Long-term Effect of Climate Change on Health: Evidence from Heat Waves in Mexico

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Abstract

This paper uses year-to-year variation in temperature to estimate the long-term effects of climate change on health outcomes in Mexico. Combining temperature data at the *district* level and three rounds of nationally representative household surveys, an individual's health as an adult is matched with the history of heat waves from birth to adulthood. A flexible econometric model is used to the identification of critical health periods with respect to temperature. It is shown that exposure to higher temperatures early in life has negative consequences on adult height. Most importantly, the effects are concentrated at the times where children experience growth spurts: infancy and adolescence. The robustness of these findings is confirmed when using health outcomes derived from accidents, which are uncorrelated to early exposure to high temperatures.

JEL classifications: I12, Q54, Q41
Keywords: Global warming, Climate change, Health, Mexico

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1. Introduction

The frequency of heat waves is increasing rapidly in Latin America and the Caribbean. In Mexico City, for example, the number of heat spells (i.e., days with temperatures over 30ºC or 86ºF) between 1991 and 2000 is almost twice the number recorded in 1970s and three times more than in the 1950s (Jáuregui, 2009). Compared to the 1870s, heat waves are now *nine* times more common. Furthermore, as shown in Figure 1 below, one important aspect of climate change in Mexico is the expected shift to the right in the distribution of temperatures. By 2070, heat waves are expected to become even more frequent than today.

What is the expected impact of this aspect of climate change on human health? This is a relatively new area of research in economics. Most studies have concentrated on the effects of climate change, measured by extreme temperatures including heat waves, in high-income countries, ignoring developing countries altogether including those in Latin America and the Caribbean.[1] Furthermore, the few studies that focus on heat waves in richer nations tend to estimate the *contemporaneous* effects on mortality rates. While mortality is an important outcome, the vast majority of the population survives heat waves. Thus, a natural question to ask is whether heat waves have a long-lasting effect. Does exposure to a heat wave as a child affect the person's adult health? If so, is the effect more pronounced when exposure occurs at a younger age?

This paper answers these questions in the context of Mexico. I use random year-to-year variation in temperature to estimate the long-term effects of exposure to high temperatures on health outcomes in Mexico. A key advantage is the use of temperature data at the *district level* (*municipalidad* in Mexico) combined with three nationally representative cross-sectional household surveys. These data allow me to match an individual's health as an adult with her history of exposure to heat waves in each stage of her life cycle until adulthood. The combined cross-sectional surveys provide a sample of over 65,000 individuals born between 1960 and 1990, a period where the frequency of heat waves was increasingly rapidly.

This paper contributes to the existing literature in several ways. First, I use temperature data *within* states, which permits a more precise estimation of the effect of climate change. Most papers in the United States use data at the state level, limiting the inference derived from these papers. Second, I estimate the long-term effects by examining whether exposure to extreme

[1] Some exceptions include Patz et al. (2005), Campbell-Lendrum and Corvalán (2007) and Huang et al. (2013).

temperatures early in life affects adult health. Using height as health outcome, I show that exposure to high temperatures has a negative impact on adult health. Third, the econometric model permits the comparison of exposure early in life vis-à-vis later periods. The results suggest that infancy (between 1 and 4 years of age) and adolescence (between 10 and 15) are the most critical periods. These periods coincide with the growth spurts of humans.

Furthermore, I conduct two falsification tests. When weight is used as a measure of adult health, my results show no effect from extreme temperatures. This is expected because, unlike height, weight is a measure of short-term health (see Strauss and Thomas, 1995, for a detailed review). Thus, the possible negative effects of heat waves on weight could be remediated by future investments. However, lacking the necessary health status to grow at critical periods cannot be reversed by future investments. I use the likelihood of experiencing an accident in the last 12 months prior to the surveys as a placebo test. The validity of the identification strategy is reinforced, as I find no effect of heat waves on this outcome.

The paper explores heterogeneous effects by gender and poverty level of the district. The results indicated no gender differences in the impact of heat waves. However, the effects are more negative for individuals growing up in poorer districts. The results of this investigation provide academics and policy makers with the most comprehensive analysis to date of the long-term effects of climate change on health outcomes in the region.

2. Brief Review of the Literature

The literature on the effects of climate change on health outcomes is small but growing. As reviewed by Deschênes (2012), the bulk of papers has focused on developed countries (however, see Burgess et al, 2012 regarding India); have mainly studied the effect of the temperature; and evaluate the contemporaneous impact. To keep this section brief and to focus the attention of this document on the contributions of my work I will discuss papers closely related to mine. For a more extensive review please see Deschênes (2012) and the papers therein.

The work by Deschênes and Greenstone (2011) is the closest to my paper. They explore the effect of extreme temperatures, both hot and cold, on the age-specific mortality rates in the U.S. during the past few decades. Their identification strategy exploits the random nature of temperature changes across states to estimate the effect on mortality during that same year, after accounting for state and year fixed effects as well as state trends. They find, for example, that an extra day with a mean temperature exceeding 90°F (the measure for heat waves in the U.S.), relative to a day in the 50°–60°F range, is associated with an *increase* in the annual age-adjusted mortality rate of about 0.11 percent. However, the effects are not linear because "a day with a mean temperature below 20° F is associated with an increase in annual mortality of roughly 0.07–0.08 percent" (p. 153). The authors find that effects are the largest for infants and the elderly. A similar strategy is used in Deschênes, Greenstone and Guryan (2009), where extreme temperatures are linked to lower birth weights, also in the United States, and by Deschênes and Moretti (2009) for the case of migration. Guerrero Compeán (2013) applies this methodology to estimate the contemporaneous effect on mortality in Mexico and finds ambiguous results.

In all of these papers, the data force the authors to aggregate their measure of temperature at the state level.[2] This is mainly due to the lack of mortality data at the county level. Thus, we could expect the precision of their findings to be somewhat comprised due to data limitations. That is not the case in my paper. Like the previous papers, I use data at the station level. However, unlike those papers, the outcome of interest is available at the individual level and I can identify the district where the person resides.[3] Thus, I can measure extreme temperatures (of heat only for Mexico) at a finer and more relevant level: the district.

