0.037*	0.027
	(0.016)	(0.019)	(0.022)
$15.0 < \text{temp} \le 17.5$	0.014	-0.026**	0.047^{***}
	(0.009)	(0.013)	(0.014)
$20.0 < \text{temp} \le 22.5$	0.014	-0.008	0.029*
	(0.010)	(0.010)	(0.015)
$22.5 < \text{temp} \le 25.0$	0.011	0.001	0.017
	(0.011)	(0.013)	(0.017)
temp > 25.0	0.017	0.016	0.019
	(0.015)	(0.019)	(0.022)
Mean of Dep Variable:	0.00	-0.19	0.15
Number of Observations	508641	226244	282380
Number of Clusters	193	193	193
R squared	0.084	0.088	0.112

Notes: Dependent variable is standardized earnings. temp is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions control for precipitation (binned at 50mm intervals) and include fixed effects for district of birth, date of birth (month and year), year the person was surveyed, and district-level trends, following the specification in equation (1). Standard errors are clustered at the province level. Statistically significant at the 90(*), 95(**), and 99(***) percent of confidence. Source: National Household Surveys, 2001-2015, and CRU database.

 Table 6: Employment

	(1)	(2)	(3)	(4)	(5)	(6)	
		nal Employn	. ,	Underemployment			
	All	Females	Males	All	Females	Males	
temp ≤ 5.0	-0.007	-0.005	-0.008	-0.004	0.005	-0.013	
	(0.010)	(0.012)	(0.014)	(0.011)	(0.015)	(0.016)	
$5.0 < \text{temp} \le 7.5$	-0.019**	-0.026**	-0.008	-0.003	-0.001	-0.007	
	(0.009)	(0.010)	(0.012)	(0.009)	(0.012)	(0.012)	
$7.5 < \text{temp} \le 10.0$	-0.017**	-0.026***	-0.005	-0.006	-0.006	-0.008	
	(0.008)	(0.009)	(0.011)	(0.008)	(0.011)	(0.010)	
	(0.000)	(0.000)	(0.011)	(0.000)	(0.011)	(0.010)	
$10.0 < \text{temp} \le 12.5$	-0.010	-0.013^{*}	-0.004	-0.007	-0.010	-0.005	
	(0.007)	(0.007)	(0.010)	(0.007)	(0.010)	(0.008)	
					.	0.011	
$12.5 < \text{temp} \le 15.0$	-0.012**	-0.018***	-0.004	-0.008	-0.005	-0.011	
	(0.005)	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)	
15.0 < temp < 17.5	-0.005	-0.008*	-0.002	-0.003	0.003	-0.008	
1010 (0011p _110	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)	(0.006)	
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	
$20.0 < \text{temp} \le 22.5$	-0.002	-0.004	-0.001	0.003	0.006	-0.000	
	(0.003)	(0.004)	(0.005)	(0.005)	(0.007)	(0.005)	
	0.000	0.000	0.000	0.000	0.000	0.000	
$22.5 < \text{temp} \le 25.0$	0.000	-0.003	0.002	0.002	0.008	-0.002	
	(0.004)	(0.005)	(0.007)	(0.006)	(0.008)	(0.007)	
temp > 25.0	0.000	-0.006	0.006	0.003	0.018^{*}	-0.007	
1	(0.006)	(0.008)	(0.009)	(0.008)	(0.010)	(0.009)	
Mean of Dep Variable:	0.18	0.12	0.23	0.17	0.15	0.19	
Number of Observations	711542	361387	350142	508641	226244	282380	
Number of Clusters	193	193	193	193	193	193	
R squared	0.167	0.140	0.234	0.063	0.072	0.072	

Notes: Dependent variables are indicators for having formal employment (cols 1-3) and for being underemployed (cols 4-6). *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions control for precipitation (binned at 50mm intervals) and include fixed effects for district of birth, date of birth (month and year), year the person was surveyed, and district-level trends, following the specification in equation (1). Standard errors are clustered at the province level. Statistically significant at the 90(*), 95(**), and 99(***) percent of confidence. Source: National Household Surveys, 2001-2015, and CRU database.

	(1)	(2)	(3)	(4)	(5)	(6)
	. ,	nemia		Intake		Days
	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor
pregtemp ≤ 5.0	0.629^{*}	0.269	-0.088	0.371***	8.241	29.680**
	(0.343)	(0.334)	(0.102)	(0.100)	(15.208)	(12.933)
$5.0 < \text{pregtemp} \le 7.5$	0.810**	-0.200	-0.071	0.322***	-1.675	24.255**
	(0.330)	(0.266)	(0.076)	(0.078)	(13.277)	(12.156)
$7.5 < \text{pregtemp} \le 10.0$	0.433	-0.177	-0.050	0.249***	4.208	22.471**
$7.5 < \text{pregremp} \le 10.0$	(0.303)	(0.211)	(0.065)	(0.249) (0.059)	(12.094)	(10.359)
	(0.303)	(0.211)	(0.003)	(0.059)	(12.094)	(10.009)
$10.0 < \text{pregtemp} \le 12.5$	0.490^{*}	-0.161	-0.060	0.171^{***}	11.246	20.543**
	(0.267)	(0.194)	(0.057)	(0.043)	(9.235)	(9.449)
$12.5 < \text{pregtemp} \le 15.0$	0.289*	-0.019	0.060	0.113***	20.501***	11.551
	(0.164)	(0.169)	(0.040)	(0.031)	(6.911)	(7.512)
$15.0 < \text{pregtemp} \le 17.5$	0.061	0.080	0.067**	0.044^{*}	18.342***	3.694
	(0.104)	(0.078)	(0.029)	(0.023)	(3.689)	(4.100)
$20.0 < \text{pregtemp} \le 22.5$	-0.177	0.010	-0.035	-0.006	-1.837	4.710
-010 (pro800mp0	(0.211)	(0.121)	(0.032)	(0.031)	(7.307)	(5.771)
	()			~ /	· · · ·	× ,
$22.5 < \text{pregtemp} \le 25.0$	-0.049	-0.041	-0.082	-0.035	-15.567^{*}	1.180
	(0.230)	(0.131)	(0.052)	(0.036)	(8.449)	(6.534)
pregtemp > 25.0	-0.170	-0.113	-0.119**	-0.020	-21.150**	5.833
	(0.245)	(0.129)	(0.060)	(0.042)	(9.227)	(6.808)
Mean of Dep Variable:	0.29	0.27	0.75	0.80	50.34	61.30
Number of Observations	3976	3005	40045	30117	39913	30013
Number of Clusters	176	119	192	175	192	175
R squared	0.432	0.298	0.212	0.155	0.253	0.251

