Moving down the energy ladder: In-utero temperature and fuel choice in adulthood

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Abstract

A growing literature shows that weather conditions during gestation can have persistent impacts on education and income, especially among females. However, the consequences of these impacts on behavior and choices during adulthood are still underexplored. To shed light on this issue, I use survey data for over 200,000 households in Peru and find that average temperature during gestation affects fuel choice during adulthood among women, with extensive margin increases in the use of dirty cooking fuels, but no changes in the likelihood of fuel stacking. Analysis of the mechanisms suggests that female head's income may be a more important driver than education. Supporting this argument, I show that the effects of in-utero temperature disappear among female beneficiaries of a conditional cash transfer program.

JEL codes: O12, O13, O15, Q56, J24

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1 Introduction

A growing body of literature shows that, through a chain of socioeconomic and physiological channels, weather conditions during gestation can have permanent effects on schooling and earnings during adulthood, mainly for females. Since female education and income are two of the most prominent determinants of the use of dirty fuels, a corollary is that weather conditions during gestation could impact fuel choice during adulthood, but this link has not been tested empirically. This paper contributes to closing this gap by studying how average in-utero temperature affects fuel choice during adulthood.

Uncovering effects of weather during gestation on fuel use during adulthood is an important policy question because of dirty fuels' detrimental effects on respiratory health and climate change. The negative health effects of dirty fuel use have been extensively documented and disproportionately affect females and young children, who are exposed to pollutant emissions while cooking (see, e.g. Smith et al., 2013, 2011). Furthermore, use of dirty fuels for cooking can affect climate because inefficient fuel combustion releases products of incomplete fuel combustion like methane and carbon monoxide into the atmosphere (Sagar and Kartha, 2007). In fact, biomass and fossil fuel cookstoves together emit 29 percent of global black carbon emissions (Ramanathan and Carmichael, 2008), and kerosene wick lamps account for an additional 7 percent (Lam et al., 2012).

The study setting is Peru, an especially interesting setting to study the effects of climate change, since it has been deemed as the third most vulnerable country worldwide by the Tyndall Centre for Climate Research (Molina and Saldarriaga, 2017). Long spells of unfavorable temperature are linked to livestock death, poor health, lower agricultural productivity and diminished accessibility in rural areas, which impact food prices and availability in urban areas. Thus, holding other factors constant, adverse temperature during pregnancy likely translate into less resources available for the pregnant mother. According to the well-established "fetal programming" or "Barker" hypothesis (Barker, 1990, 1995), poor maternal nutrition during pregnancy can hinder fetal development with effects that last through adulthood. Hence, there are reasons to believe that unfavourable in-utero weather may hurt human capital accumulation during childhood (Almond, Mazumder, and Ewijk, 2015), which in turn can have permanently negative consequences on adult life outcomes (Elango et al., 2015).

To study the relation between in-utero weather and fuel choice during adulthood I use data on socioeconomic outcomes and weather conditions during gestation for the principal couple (or the household head if he or she does not have a spouse) of the roughly 200,000 households that responded to Peru's National Household Survey between 2005 and 2015. The focus is on the principal couple because the decision on use of fuel is likely made by one – or the both – of them. The National Household Survey has information on socioeconomic outcomes, date, and district of birth. Temperature data were obtained from the Climatic Research Unit at the University of East Anglia. While most of the literature focuses on extreme events like droughts or heat days, I study the role of average in-utero temperature. The idea behind using average temperature is to show that temperature levels are indeed important, as explored by a small branch of the literature (Schlenker and Roberts, 2009; Burke, Hsiang, and Miguel, 2015; Barron, Heft-Neal, and Perez, 2018; Fishman, Russ, and Carrillo, 2015; Torres and Santa Maria, 2017).

The main explanatory variable is average temperature during gestation in the district of birth, henceforth *temp*. Following Barron, Heft-Neal, and Perez (2018) and Schlenker and Roberts (2009) I estimate a step regression, which provides considerable flexibility in estimating nonlinear relations. The specification compares individuals born in the same district at different points in time, and hence exposed to different average in-utero temperature, accounting for factors that vary across districts over time with district-by-year fixed effects. A number of findings come to light. First, females exposed to *temp* below 12.5C have higher probability of using dirty fuels for cooking relative to the comparison category, but there are no effects on dirty fuels for lighting or fuel stacking. These effects are nonlinear, starting at 6.5 percentage points (12% of the mean) for *temp* below 5C and decreasing monotonically for higher values of *temp*. Effects are not statistically significant for females born in *temp* above 12.5C or for males. Not only the effects of exposure to *temp* below 12.5C are sizable, they are statistically significant for 40% of females in the sample.

Second, I investigate potential mechanisms behind these effects. In the same setting, Barron, Heft-Neal, and Perez (2018) find that low average in-utero temperature reduced female – but not male – schooling and income, two key drivers of dirty fuel usage (Muller and Yan, 2018; Lewis and Pattanayak, 2012). Hence, I explore the role of these variables as mechanisms driving the results documented in this paper. The same pattern of magnitudes and statistical significance found in dirty fuel use appears in female income, but not in schooling or in household poverty status. This suggests that lower female income could be a driving force behind the increase in use of dirty fuels for cooking, even more important than household socioeconomic status.

Third, I analyze partner characteristics and intra-household bargaining power. I find that *temp* has no effect on the likelihood of having a partner. Then, conditional on having a partner, neither the difference between male and female schooling nor the female share of income respond to *temp*. However, exposure to *temp* below 15C reduces the likelihood that the female's partner has post-primary education, a measure of partner quality, by 6.3-8.5 percentage points.