Second, as shown above, extreme temperatures are associated with higher mortality rates but the effects are very small (or ambiguous.) Thus, the vast majority of people survive a heat wave, including children. However, are the effects limited to mortality? The main contribution of my paper is to show the long-lasting effects of heat waves. Given my findings, concentrating only on mortality will underestimate the effect of heat waves on health. Thus, I take advantage of the richness of my data and ask whether a person's adult health could be linked to exposure to heat waves while growing up. The exploration of the long-term effects addresses the limitation that Deschênes (2012) has identified in the existing literature. Most importantly, using a model borrowed from the literature on skill formation, I test which are the most vulnerable stages of a person's life cycle until adulthood in regards to health. This model is described below.

[2] Similar to my paper, Guerrero Compeán (2013) uses data at the district level.
[3] Below I discuss why between-state mobility is not a limiting factor for my analysis of Mexico.

3. Conceptual Framework

To identify the long-term effect of exposure to extreme temperatures across different stages of the life cycle on health outcomes I adapt the model of "skill formation" introduced by Cunha et al. (2006).[4] A key issue in this model is the departure from the previous literature where "childhood" was treated as a single period (e.g., Becker and Tomes, 1986) Instead, Cunha et al. (2006) consider a model where inputs at different stages of child development could have a differential impact and these inputs could be seen either as complements or substitutes. To adapt this model in terms of estimating the effect of climate change, consider the health status of a person at time t as h_t. In its simplest form, h_t is a scalar, but the model can be easily extended to the case where h_t is a vector. The goal of the model is to describe how health evolves over time and what is the (possibly) differential role of exposure to *disinvestments* such as extreme weather in early (e.g., childhood) vis-à-vis later periods (e.g., adolescence).[5]

Assume that the technology of production of health when a person is t years old is given by

$$h_{t+1}=f_t(x, h_t,W_t) \qquad t=1,2,\ldots,T \qquad (1)$$

where h_{t+1} and h_t are the stocks of health at time t+1 and t, respectively, for a child who was born with health endowment h_0, while parents' characteristics are captured in x (and are assumed to be time invariant). Children are exposed to weather shocks W_t in each period. Thus, a recursive representation of equation (1) leads to

$$h_{t+1}=m_t(x, h_0,W_1,\ldots,W_t) \qquad t=1,2,\ldots,T \qquad (2)$$

Equation (2) implies that future health status depends on the initial health endowment h_1, parental characteristics and the full history of weather shocks since t=1. It is straightforward to see how this equation helps us study how weather shocks affect adult health status. First, we set T=21 years of age, as most humans in the Western world, for example, reach their adult height at that age (see Deaton, 2007; Case and Paxson, 2009; and Agüero and Deolalikar, 2013, for references). Second, because data on birth weight are not available for adults in the household

[4] Almond and Currie (2011) use this model, for example, to consider the case of the formation of human capital before age five.

[5] The full model could consider overlapping generations (parents and their children) each living for T periods with common preferences and inelastic labor supply and discusses the optimal timing of investments. Adding these features to this simplified version does not affect the main conclusions of this model.

survey described below, I assume that initial health status, h_0, is a function of the person's gender, birth cohort and location. Third, the parental characteristics (e.g., mainly education and access to durable goods) are approximated using Census data matched by the birth cohort. Finally, the sequence of weather shocks $W_1, W_2, \ldots, W_T$ is captured by the temperature recorded in each period.

This model will allow me to evaluate how adult health (at T+1) depends on weather shock at time t, that is, W_t for $t \leq T$. Formally, this is given by

$$\frac{\partial h_{T+1}}{\partial W_t} = \theta_t \text{ for t=1,2,}\ldots\text{,T.} \qquad (3)$$

Furthermore, the model permits the comparison of exposure to hotter days in different stages of the life cycle. For example, we can compare the effect on early childhood (θ_{early}) vis-à-vis adolescence ($\theta_{adolescence}$). This will identify the sensitive periods regarding adult health. The next section discusses the data to be used in the estimations.

4. Data Sources

There are three main data sources for this paper. The data on health status come from three rounds of the *Encuesta Nacional de Salud y Nutrición* (ENSANUT), Mexico's nationally representative health and nutrition survey. The three cross-sectional surveys were conducted in 2000, 2006 and 2012, and they cover all health aspects of a randomly selected sample of households. Relevant to this paper is the inclusion of questions such as height and weight. In order to conduct placebo tests, I include an outcome that is unlikely to be related to heat waves: accidents. Having access to these three outcomes is an important advantage of the ENSANUT. The average sample size of adults between the ages of 21 and 50 is close to 65,000 for all three surveys.[6]

In addition to this rich set of health outcomes, the ENSANUT includes information about the person's age and location. I use this information to construct the sequence of heat waves. The second main data source comes from Mexico's National Weather Service, which collects daily information from all the meteorological stations across the nation. Figure 2 shows the location of each of the more than five thousand weather stations across Mexico. For each station and day,

[6] See http://ensanut.insp.mx/ for more details about the three surveys.

the maximum and minimum temperatures are collected together with information about precipitation levels. I match the household data with the weather information using the coordinates of each station and the location of the district where the individual lives from the ENSANUT. It is important to note that between-state migration is *unlikely* to be a source of bias for this paper. The Mexican census of the last 20 years shows that over 90 percent of individuals live in the same district (and state) as in the previous iteration, reducing the downward bias that migration could introduce into the estimates.[7]

The third main source of data comes from Mexico's National Population Council (CONAPO). We use CONAPO's district-level poverty index to explore heterogeneous effects.[8] The poverty index is a function of measures of education (percent of population that are illiterate or without primary education), housing (percent of houses without water, sewage, electricity, non-dirt floors), and access to goods (having a refrigerator) in a given locality. These three main datasets will be used to estimate the effects of changes in temperature as described in equations (2) and (3) above.

5. Methods

Equation (4) below describes the main regression model:

$$h_{ijscy} = \sum_{t=1}^{T=21} g_{jc}(t) + \lambda z_{ijscy} + \alpha_j + \alpha_c + \alpha_y + \alpha_{sc} + e_{ijscy} \qquad (4)$$

where h_{ijscy} refers to adult health status (i.e., height) of person i, from district j, located in state s, born in cohort c and observed in survey year y. Equation (4) includes fixed effects at the district (α_j), birth cohort (α_c) and survey year (α_y) as well as state trends (α_{sc}). These controls account for the possible unobserved factors that remain constant over time and those which, nationwide, vary year of birth of the cohort, by survey year and by state over time. Vector z_{ijscy} includes controls to approximate the initial health endowment (h_0, in the model described in Section 3) as well as parental characteristics (x). These variables include gender, marital status, and education of the individual.