Table 7: Maternal anemia and intake of iron supplements during pregnancy

Notes: Dependent variables are anemia prevalence (cols 1-2), share of pregnant women that take iron supplements (cols 3-4), and number of days pregnant women took iron supplements (cols 5-6). *pregtemp* is average temperature during pregnancy (in degrees Celsius). The comparison category is 17.5-20C. All regressions control for precipitation during pregnancy (binned at 50mm intervals) and include fixed effects for district of birth, the child's date of birth (month and year), year the person was surveyed, and district-level trends, following the specification in equation (3). Standard errors are clustered at the province level. Statistically significant at the 90(*), 95(**), and 99(***) percent of confidence. Source: Demographic Health Surveys, 2004-2015, and CRU database

	(1)	(2)	(3)	(4)	(5)	(6)
	Prenat	al control	Month o	of 1st control	Number	of controls
	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor
pregtemp ≤ 5.0	-0.073	-0.017	0.209	0.174	-0.194	0.355
	(0.051)	(0.018)	(0.534)	(0.360)	(1.017)	(0.761)
	0.005	0.000	0.010	0 1 4 6	0 6 4 1	0.055
$5.0 < \text{pregtemp} \le 7.5$	-0.065	-0.003	0.219	0.146	-0.641	0.855
	(0.044)	(0.013)	(0.392)	(0.338)	(0.704)	(0.641)
$7.5 < \text{pregtemp} \le 10.0$	-0.057	0.022^{*}	0.116	-0.066	-0.720	1.336***
1 0 1 -	(0.040)	(0.011)	(0.367)	(0.173)	(0.668)	(0.375)
	()	()	()	()		(<i>'</i>
$10.0 < \text{pregtemp} \le 12.5$	-0.052	0.015	0.299	-0.114	-1.122^{*}	0.967^{**}
	(0.036)	(0.010)	(0.329)	(0.128)	(0.615)	(0.375)
	0.001	0.010**	0.000	0.000***	0.223	0 679**
$12.5 < \text{pregtemp} \le 15.0$	0.001	0.019^{**}	0.029	-0.266^{***}		0.673**
	(0.020)	(0.010)	(0.271)	(0.097)	(0.379)	(0.298)
$15.0 < \text{pregtemp} \le 17.5$	0.012	0.012	-0.180	-0.024	0.460	0.355**
	(0.014)	(0.008)	(0.167)	(0.070)	(0.292)	(0.147)
	()	()	()	()		()
$20.0 < \text{pregtemp} \le 22.5$	-0.001	0.009^{***}	0.015	0.053	-0.156	-0.231
	(0.020)	(0.003)	(0.192)	(0.080)	(0.521)	(0.150)
$22.5 < \text{pregtemp} \leq 25.0$	-0.010	0.017^{***}	0.133	0.105	-0.589	-0.363
$22.5 < \text{pregremp} \leq 25.0$						
	(0.031)	(0.006)	(0.199)	(0.135)	(0.602)	(0.298)
pregtemp > 25.0	-0.047	0.012^{*}	0.188	-0.006	-1.281*	-0.229
	(0.036)	(0.007)	(0.216)	(0.140)	(0.674)	(0.319)
Mean of Dep Variable:	0.95	0.99	3.12	2.56	7.14	8.67
Number of Observations	40074	30136	37939	29728	39994	30082
Number of Clusters	192	175	192	175	192	175
R squared	0.182	0.105	0.132	0.096	0.246	0.125

Table 8: Pre-natal care visits

Notes: Dependent variables are share of pregnant women that had at least one prenatal care visit (cols 1-2), month of the first visit (cols 3-4), and number of visits during the pregnancy (cols 5-6). *pregtemp* is average temperature during pregnancy (in degrees Celsius). The comparison category is 17.5-20C. All regressions control for precipitation during pregnancy (binned at 50mm intervals) and include fixed effects for district of birth, the child's date of birth (month and year), year the person was surveyed, and district-level trends, following the specification in equation (3). Standard errors are clustered at the province level. Statistically significant at the 90(*), 95(**), and 99(***) percent of confidence. Source: Demographic Health Surveys, 2004-2015, and CRU database