Fourth, consistent with Kumar, Molitor, and Vollmer (2014), the effects on fuel use are mostly driven by average temperature during the first trimester of the pregnancy, although neither income nor schooling follow this pattern. The effects on fuel use are significant for females born in rural districts, and are not significant for females born in urban districts, suggestive of a story of reduced production and accessibility in rural areas as a result of unfavorable weather. In addition, the effects are more precisely estimated for females over 42 years old (the sample median), but the point estimates are similar above and below the median.

I conduct three types of robustness check to assess the trustworthiness of these results. First, I (i) expand the definition of dirty fuels to include "other fuels" and (ii) narrow it to only the most common fuel for cooking. Second, I employ a wide set of empirical specifications, exploring the consequences of changing the fixed effects. In both cases the results remain unchanged. Third, as falsification test I use temperature the trimester prior to the start of the pregnancy. The resulting coefficients are small in magnitude and not statistically significant.

In section 6.1 I conduct back-of-the-envelope calculations to estimate the health costs derived from these results. The analysis suggests that average in-utero temperature has increased use of dirty fuels by 1.8%. Based on calculations by Triana et al. (2007), this amounts to annual losses of US$ 4.8 million. Section 6.2 shows that climate change is has not reduced the likelihood of exposure to low *temp* during the study period (1950-2015). In contrast, section 6.3 provides evidence that the effects of *temp* fade among recipients of a conditional cash transfer program, JUNTOS, compared to non-recipient poor households. This is supportive evidence of income as an important driving force behind the effects of *temp* on fuel use.

This paper contributes to the literature of long-term effects of weather conditions around time of birth, which is reviewed in Section 2. Its main contribution is to provide evidence that in-utero temperature affects an important outcome that has not been explored yet: fuel choice during adulthood. I explore two margins of this relation: the extensive margin use of dirty fuels and fuel stacking.[1] Secondly, it offers evidence on the mediating channels behind these effects, pointing at income as a likely important driver of this relation. Third, in line with Schlenker and Roberts (2009); Burke, Hsiang, and Miguel (2015); Barron, Heft-Neal, and Perez (2018); Fishman, Russ, and Carrillo (2015) and Torres and Santa Maria (2017) it provides further evidence that temperature levels matter, not only extreme events, like heat days or droughts, which are the focus of most of the literature.

More generally, this study contributes to the literature of long-term effects of events

[1] In the empirical analysis, dirty fuels include firewood, charcoal, and kerosene, while clean fuels include LPG and electricity (which in Peru is mostly hydro-powered). “Fuel stacking” consists the use of both clean and dirty fuels by the same household.

during early life, which shows that such diverse events as exposure to pollution, radioactive fallout and fasting in this period can have consequences on childhood and adulthood. For instance, in Chile, Bharadwaj et al. (2014) show that fetal exposure to air pollution reduced academic performance among fourth graders. Rau, Urzúa, and Reyes (2015) find a similar effect for early exposure to toxic waste. Black et al. (2013) explore the effects of radioactive fallout in Norway. Exposure to nuclear radiation reduced schooling attainment and earnings among men and women. Importantly, the authors even find evidence of intergenerational effects in the same spirit as this study. Almond, Mazumder, and Ewijk (2015) provide evidence of the effects of maternal nutrition on test scores using exposure to Ramadan as a natural experiment. Test scores at age 7 are 0.05 to 0.08 standard deviations smaller for children exposed to Ramadan early in the pregnancy. Butikofer, Løken, and Salvanes (2015) find that a Norwegian early-life health program increased education and earnings in adulthood, with differentially stronger effects for children from low socioeconomic background.

The next section reviews the literature in more detail and develops the conceptual framework that guides the analysis, which is especially important given the long chain of causality investigated in this paper. Section 3 details the data and provides descriptive statistics of the study setting. In section 4 I describe the empirical approach, highlighting the assumptions required for identification of causal effects. Section 5 presents the main results of the paper, together with heterogeneity analysis, and sheds light on some of the most important mechanisms behind them. This section also presents robustness checks. Section 7 presents the main conclusions.

2 Literature Review

This section reviews evidence on the long term effects of in-utero weather, and outlines how it can affect use of dirty fuels during adulthood. Burke, Hsiang, and Miguel (2015) show that temperature affects economic production and productivity worldwide, and that these effects are not constrained to agricultural production.[2] Beyond the local effects on rural incomes, weather conditions also have economy-wide effects through food prices and availability (Hoddinott, 2006; Skoufias and Vinha, 2012; Kim and Lafortune, 2010; Rosales, 2014; Mendiratta, 2015), which can hurt the nutritional status of pregnant women (Aguilar and Vicarelli, 2011). Nutritional deprivation of pregnant women can impact the fetus, leading to impaired fetal development, with consequences that persist even through adulthood (Barker, 1990, 1995).

The economics literature has explored some of these effects. A number of studies have shown that weather conditions during gestation affect birth outcomes like mortality, weight and height (Yamauchi, 2012; Pereda, Menezes, and Alves, 2014; Rose, 1999; Rocha and Soares, 2015; Molina and Saldarriaga, 2017; Hu and Li, 2016; Andalón et al., 2014; Kudamatsu, Persson, and Strömberg, 2012). Moreover, there is increasing evidence that these shocks can affect early life outcomes. In fact, Almond, Mazumder, and Ewijk (2015) show that maternal nutrition can shape human capital formation in childhood even in developed countries. In India, several studies find that adverse rainfall conditions in-utero had detrimental effects on the nutritional status of children under 5 (Kumar, Molitor, and Vollmer, 2014; Mendiratta, 2015; Lokshin and Radyakin, 2012).[3] In turn, Shah and Steinberg (2017) show that rural primary school students in India exposed to droughts during gestation and early life score significantly worse on math and reading tests. In Latin America, Aguilar and Vicarelli (2011) and Rosales (2014) show that floods during early stages of life can affect cognitive development and height during the first years of primary education in Mexico and Ecuador, respectively.