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[7] Migrants out of Mexico are not included in the household survey. While this does not affect the internal validity of the paper it could reduce its external validity. Exploring this issue goes beyond the scope of this paper and should be addressed in future work.
[8] The index can be downloaded for free from
http://www.conapo.gob.mx/es/CONAPO/Indices_de_Marginacion_2010_por_entidad_federativa_y_municipio.

Function *g(t)* captures the association between adult health and temperatures at different stages of the life cycle. Note that *g(t)* varies by birth cohort and district, but to focus on the functional form I suppress these indexes in the discussion below. I follow Deschênes and Greenstone (2011) and consider a flexible form that divides the temperature at stage *t* in 10ºF bins. In this case *g(t)* is characterized by

$$g(t)=\Sigma_b \theta_{bt} TEMP_{tb} \qquad \text{for } t=1,\dots,T \quad (5)$$

The variables $TEMP_{tb}$ denote the number of days in stage *t* where the daily mean temperature is in the *b*-th of the 10 bins between 50ºF to 90ºF. A key functional form assumption is that the impact of the daily mean temperature on adult health status is constant within 10° F intervals.

Consistent with the current literatue, the validity of this paper's empirical strategy is based on the assumption that the estimation of equation (4) will produce unbiased estimates of the θ_{bt} vector for all *t*. Vector θ is identified from district- and cohort-specific deviations in weather (i.e., the fixed-effects discussed above) after controlling for shocks common to all districts in a state. Furthermore, due to the random year-to-year variation in weather, it seems reasonable to believe that this variation is orthogonal to unobserved determinants of health status. Therefore, for the case of the *b*-th temperature variable, the identifying assumption that $E[g_{jc}(t)\ e_{ijscy} \mid g_{jc}(t), \lambda z_{ijscyc}, \alpha_j, \alpha_c, \alpha_y, \alpha_{sc}] = 0$ is very likely to be valid. In this regard, the identification assumptions made in this work are analogous to the papers by Deschênes and Greenstone (2011) and Deschênes, Greenstone and Guryan (2009).

As shown in Figure 3, there is enough within-year variation to estimate the effects. For example, I plot the residuals from regressing the percentage of days in a year where the temperature is above 80˚F in each weather station against station fixed effects. The figure shows that for each year, the percentage of hot days is between 20 and 83 percent and that half of the data exhibits a variation larger than 10 percentage points.

Also, it is likely that the error terms are correlated within district or within district-by-cohort groups over time. To address this issue, I ran all regressions with standard errors that allow for heteroskedasticity of an unspecified form and that are clustered at the district level and a second specification clustering at the district-by-cohort group level. I found no difference between these approaches, so in this paper I present the former; however, the results using the latter method of clustering are available upon request. The estimates of equations (4) and (5) are shown in the next section.

6. Does Exposure to Hotter Temperatures Have Long-Lasting Effects?

6.1 Main Results

Table 1 shows the trends in hot temperatures in Mexico. There, I regress the percentage of hot days against a linear trend and station fixed-effects. In Panel A, I limit the sample to years from 1960 to 2011. In column (1), an additional year is associated with an increase in the proportion of days above 80˚F of .0012. This means that in 20 years, the proportion of those hot days increases by 3.95 percent (=.0012*20/.608). The corresponding number for days above 85˚F is higher. In 20 years Mexico has experienced a 4.44 percent increase of these hot days (column 2). For days above 90˚F, the number is even bigger: 7.52 percent over two decades (column 3). Note that this increase is observed after controlling for the time-invariant characteristics of the districts. Furthermore, as shown in Panel B, in the years since 1980, the corresponding increments are larger. In 20 years, the percentage of days with temperatures 90˚F or more has increased by 9.6 percent. What is the effect of these higher temperatures on those exposed while growing up?

To answer this question I estimate equation (4) and the results are shown in Appendix Table A.1. To simplify the number of parameters in vector θ, I aggregated the stages of the life cycle into four groups: in utero (exposure in the year before birth), infancy (aged between 1 and 4), childhood (5-9) and adolescence (10-15.) Also, the temperature variables capture the proportion of days above T˚F, where T={50, 60, 70, 80, 85 and 90}. To ease their interpretation, I calculate the effect on adult outcomes of having more hot days relative to 50˚F, after controlling for fixed effects at the district, birth cohort and survey year as well as state trends and individual characteristics (i.e., education, marital status and gender.) For example, let θ_{50} and θ_{80} be, respectively, the parameters capturing the effect on height of having days in the 50s˚F and days in the 80s˚F when the person was an infant and reported in Table A.1 (column 1). Thus, I plot the effect relative to the impact of temperature at 50˚F, that is θ_{80}-θ_{50} (solid lines), as well as its 95 percent confidence interval (dashed lines). These estimates are shown in Figures 4-6 below.

In Figure 4, I use height as the adult health outcome. The figure shows its association with temperature for the four stages of the life cycle described above. The results indicate that exposure to hotter temperatures relative to mild ones (50˚F) is *negatively* associated with height as an adult. This negative association is also found in the other growth-spurt period: adolescence. Not surprisingly, I found no effect for the periods where human growth is slower.

I repeat this analysis but now focusing on weight as measure of health. Unlike height, weight measures short-term health and it should be less affected by temperature while growing up. This is precisely what it is shown in Figure 5. Exposure to colder or hotter temperatures rather than 50˚F is not associated with the weight, and this is true for all stages of the life cycle. In Appendix Figure A.1 I considered an alternative measure of health: self-reported overall good health. This variable is equal to one if the individual feels that she is "satisfied" or "very satisfied" with her overall health status. However, a main concern with this variable, beyond the fact that is self-reported and lacks the accuracy of anthropometric variables such as height and weight, is that a person could *internalize* a chronic health condition and be less likely to report it as a problem. In this case, a true negative impact of heat waves would not be observed. This is precisely what is observed in Figure A.1, where exposure to higher temperatures does not change the individual's perception of her health.