A handful of studies shows that the effects on early life and childhood can have persistent effects on life outcomes like schooling achievement and earnings – mostly among females. In

[2]Using a similar empirical approach and identification strategy as this paper, Schlenker and Roberts (2009) find that temperature levels significantly affect US crop yields. Burke and Emerick (2016) find that US farmers do not show signs of adaptation to climate change.

[3]Kumar, Molitor, and Vollmer (2014) find that these effects are stronger for children exposed to drought in the first trimester of pregnancy.

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. In turn, Hu and Li (2016) show that high temperature days during pregnancy reduce schooling and height during adulthood in China, with impacts concentrated in the first and third trimesters. On the other hand, in a sample of Ecuadorian formal workers, Fishman, Russ, and Carrillo (2015) find statistically significant but small negative effects of average in-utero temperature on female earnings. Barron, Heft-Neal, and Perez (2018) show that exposure to average in-utero temperature below 12.5C reduces schooling and earnings in Peru among females, but not males. Torres and Santa Maria (2017) argue that this difference may be due to household resource reallocation. The authors document that, following a gestation period with low average temperature, mothers wean their boys, but not their girls, at a later age.

At the current state of knowledge, the next step consists in understanding the consequences of the reductions in schooling and earnings that arise from unfavorable weather, especially since females seem to bear most of the negative effects. Given that female schooling and earnings are two of the most prominent determinants of use of dirty fuels[4] (see the reviews by Muller and Yan, 2018; Lewis and Pattanayak, 2012) weather during gestation could feasibly affect fuel choice during adulthood. This choice is particularly important due to the detrimental effects of biomass combustion on health[5] (see e.g. Jeuland, Pattanayak, and Bluffstone, 2015; Smith et al., 2011, 2013) and the environmental externalities it generates (Sagar and Kartha, 2007; Ramanathan and Carmichael, 2008).

[4]Other determinants include urban location, fuel availability, fuel prices, household size and composition, sex of the household head, credit, supply chain, and social marketing (Muller and Yan, 2018; Lewis and Pattanayak, 2012).

[5]Indoor air pollution (IAP) is the third leading risk factor for global disease burden, after high blood pressure and smoking (Lim et al., 2012). In Peru, Gajate-Garrido (2013) finds negative health effects of biomass cooking on children under six.

3 Data and study setting

3.1 Socioeconomic outcomes

[INSERT TABLE 1 AROUND HERE]

The main data source for socio-economic variables and fuel use is Peru's National Household Survey (in Spanish, *Encuesta Nacional de Hogares*, or ENAHO) pooled from 2005 to 2015. Since the objective is to understand household fuel choices, the focus of this paper is the household head and his or her partner, who are likely in charge of the decision of fuel choice. The pooled survey data consists of around 200,000 households, with 330,000 individuals between the household head and partners. The survey includes information on the district and date of birth, which allows matching household survey with weather data at the time of birth.

Table 1 shows the main descriptive statistics of the sample. Panels A and B report the descriptive statistics for females and males, respectively. Females in the sample are on average 42 years old, have 7.3 years of schooling and earn 607 Soles (spatially and temporally deflated using as base the price level of Lima, the capital, in 2015, roughly equivalent to USD 175[6]), while males are on average 43.4 years old, have 8.8 years of schooling, and earn 1109 Soles per month (around USD 320). Twenty-nine percent of females are single household heads, while the figure for males is 17 percent. The poverty rate in both groups is 33 percent, and around two-thirds of the sample were born in rural areas. Average temperature during gestation was 15.0C for males and 15.1C for females.

Panel C reports use of dirty fuels, the main outcome of interest. As in most developing countries, females are in charge of cooking in Peru, so they carry a disproportionate share of the burden of dirty fuel use (Gajate-Garrido, 2013). Sixteen percent of households in the sample use dirty fuels for lighting, but over fifty percent of the sample uses dirty fuels for

[6] The exchange rate was fairly stable during the 11-year period, from 3.27 Soles per USD in January 2005 to 3.44 Soles per USD in December 2015.

cooking. This is likely an underestimate since the survey does not include dung as an independent category, and instead lumps it as "other fuels". "Dirty fuels" include firewood (39 percent), charcoal (14 percent), and kerosene (2 percent). Twenty-five percent of households report using other fuels, but there is no information on which are these other fuels, so in the main analysis the "dirty fuels" category is defined as firewood, charcoal or kerosene, but in section 5.4 I show that the main results are robust to changing the definition to include "other fuels". Twenty-two percent of households simultaneously use clean and dirty fuel sources for cooking, a behavior known in the literature as "fuel stacking".

[INSERT FIGURE 1 AROUND HERE]

Figure 1 shows the trends in use of dirty fuels for cooking and lighting from 2005 to 2015. There has been a steady improvement, with use of dirty fuels for lighting falling from nearly 35 percent to 8 percent. The use of dirty fuels for cooking fell from 65 percent in 2005 to 47 percent in 2015. Fuel stacking, on the other hand has increased from 15 percent in 2005 to 29 percent in 2015, as households gained access to clean sources like natural gas while keeping the dirty sources generally as backup.

3.2 Weather data

Weather data were obtained from the Climatic Research Unit at the University of East Anglia (CRU). The monthly data has a resolution of 0.5 x 0.5 degrees (Mitchell and Jones, 2005). Since districts typically cover parts of multiple grid cells, area-weighted averages were constructed using the grid cells overlapping the district.

There are three sources of measurement error in the empirical measurement of average temperature during gestation. First, being based on projections and interpolations, the dataset contains measurement error in each grid. Second, average temperature during gestation was constructed assuming nine-month pregnancy periods. For instance, a female born in September 1976 is assigned average temperature from January to September 1976. This may incorporate measurement error in average in-utero temperature, since gestation may have lasted more or less than nine months. Third, some districts are large, so weather conditions in the location of birth may not be accurately represented by the district average. Hence, an individual's true average temperature during gestation may be higher or lower than my empirical approximation. The likely consequence on the estimated effects is attenuation bias, in which case the estimated coefficients should be interpreted as lower bounds (in absolute magnitude) of the true effects of average in-utero temperature.