6.2 Robustness Checks and Heterogeneous Effects

The findings suggest that exposure to hotter temperatures (relative to 50˚F) has a negative association if it happens at stages of the life cycle where human growth is faster. That is, individuals exposed to these weather shocks have not been able to (completely) buffer these negative effects. The lack of an effect for short-term outcomes such as health serves as a placebo test. In Figure 6, I take this test even further and focus on an outcome that is not linked to temperature: the likelihood of suffering an accident in the last 12 month prior to the household survey. As shown in that figure, there is no link between the likelihood of accidents and exposure to different temperatures while growing and this reinforces the validity of the identification strategy.

I consider now whether the effects of higher temperatures have differential impacts by gender and by the poverty status of the district. In both cases I altered equation (4) to include an interaction term with all the temperature variables. The results for the case of gender are shown in Figure 7. There is no significant difference in the impact of weather on height by gender. However, as shown in Figure 8, we can observe that the effect is *more negative* for individuals living in areas with higher levels of marginalization (poorer areas) when they experience higher temperatures during adolescence. These differential effects are not present for other stages of the life cycle.

6.3 Mechanisms

The findings presented above provide robust evidence of the long-term effect of heat waves. Exposure to heat waves not only affects health outcomes by the contemporaneous effect on mortality but has long-lasting consequences as shown on adult height. In this subsection I discuss some possible mechanisms leading to this long-lasting impact. First, exposure early in life to higher temperatures can affect adult health via the impacts on pollution. For example, Bharadwaj and Eberhard (2010), in the case of Chile, show that changes in temperature negatively affect birth outcomes through augmenting the level air pollution.

Second, Epstein et al. (1980), Ramsey (1995), Hancock, Ross, and Szalma (2007), Pilcher, Nadler, and Busch (2002) show significant negative effects of high temperature on cognitive performance. This is important, as Case and Paxson (2009) demonstrate that cognitive performance and nutrition share the same inputs. A third possible mechanism could arise from changes in agricultural productivity and the availability of food. This is discussed, for example, by Guerrero Compeán (2013) and by macroeconomists explaining cross-country differences in income (Sachs and Warner, 1997).

7. Conclusions

This paper shows that the negative effect of high temperatures goes beyond contemporaneous effects on mortality. Using three large and nationally representative surveys in Mexico, combined with district-level temperature information, I show that exposure to high temperatures early in life has long-lasting consequences. In particular, higher temperatures during infancy (1-4 years of age) and adolescence (10-14) have significant negative effects on adult height.

The methodology used in this paper is validated by the use of falsification tests where no effects are found on weight, a short-term of health, and the likelihood of having accident, an unrelated measure of health. While there are not significant differences by gender, the paper shows that the negative effects are stronger for individuals living in poorer districts. Thus, the effects of high temperature would lead to an overall decline in health that is going to *amplify* health differences by socio-economic status. These differences are critical to the design of effective policies to buffer the negative effect on health produced by climate change.

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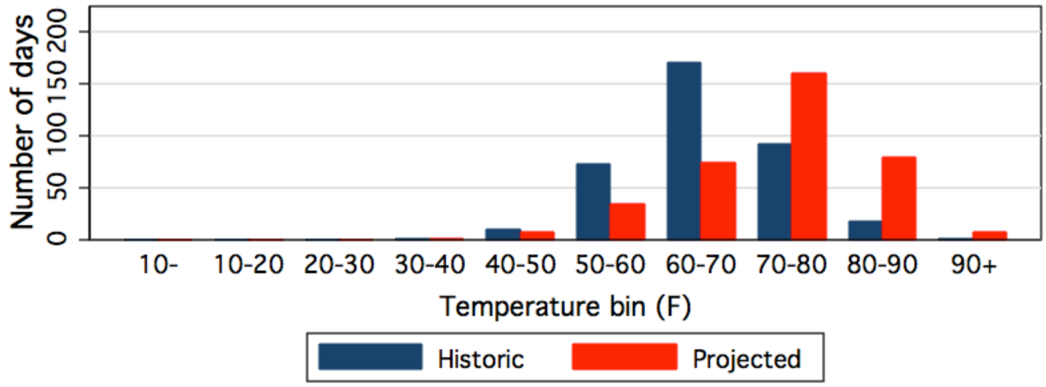
Figure 1. Number of Days in Temperature Bins from Historic and Projected Data in Mexico



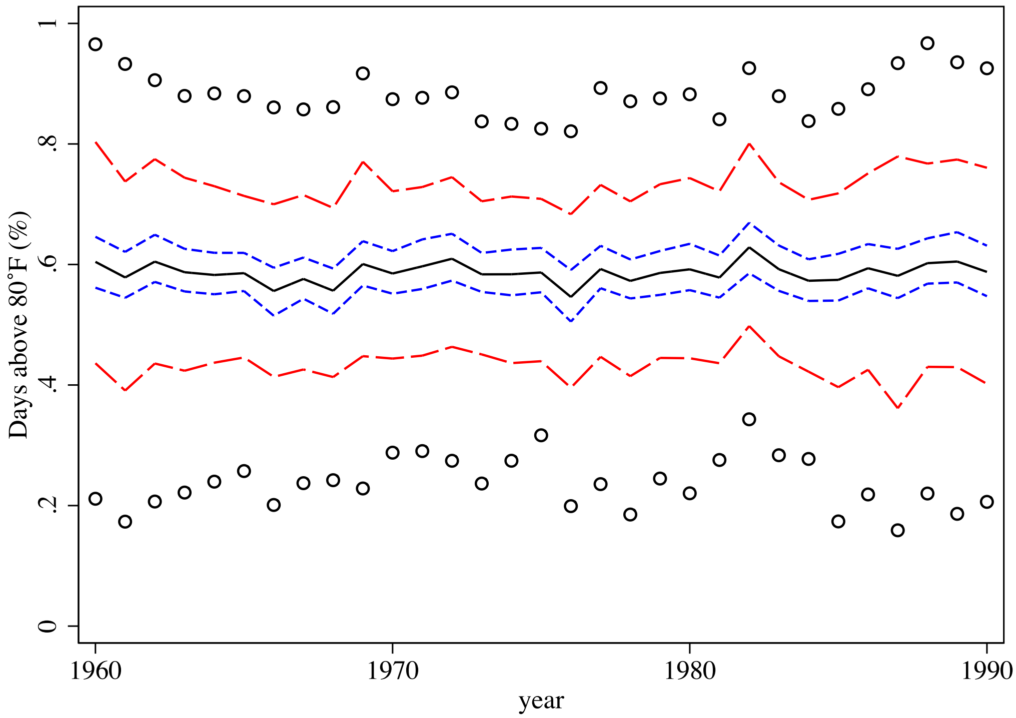
The blue bars represent the average number of days in 1979-2008 that the average daily temperature in Mexico was in the range at the bottom of the figure. The red bars represent the average number of days in 2070-2099 that the average daily temperature in Mexico is predicted to be in the range at the bottom of the figure. Together, they illustrate how climate change will affect temperatures between now and the end of the century in Mexico. We have written a technical note (see link below) that describes the data and how we calculated the temperature distributions found in this figure.

Source: http://cesm.ucar.edu/models/ccsm3.0/

Figure 2. Geographical Distribution of Weather Stations in Mexico

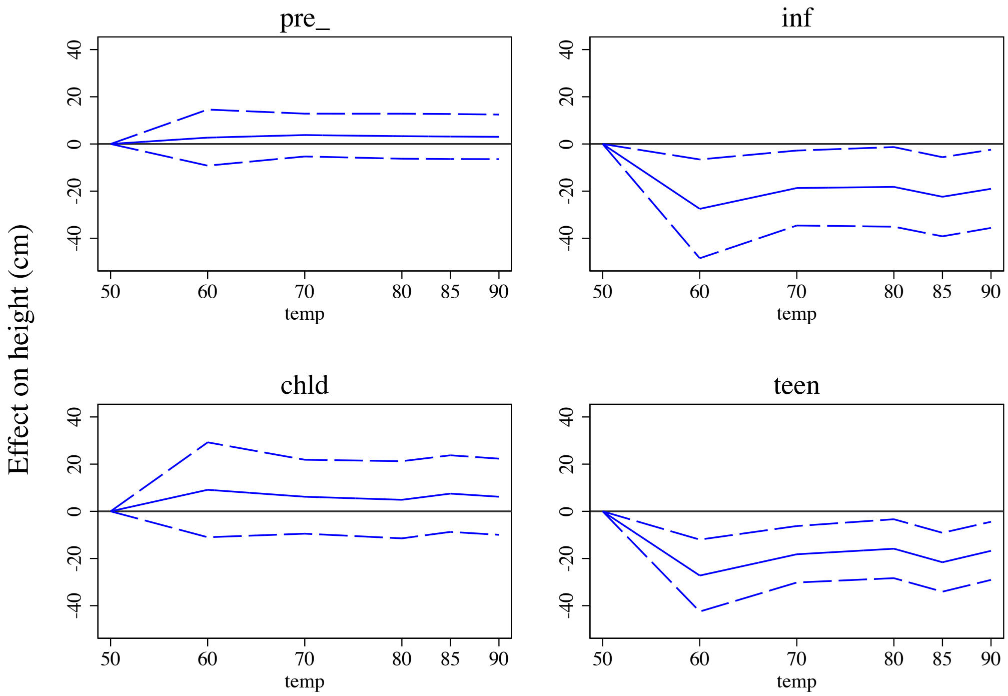
Note: Each red dot represents a weather station in Mexico. Source: Author's calculation based on GIS data from http://www.conabio.gob.mx/informacion/gis/

Figure 3. Within-Year Variation in Extreme Temperatures



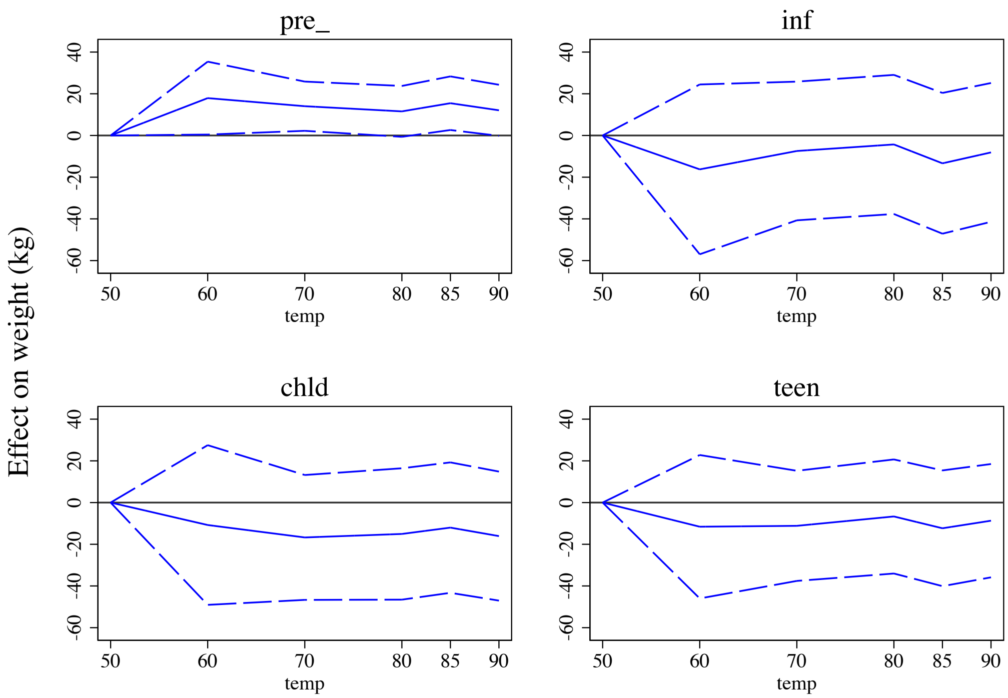
Note: The numbers shown are the residuals of regressing the proportion of days in a year above 80˚F per weather station against station fixed-effects. The black solid line refers to the mean across all stations within a year. The blue dashed lines are the 25 and 75 percentiles, the red broken lines are the 5 and 95 percentiles. The hollow circles capture the 1 and 99 percentiles.