[INSERT FIGURE 2 AROUND HERE]

Figure 2 plots the histogram of average in-utero temperature for males and females. The distributions are almost exactly identical across groups. The vertical lines denote the quartiles of the full sample. The median value is 14.5C, while 25 percent of the sample was exposed to average in-utero temperature below 9C and 25 percent was exposed to average in-utero temperature above 21C.

4 Empirical approach

I use a step estimating equation to allow for considerable flexibility regarding the nature of the relationship between weather variables and the outcomes of interest (Schlenker and Roberts, 2009; Barron, Heft-Neal, and Perez, 2018). The main estimating equation is of the form:

$$y_{idbt} = \alpha_0 + \sum_j \beta_j \times \text{I(Temp=j)}_{idbt} + \sum_j \theta_j x_{idbt} + \delta_b + \gamma_{dt} + \varepsilon_{ipbt} \tag{1}$$

where y is the outcome of interest for individual i born in district d on date b,[7] and surveyed in year t. Temperature is measured in degrees Celsius, binned at 2.5C intervals. I use the bin that includes 18C ($\approx$ 65F) which is usually deemed as "thermal comfort", as a

[7]Date of birth is month and year of birth, e.g. May 1979

comparison category. In addition, x_{idbt} is the number of months that in-utero temperature fell in bin j. In this variable, the comparison category is also 17.5-20C. Hence, the comparison category is formed by people exposed to average in-utero temperature of 17.5-20C, and who were not exposed to average monthly temperatures outside that bin. In other words, β_j measures the difference in outcomes between a person exposed to average in-utero temperature in bin j and a person who was only exposed to monthly in-utero temperature between 17.5 and 20C.

I also employ average temperature by trimester of the pregnancy and, for a falsification test, average temperature during the three months prior to the pregnancy.[8] The sample is composed of the members of the principal couple or the household head, if he or she is single. Regressions are estimated separately for males and females.

The specification includes fixed effects for month-by-year of birth, and district of birth by year of the survey. In words, the coefficients are estimated by comparing outcomes across individuals born in the same district, controlling for economy-wide shocks at the time of their birth. In addition district-by-year fixed effects account flexibly for annual changes in outcomes across and space. To account for spatial correlation of weather, standard errors are clustered at the province level.[9] After controlling for fixed effects as described above, if monthly variations in temperature are exogenous to the individual, OLS provides consistent and unbiased estimates for β. This identification assumption is similar to Schlenker and Roberts (2009); Barron, Heft-Neal, and Perez (2018); and Molina and Saldarriaga (2017).

There are three threats to identification worth considering in this setting. First, there could be selection into pregnancy, as in most of the papers in this literature. Higher income or more educated households could choose the timing of their pregnancy for specific reasons which might correlate with temperature, and this self-selection would be the actual cause of the differences in outcomes during adulthood. Ideally, one would show that *temp* is

[8] Given the uncertainty about the exact duration of the pregnancy, I do this two ways: using months 10 to 12, and 11 to 13 prior to the birth. Results are essentially identical.

[9] There are 196 provinces in the country, which group approximately 10 districts each.

not correlated with household characteristics at the time of birth, but this information is not available in the household survey. However, there is indirect evidence against this story. Section 5.1 below shows that *temp* had statistically significant effects on outcomes for females, not for males. For this to be consistent with a "selection into pregnancy" story would require pregnant mothers of males to seek more favorable temperatures. However, as shown in Figure 2, the distribution of *temp* for males and females is essentially identical. Hence, there does not seem to be a strong concern for selection into pregnancy.

Second, there could be sex-selection in-utero, as proposed by the Trivers-Willard hypothesis (Trivers and Willard, 1973), and recently documented by Dagnelie, De Luca, and Maystadt (2018) and Valente (2015). These studies show that civil conflict in Nepal and Congo led to a higher share of female births, which could lead to the selection of other characteristics and bias the results. If this were the case in this sample, we would observe fewer males being born in cold temperatures. However, Figure 2 suggests that this is not a concern in this sample, as the distribution of average in-utero temperature is essentially identical between males and females.

A third threat to identification of β is that there could have been supply side changes with regard to fuel access and prices, which could affect the internal validity of β if these changes were correlated with *temp*. Although the available data do not allow to rule this out directly, to ameliorate this concern, at least to a degree, equation (1) includes district-by-year fixed effects.

Using average temperature during gestation involves a few empirical limitations worth discussing. First, hot and cold months could cancel each other out, so pregnancies with high temperature variability could appear as if they had usual temperature. The role of θ_j in equation (1) is to hold constant the number of months in each bin, addressing this concern. Second, according to this definition a one-degree increase for one month is treated equally as a one-ninth degree increase over the entire pregnancy, but there is no biological evidence to back up this statement.[10]

5 Results

5.1 Main results

Table 2 reports the main results in the paper. The main explanatory variable is average temperature during gestation (*temp*). The dependent variables are dichotomous indicators of dirty fuel use at the time of the survey (when subjects were 18 years old or older). The sample is composed by household heads and their spouses. The dependent variable in columns (1) and (4) is an indicator of use of dirty fuels for lighting; in columns (2) and (5), dirty fuel use for cooking. The dependent variable in columns (3) and (6) is a dichotomous indicator that turns on for households that use simultaneously clean and dirty fuels for cooking, allowing to investigate the effects of *temp* on fuel stacking. The results of Table 2 are summarized in panels (a) and (b) of figures 3 and 4.