Figure 4. Adult Height (cm.) and Average Daily Temperature at Each Stage of the Life Cycle



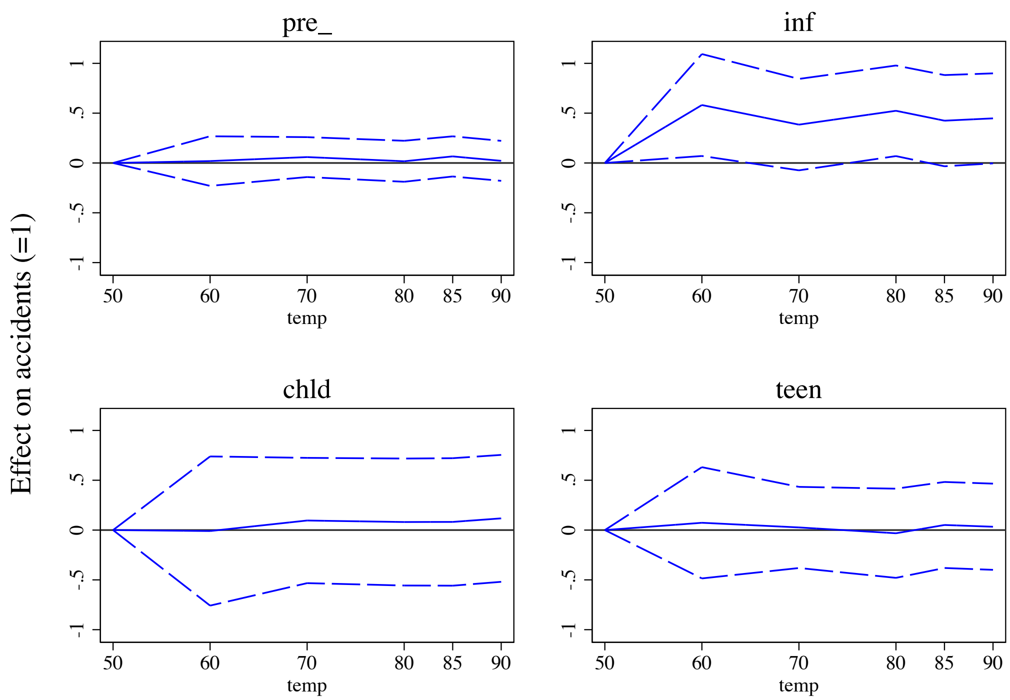
Note: In each graph, the solid blue line represents the point estimate and the dashed line the 95% confidence intervals. Each estimate shows the effect on adult health outcomes of having more days with temperature above 50˚F. The stages of the life cycle were aggregated into four groups: *Pre*, which represents in utero exposure (i.e., the year before birth), *Inf* (aged between 1 and 4), *Child* (5-9) and *Teen* (10-15.) All regressions control for fixed effects at the district, birth cohort and survey year as well as state trends and individual characteristics (i.e., education, marital status and gender.)

Figure 5. Adult Weight (Kg.) and Average Daily Temperature at Each Stage of the Life cycle



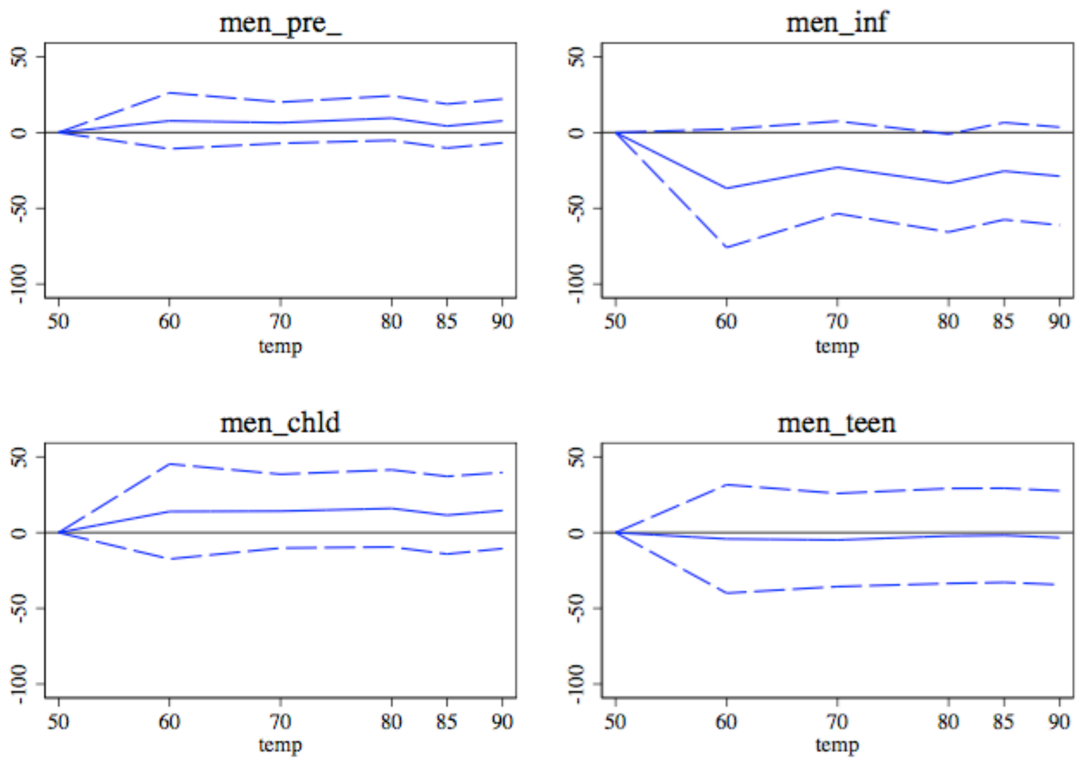
Note: In each graph, the solid blue line represents the point estimate and the dashed line the 95% confidence intervals. Each estimate shows the effect on adult health outcomes of having more days with temperature above 50˚F. The stages of the life cycle were aggregated into four groups: *Pre*, which represents in utero exposure (i.e., the year before birth), *Inf* (aged between 1 and 4), *Child* (5-9) and *Teen* (10-15.) All regressions control for fixed effects at the district, birth cohort and survey year as well as state trends and individual characteristics (i.e., education, marital status and gender.)