[INSERT FIGURE 3 AROUND HERE]

[INSERT FIGURE 4 AROUND HERE]

[INSERT TABLE 2 AROUND HERE]

Columns (1)-(3) report the results for females. The point estimates of *temp* on the likelihood of using dirty fuels for lighting are small and only one of them is significant at the 90% of confidence. In contrast, exposure to low *temp* has sizable impacts on the probability of using dirty fuels for cooking during adulthood. Exposure to *temp* below 12.5C increases the probability of using dirty fuel sources for cooking by 3.5-6.5 percentage points relative to the comparison category, around 6-12 percent of the mean. This is the same temperature

[10] An alternative definition would use the number of hot months or cold months as a regressor, although doing so would not allow to evaluate the effects of temperature along the distribution of temperature, which is my primary objective.

range for which Barron, Heft-Neal, and Perez (2018) find statistically significant effects on schooling and labor market outcomes. The point estimate loses significance and decreases to 2 percentage points for *temp* between 12.5 and 15C, and fades as *temp* approaches the comparison category. For *temp* greater than the comparison category, the coefficients are small and not statistically significant. The coefficients in column (3) are close to zero in all cases and only one of them is significant at the 90% of confidence, indicating that *temp* is not a major driver of the likelihood of fuel stacking. This finding holds for alternative definitions of fuel stacking, including the combination of clean and dirty fuels for cooking and lighting, and alternative specifications in the same fashion as the robustness checks discussed in section 5.4.

The next three columns show the effects of the male *temp* on the same variables. The point estimates are small relative to the outcome mean and, with a few exceptions, are not statistically significant, indicating that male *temp* has no extensive margin effects on the use of dirty fuels or on fuel stacking. There are two exceptions worth noting: exposure to *temp* between 20 and 22.5C increases the use of dirty lighting by 2 percentage points and decreases the use of dirty fuels for cooking by the same amount, both at the 90% of confidence.

The following tables examine the effects of *temp* on related outcomes and mechanisms. To streamline the exposition, I will analyze the pattern of significance first for females exposed to *temp* below 12.5C, then for females exposed to *temp* above 12.5C, and then for males.

[INSERT TABLE 3 AROUND HERE]

Table 3 analyzes more closely effects on fuel choice among females. Columns (1)-(3) analyze the effects of *temp* on the most common dirty fuels in the sample: firewood, charcoal, and kerosene.[11] First, let's focus on females exposed to *temp* below 12.5C. The effects on firewood are large and statistically significant: from 5 percentage points in the 10-12.5C bin

[11] The survey includes an "other fuels" category which includes dung, used by 8 percent of rural households for cooking according to the 2017 Census (Instituto Nacional de Estadística e Informática, 2017), but the other fuels are not detailed so this category is not categorized as dirty fuels in the main results. Section 5.4 shows that the results of this table hold if "other fuels" are included into dirty fuels.

to 9 percentage points in the coldest bin, from 12 to 22 percent of the mean. The effects on charcoal and kerosene, on the other hand, are small and not statistically significant. Hence, most of the variation in use of dirty fuels arising from exposure to *temp* below 12.5C stems from firewood use. Exposure to *temp* above 12.5C has no statistically significant effects on fuel use, with three exceptions. Exposure to *temp* between 12.5-15C increased firewood use by 3 percentage points (at the 90% of confidence), while exposure to *temp* between 20 and 22.5C increased firewood use by 2 percentage points (at the 95% of confidence). Lastly, exposure to *temp* above 25C increased kerosene use by one percentage point, at the 90% of confidence.

Columns (4) and (5) explore the use of dirty fuels for cooking between females born in rural versus urban areas. District's rurality status at the time of the survey is used as a proxy for rurality at the time of birth. Since some rural districts have become urbanized with the passing of time, but not the converse, the measurement error in this proxy leads to compare people born in the most rural districts (those that did not become urban in the last 50 years) to the rest of the country (those that either became urban or were urban all along). However, note that over 60% of the sample was born in these "most rural" districts, so urbanization of rural districts does not seem to be too strong. With this in mind, we turn to analyze the effects by area of birth. Starting the analysis for the group with *temp* below 12.5C, the effects are statistically significant for females born in rural areas, with an effect of 8 percentage points for rural women in the coldest *temp* bin, to 4 percentage points for women in the bin with *temp* between 10-12.5C. The coefficients are not statistically significant for other temperatures or for women born in urban areas. However, this is not conclusive evidence that the effect is not present among females from urban areas, as the lack of significance in the colder bins is partly due to larger standard errors. In turn, the increase in standard errors may owe to a smaller number of observations and, more importantly, fewer clusters in this subsample, as only 64 provinces had urban areas.

Columns (6) and (7) split the sample by median age at the time of the survey (42 years old). As before, let's start with the analysis of exposure to *temp* below 12.5C. With the exception of women exposed to *temp* below 5C, the point estimates are fairly similar across groups, suggesting no considerable effect heterogeneity by age. However, the point estimates for women under 42 are less precisely estimated, and are significant only at the 90% level of confidence for *temp* between 5-10C, while the coefficient for women under 42 exposed to *temp* between 10-12.5C is not significant. The lower precision of the coefficients for the younger females may signal that the effects of weather in utero have started to fade towards the end of the study period. The year-by-district fixed effects would capture time varying variables if they were common to both cohorts, like improved availability of clean fuels or more widespread knowledge of their adverse effects. Thus, the loss in precision may be due to differential knowledge or changes in preferences across cohorts, but our data does not allow to test this. As in previous tables, most of the coefficients for *temp* above 12.5C are small and not statistically significant.[12]

5.2 Mechanisms

[INSERT TABLE 4 AROUND HERE]

The literature suggests education and income as two potential driving forces behind the use of dirty fuels. Table 4 examines their relation with *temp*, distinguishing between own income (in Soles of 2015 Lima) and the poverty status of the household, a measure of aggregate household wellbeing. The first three columns report results for females and the last three for males. Column (1) shows that exposure to *temp* below 12.5C does not affect schooling significantly. However, column (2) shows that exposure to *temp* below 7.5C reduces own income by up to S/ 200 (one-third of the sample mean), by S/ 134 for *temp* between 7.5-10C, and by S/ 90 in the 10-12.5C bin, although the last coefficient is not statistically significant. Column (3) shows that exposure to *temp* below 12.5C also increases poverty,

[12]The only statistically significant coefficient for *temp* above 12.5C is appears in the 12.5-15C bin for women over 42.

although the coefficients are not statistically significant below 7.5C.