Figure 6. Likelihood of Recent Accidents and Average Daily Temperature at Each Stage of the Life Cycle



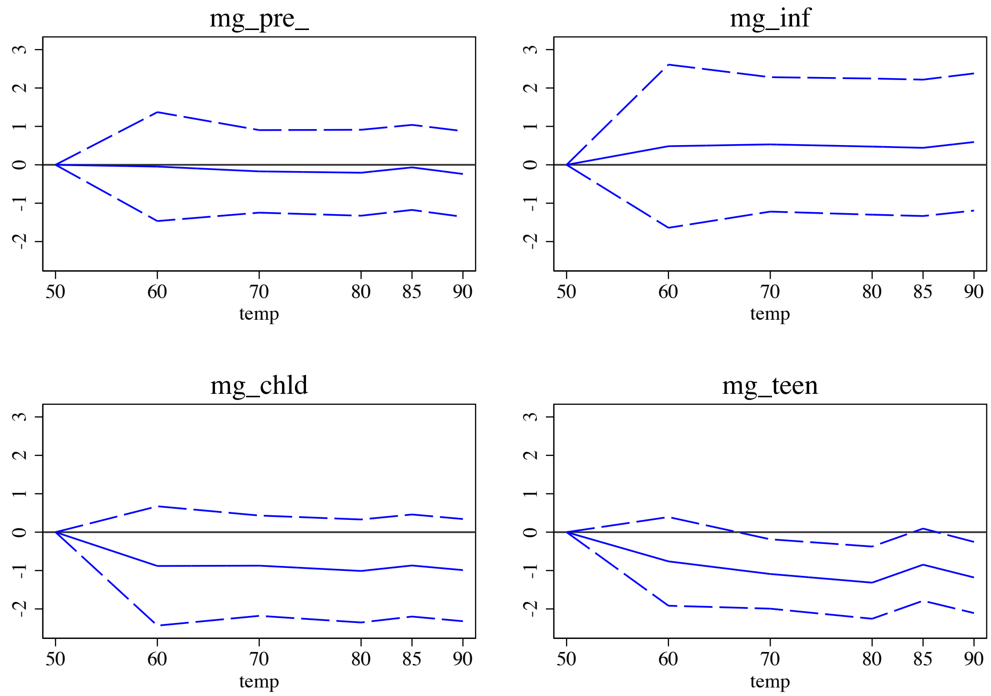
Note: In each graph, the solid blue line represents the point estimate and the dashed line the 95% confidence intervals. Each estimate shows the effect on adult health outcomes of having more days with temperature above 50˚F. The stages of the life cycle were aggregated into four groups: *Pre*, which represents in utero exposure (i.e., the year before birth), *Inf* (aged between 1 and 4), *Child* (5-9) and *Teen* (10-15.) All regressions control for fixed effects at the district, birth cohort and survey year as well as state trends and individual characteristics (i.e., education, marital status and gender.)

Figure 7. Heterogeneous Effects on Height by Gender (in cm.)



Note: In each graph, the solid blue line represents the point estimate and the dashed line the 95% confidence intervals. Each estimate shows the effect on adult health outcomes of having more days with temperature above 50˚F. The stages of the life cycle were aggregated into four groups: *Pre*, which represents in utero exposure (i.e., the year before birth), *Inf* (aged between 1 and 4), *Child* (5-9) and *Teen* (10-15.) All regressions control for fixed effects at the district, birth cohort and survey year as well as state trends and individual characteristics (i.e., education, marital status and gender.)

Figure 8. Heterogeneous Effects on Height by Level of Marginalization (in cm.)



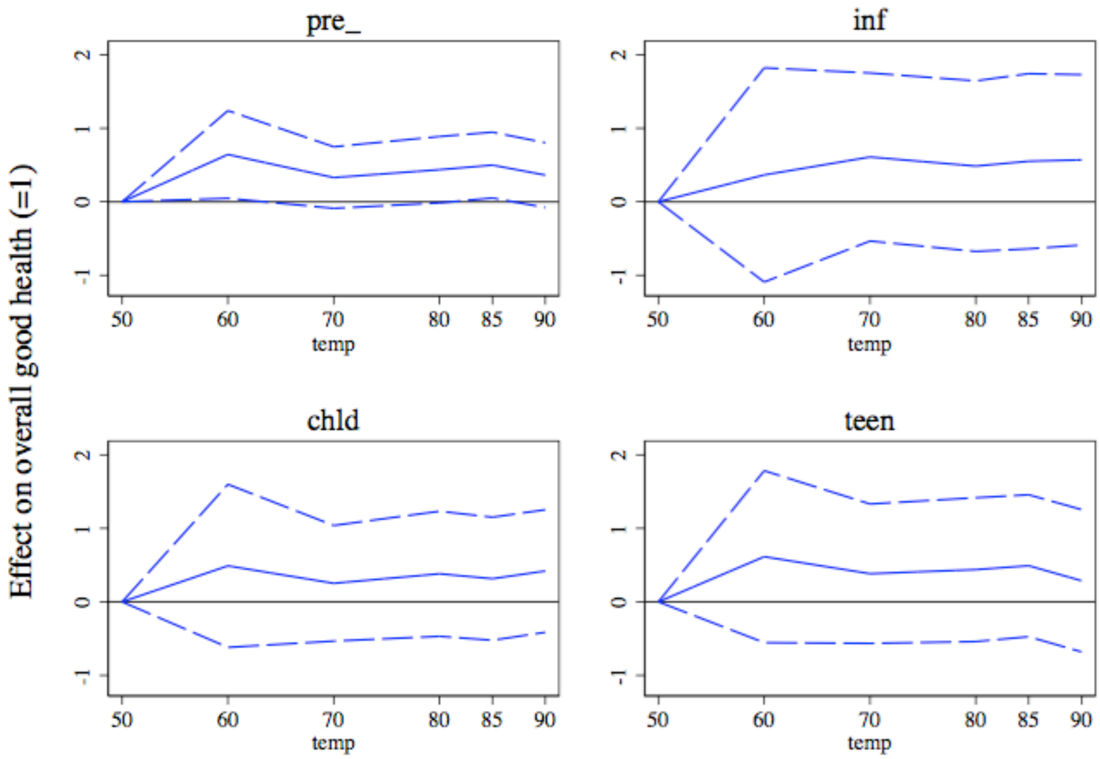
Note: In each graph, the solid blue line represents the point estimate and the dashed line the 95% confidence intervals. Each estimate shows the effect on adult health outcomes of having more days with temperature above 50˚F. The stages of the life cycle were aggregated into four groups: *Pre*, which represents in utero exposure (i.e., the year before birth), *Inf* (aged between 1 and 4), *Child* (5-9) and *Teen* (10-15.) All regressions control for fixed effects at the district, birth cohort and survey year as well as state trends and individual characteristics (i.e., education, marital status and gender.)

Table 1. Trends for Hot Temperatures

Dependent variable:	Percentage of days above:		
	80˚F	85˚F	90˚F
	(1)	(2)	(3)
	Panel A. Since 1960		
Mean of dep. var.	0.608	0.450	0.266
Trend	0.0012***	0.0010***	0.0010***
	[0.0001]	[0.0001]	[0.0001]
Observations	142,125	142,125	142,125
Number of weather stations	5,259	5,259	5,259
	Panel B. Since 1980		
Mean of dep. var.	0.610	0.452	0.270
Trend	0.0016***	0.0012***	0.0013***
	[0.0001]	[0.0001]	[0.0001]
Observations	94,197	94,197	94,197
Number of weather stations	4,824	4,824	4,824

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors clustered at the district level. Controls include district fixed-effects.

Figure A1. Self-Reported Overall Health Status (=1) and Average Daily Temperature at Each Stage of the Life cycle



Note: In each graph, the solid blue line represents the point estimate and the dashed line the 95% confidence intervals. Each estimate shows the effect on adult health outcomes of having more days with temperature above 50˚F. The stages of the life cycle were aggregated into four groups: *Pre*, which represents in utero exposure (i.e., the year before birth), *Inf* (aged between 1 and 4), *Child* (5-9) and *Teen* (10-15.) All regressions control for fixed effects at the district, birth cohort and survey year as well as state trends and individual characteristics (i.e., education, marital status and gender.)

Table A1. Main Regressions

		Adult health outcome:			
		Height (cm)	Weight (kg)	Accident (yes=1)	Good health (=1)
		(1)	(2)	(3)	(4)
In utero exposure	50˚F	-3.2208	-13.7264	-0.0387	-0.4285
		(4.7897)	(6.1352)	(0.1010)	(0.2222)
	60˚F	-0.5334	4.1877	-0.0197	0.2149
		(1.9878)	(3.6795)	(0.0389)	(0.1096)
	70˚F	0.5503	0.3068	0.0203	-0.0991
		(0.7551)	(1.4550)	(0.0236)	(0.0535)
	80˚F	0.0718	-2.176	-0.0216	0.0078
		(0.6598)	(1.6334)	(0.0251)	(0.0570)
	85˚F	-0.0700	1.7479	0.0273	0.0704
		(0.7562)	(1.7872)	(0.0257)	(0.0547)
	90˚F	-0.2012	-1.6486	-0.0174	-0.0657
		(0.5801)	(1.1346)	(0.0148)	(0.0380)
Infant (1-4 yrs.)	50˚F	20.1018	9.0504	-0.4511	-0.5236
		(8.4273)	(16.9150)	(0.2299)	(0.5923)
	60˚F	-7.4093	-7.2069	0.1307	-0.1585
		(2.8699)	(5.8920)	(0.0720)	(0.2059)
	70˚F	1.4214	1.6144	-0.0662	0.0853
		(1.2670)	(2.4275)	(0.0404)	(0.0917)
	80˚F	1.9027	4.7436	0.0728	-0.0385
		(1.2251)	(2.1731)	(0.0403)	(0.0900)
	85˚F	-2.2869	-4.3085	-0.0264	0.0275
		(1.3846)	(2.4886)	(0.0377)	(0.0998)
	90˚F	1.0903	0.9312	-0.0032	0.0465
		(0.8504)	(1.7507)	(0.0232)	(0.0665)
Child (5-9 yrs.)	50˚F	-6.6191	13.7291	-0.091	-0.358
		(8.1893)	(15.6738)	(0.3236)	(0.4178)
	60˚F	2.5033	2.9572	-0.1007	0.1318
		(2.9494)	(5.7275)	(0.0801)	(0.1873)
	70˚F	-0.4325	-3.0029	0.0048	-0.1057
		(1.2705)	(2.5228)	(0.0383)	(0.0899)
	80˚F	-1.735	-1.3251	-0.0104	0.0235
		(1.0693)	(2.4374)	(0.0407)	(0.0936)
	85˚F	0.8832	1.708	-0.0095	-0.0432
		(1.3233)	(3.0201)	(0.0419)	(0.1061)
	90˚F	-0.4365	-2.3539	0.0264	0.0613
		(0.8125)	(1.8932)	(0.0254)	(0.0625)

Table A1., continued

		Adult health outcome:			
		Height (cm)	Weight (kg)	Accident (yes=1)	Good health (=1)
		(1)	(2)	(3)	(4)
Adolescent (10-15 yrs.)	50˚F	18.6008	9.792	-0.0192	-0.4047
		(6.2349)	(13.7611)	(0.2190)	(0.4891)
	60˚F	-8.6361	-1.7968	0.0538	0.2097
		(2.2680)	(5.2151)	(0.0823)	(0.1939)
	70˚F	0.3974	-1.375	0.0072	-0.0215
		(1.0644)	(2.2352)	(0.0358)	(0.0919)
	80˚F	2.7452	3.1232	-0.0514	0.0334
		(1.0453)	(2.3629)	(0.0400)	(0.0808)
	85˚F	-2.9906	-2.5462	0.0317	0.0864
		(1.2028)	(3.0491)	(0.0408)	(0.0930)
	90˚F	1.8507	1.1009	0.014	-0.1176
		(0.8388)	(2.0613)	(0.0236)	(0.0659)
Observations		61,158	61,040	66,400	41,123

Note: Robust standard errors clustered at the district level are shown in parenthesis.