Let's turn to analyze the coefficients for females exposed to *temp* above 12.5C. Recall that in this temperature range there are no statistically significant differences in use of dirty fuels for cooking with respect to the comparison category (17.5-20C). First, *temp* between 15-17.5C increased schooling by 0.26 years with respect to the comparison category, while *temp* between 20-22.5C reduced it by the same magnitude. Exposure to other values of *temp* did not lead to statistically significant differences in schooling. This erratic pattern is inconsistent with the pattern of the main outcome variable, suggesting that schooling is not a main driving force behind the results reported in section 5.1. Next, the effects on income for *temp* bins above 12.5C are not statistically significant, consistent with the lack of significant effects in the main outcome variable in these bins. In turn, column (3) for females exposed to *temp* above 12.5C shows that exposure to this temperature in-utero significantly increased the probability that females live in a poor household with respect to the comparison category, except for the 20-22.5C bin. This lack of consistency with the patterns in the main specification suggests that household wellbeing does not drive the use of dirty fuels for cooking in this sample, but rather the female's own income.

Columns (3)-(6) study the same variables for males. Schooling is unaffected by *temp* for this subsample, as is their household's poverty status. However, male income also responds to *temp*, but in the opposite direction as female income: exposure to *temp* below 12.5C increased incomes by roughly S/100 to 165 (9-15% of the sample mean).[13] Income is also higher for males with *temp* between 15 and 17.5C.

[INSERT TABLE 5 AROUND HERE]

Table 5 sheds further light on the driving mechanisms by analyzing partner characteristics and females' intrahousehold bargaining power. The dependent variable in column (1) is an indicator that the female has a partner. In columns (2) and (3), the dependent variables are

[13]The regressions for males and females report different results due to (i) single-headed households and (ii) different values of the explanatory variables: male *temp* and female *temp*.

difference in years of schooling and female income as percentage of the couple's total income, two commonly used measures of female bargaining power in the household.[14] Columns (3) and (4) explore partner characteristics. The first column shows that female *temp* has no effect on the probability of having a partner, which suggests that splitting the sample by this post-treatment variable should not generate major concerns about selection issues. However the results of this exercise are merely suggestive and subject to the usual caveat that splitting the sample by a post-treatment variable could bias the results. In columns (2) through (5), the sample is restricted to households where the head has a partner.

Column (2) examines how differences in schooling between the female and the male respond to female *temp*. This variable is defined in a way that negative numbers reflect that male schooling is higher than female schooling. The coefficients are negative, although not statistically significant in the same pattern as in the previous tables. In fact, another erratic pattern arises, suggesting that education is not a channel through which *temp* affects fuel choice. Column (2) shows that *temp* doest no affect the female income share, with coefficients that are small in magnitude and not statistically significant. Column (3) shows that exposure to *temp* below 12.5C reduces the probability of the partner having post-primary studies by 7-9 percentage points relative to the comparison category. The only other statistically significant coefficient is the 12.5-15C bin. Column (4) shows that effects on partner income are large (especially for *temp* below 12.5C) but imprecisely estimated.

Taken together, the evidence in this section suggests that female income and partner "quality" could be driving the effects of *temp* on fuel choice reported in section 5.1. However, it is also possible that lack of differences in schooling could be masking differences in learning outcomes, and these learning outcomes are generating differences in income. Further evidence is needed to explore the education channel more closely.

[14]These are the main intrahousehold bargaining indicators that can be constructed with the ENAHO survey data. A limitation of these variables is that they do not measure actual decision making. Other surveys, like the Demographic and Health Survey (DHS), include information on decision making in daily purchases, large purchases, freedom of movement, decision over the use of own income, as well as domestic violence. However, the DHS does not include information on place of birth, so it is impossible to construct an estimate of weather during gestation.

5.3 Effects by Trimester

Table 6 investigates differential effects by trimester of pregnancy. Previous literature has found that shocks in the first trimester have larger effects than shocks in the rest of the pregnancy[15] (e.g. Almond, Mazumder, and Ewijk, 2015; Rosales, 2014; Kumar, Molitor, and Vollmer, 2014). In addition, analyzing temperature by trimester also allows to ameliorate the limitation that hot and cold months may cancel each other out. However, by covering a shorter timespan, average temperature in a given trimester has potentially less scope to affect life outcomes than average temperature during the whole pregnancy period. Columns (1) through (3) show the effects of female *temp* by trimester on the likelihood of use of dirty fuels. In line with previous literature, the first trimester of gestation seems to be the most important. Female exposure to first trimester *temp* below 12.5C significantly increases the use of dirty fuels along the extensive margin, by 2-5 percentage points, while the effects of first trimester *temp* above 12.5C are small and not significant. Effects in the second or third trimester are not statistically significant, with the exception of third trimester *temp* above 25C, which reduced dirty fuel use for cooking by 2 percentage points.

Table 7 examines effects of temperature on schooling and income by trimester of the pregnancy. To ease the exposition, I start the analysis with the first trimester, which drives the results of fuel use. Contrary to the findings in Table 6, the effects on schooling are not significant for first trimester *temp* below 12.5 (with one exception at the 90% of confidence), but are significant for *temp* over 20C. The effects of exposure to first trimester *temp* below 12.5C on income are not significant, but their large standard errors do not allow to reject reductions of 15% of the mean or more. In contrast to Table 6, exposure to first trimester *temp* between 12.5C and 17.5C decreased income by 7-8%, while the point estimates for values over 20C are not significant. In addition, there are statistically significant negative effects of second trimester *temp* above 20C on schooling and income, together with mixed results of third trimester *temp*.

[15] Hu and Li (2016) find stronger effects in the first and third trimester.

[INSERT TABLE 6 AROUND HERE]

[INSERT TABLE 7 AROUND HERE]

5.4 Robustness checks

This section reports the results of three sets of robustness checks to assess the reliability of the estimates presented in this study. The first set of robustness checks is presented in Appendix Table A.1, and consists in changing the definition of dirty fuel use. The definition used in all columns is a dichotomous indicator that the household uses any dirty fuel, which includes households that rarely use dirty fuels. In column (1) the dependent variable is an indicator that *the main* fuel for cooking used by the household is dirty (firewood, kerosene, or charcoal). Recall that in the survey, dung is lumped together with other potentially clean fuels in the "other fuel" category. Column (2) presents the results changing the definition to include "other fuel" as dirty fuel. Results are almost identical to those presented in Table 2, with two exceptions. First, the coefficient for the 10-12.5C bin in column (2) is not statistically significant, unlike the main specification. Second, that exposure to *temp* between 20 and 22.5C increases the use of dirty fuels according to these definitions.

The second set of robustness checks is presented in Appendix Table A.2. These robustness checks relate to the econometric specification. To ease comparison, column (1) reports the main results in Table 2. Column (2) removes θ_j, the count of months in each bin that were included to control for temperature variation within the nine-month gestation period. Results are essentially unchanged when this variable is removed. Column (3) replaces θ_j by the standard deviation of in-utero temperature (SDT). The coefficient on SDT is small (0.006) and not significant (SE=0.005). The 95% confidence interval for the effect of a one-standard deviation increase in SDT (0.66 C) on the likelihood of cooking with dirty fuels runs from a 0.9 percentage point reduction to a 0.2 percentage point increase. Being a non-significant variable with a tight confidence interval, SDT can be safely omitted from the regression.[16] Column (4) includes fixed effects for district of residence. Note that this is an endogenous regressor, since households self-select into moving across districts, and select their destination. The effects in this column are estimated off of households that migrate, who are arguably better-off than those who do not migrate. The effects of *temp* are not statistically significant, which would suggest that the significant effects are concentrated on households who did not migrate (subject to the caveat of splitting the sample by a post-treatment regressor).

The third set of robustness checks is a falsification test, presented in Appendix Table A.4. The explanatory variable is average temperature during the trimester prior to conception, defined as months 10-12 prior to birth.[17] In this table, the dependent variables are indicators of use of dirty fuels for cooking. The first column corresponds to the main definition, use of any dirty fuel for cooking by the household, while the second and third columns employ the alternative definitions reported in Table A.1. The point estimates are essentially zero and none of them is statistically significant, providing further evidence that the findings in the previous tables are not artifacts of the data.

6 Discussion

6.1 Health Costs

In this section I perform back-of-the-envelope calculations to provide a monetary estimate of the health costs generated by the increased use of dirty fuels arising from the exposure to low average in-utero temperature. In the sample, 54.4% of females use dirty fuels for cooking, and 40% were exposed to *temp* below 12.5C.[18] If none of them had been exposed

[16] Table A.3 shows the interaction of SDT with the binned values of *temp*. At the mean value of SDT, the confidence intervals of the marginal effects of *temp* on the use of dirty fuels overlap with the results of the main specification.

[17] Appendix Table A.5 replicates the analysis using months 11-13 prior to birth with the same results.

[18] The breakdown by bins is: 3.5 % were exposed to *temp* below 5C, 10% to *temp* between 5 and 7.5C, 16.7 % to *temp* between 7.5 and 10C, and 9.8% to *temp* between 10C and 12.5C. The remaining 60% were exposed to *temp* above 12.5C.

to *temp* below 12.5C, the model predicts that the share of households using dirty fuels for cooking would have fallen by 1.8 percentage points in the country. The estimated reductions in use of dirty fuels are stronger among more vulnerable women: for instance they are larger for women born in rural areas (2 percentage points vs 1 percentage points in urban areas) and among women with only primary education (2 percentage points vs 1.6 for women with post-primary).

Triana et al. (2007) estimate the average annual health costs of biomass fuels in Peru at US$ 270 million, of which two-thirds are attributable to adverse health effects on children. Using this figure as benchmark implies that the 1.8% increase in dirty fuels for cooking attributable to cold in-utero weather amounts to health losses of US$ 4.9 million per year.

6.2 Can climate change "solve" this problem?

Since the negative effects estimated in this study arise from exposure to low in-utero temperature, one could argue that climate change would solve the problem, as it leads to warmer weather. In this section I argue this has not been the case in Peru, as the likelihood of a 9-month period with average temperature below 12.5C has not decreased in the last 60 years.

With the CRU weather dataset, I calculated 9-month temperature averages in each district of the country, from January 1950 to December 2014. This variable, denoted τ, is a measure of the average in-utero temperature to which a fetus would be exposed in the country over this period. As in the main analysis, τ is binned at 2.5C intervals. Figure 5 shows the probability of τ falling in each bin at each month in the dataset.

[INSERT FIGURE 5 AROUND HERE]

The figure shows that the likelihood of exposure to average in-utero temperature below 12.5C, as well as the other bins, has remained fairly stable from that point to the end of the sample. Because of the timing of the surveys and the requirement that individuals are over 18 years old to be included in the main analysis, 99% of individuals in the sample were born before 1991. The findings in this paper suggests that as the younger cohorts become heads of their own households we could expect similar effects on fuel use.

However, in the future, climate change is expected to accelerate, so nine-month periods below 12.5C may become less likely. Indeed, by 2065 the World Bank's climate projections for Peru point to increases in average maximum temperatures of 2-3C and of average minimum temperatures by 4-6C,[19]. However, these temperature increases will likely alter the country's entire productive structure, in which case the relation between in-utero temperature and fuel choice estimated here would not hold.

6.3 Policy Implications

The evidence shown thus far puts forward female income as a potentially important mechanism behind the effects of *temp* on use of dirty fuels for cooking. If this were the case, income transfers could mitigate the impact of exposure to low in-utero temperature. To test this hypothesis, albeit indirectly, I analyze whether a large conditional cash transfer program targeted at poor households, JUNTOS, mitigated the effects of average in-utero temperature. Importantly, JUNTOS is a CCT targeted at women, so it allows to test whether changes in female income alter the effect of *temp* on the use of dirty fuels for cooking.

[INSERT TABLE 8 AROUND HERE]

Table 8 shows the results. Since the program started in 2009, the first column reports the results of the main specification for all households in the 2009-2015 sample, showing that these are essentially the same as the results for the whole study period (2005-2015). Both the magnitude and the statistical significance of the coefficients are similar to the results in Table 2. The second column reports the results for females from poor households who were not CCT recipients. The point estimates in this subsample are larger than for the full sample. The third column reports the results for female CCT recipients. The coefficients

[19] https://climateknowledgeportal.worldbank.org/country/peru/climate-data-projections, accessed June 19, 2021

become smaller and lose statistical significance, suggesting that the conditional cash transfer counteracted the effect of exposure to low average in-utero temperature.

There are two important caveats with this test. First, since poverty and beneficiary status are potentially endogenous outcomes, this test is far from perfect. Second, since CCTs are given to females, higher income mechanically increases female income share and intra-household bargaining power, so the effect could be operating through these variables instead of income.

7 Conclusions

A growing body of evidence has shown that weather conditions in utero can have strong effects on birth outcomes, early childhood development and education and labor market outcomes. This paper shows that there are effects on tangible choices during adulthood, like the use of dirty fuels for cooking. Exposure of females to average in-utero temperature below 12.5C (roughly 40% of the sample) increases the likelihood of using dirty fuels for cooking by 3.5-6.5 percentage points compared to females born in the comparison category of 17.5-20C, a 6-12% increase. These results are robust to three types of robustness checks, and a falsification test supports the argument that these findings are not artifacts of the data.

Female education and income are two of the most important determinants of fuel choice (Lewis and Pattanayak, 2012; Muller and Yan, 2018). The analysis in this paper supports the role of income as a likely channel through which exposure to low *temp* affects fuel choice. Further research is needed to draw a clearer conclusion especially given the results by trimester, but altogether the evidence in this study suggests that interventions aimed at increasing female income could effectively counteract the increased use of dirty fuels attributable to exposure to low *temp*. However, it is important to note that lower income is in itself an intermediate outcome, a result of changes physiological and socioeconomic changes unleashed by exposure to low average in-utero temperature. Other complementary measures like incentivizing thermal insulation of dwellings and barns, or the diffusion of cold-resistant crops could also be considered.

A possible reason for the gender gap in the effects of temperature on income is household resource reallocation to favor boys. In fact Torres and Santa Maria (2017) show that households in Peru respond to average temperature during gestation below 12.5C by weaning boys, but not girls, at a later age. This could point at households reallocating resources to compensate the adverse developmental effects of in-utero temperature on boys, but not girls.

Average temperature during gestation has no effects on fuel stacking, a common practice in the study setting as well as in most developing regions that consists in using dirty and clean fuels, the former usually as backup. This finding suggests that changes in fuel stacking may require stronger changes in education, income, or intrahousehold bargaining power than those required to change the likelihood of using dirty fuels.

Most of the statistically significant coefficients correspond to females exposed to *temp* below 12.5C. However, there are some statistically significant coefficients outside this subsample, either for females in higher *temp* or for males, but these are scattered, with the exception of *temp* between 20 and 22.5C. Overall, exposure to *temp* between 20 and 22.5C seems to increase the use of dirty fuels. First, this is the only bin that had significant effects on the use of dirty fuels for lighting (of 2 percentage points, for both males and females). Second, females exposed to *temp* between 20 and 22.5C were the only group that had significantly lower likelihood of fuel stacking than the comparison category. Third, female exposure to *temp* between 20 and 22.5C increased the use of dirty fuels for cooking (with the definitions in Tables A.1) by 3 percentage points and the use of firewood by 2 percentage points. However, male exposure to *temp* in this bin reduced the use of dirty fuels for cooking by 2 percentage points. The story regarding the mechanisms is also contrary to the findings for *temp* below 12.5C: exposure to *temp* in the 20-22.5 bin does not reduce female income, but reduces female schooling in absolute terms and relative to their partners. This suggests that different mechanisms may operate in cold versus warm *temp*, but the available data cannot provide a convincing explanation.

A second limitation relates to the lack of information on respiratory health in children. Increases in use of dirty fuel for cooking likely affect respiratory health among children, but the data does not allow to test these effects empirically. The National Household Survey lumps together respiratory problems with headaches and "other symptoms", making it unsuitable for this purpose.[20] A third important limitation is that the analysis focuses on the extensive margin exclusively. However, working with intensive margins requires having trustworthy measures of consumption, which are not available in this setting since firewood is collected by household members, and when it is bought in the market, it is usually measured in non-standard units like "bunches" instead of kilograms.

The main message of this paper is that, among Peruvian females, exposure to average temperature during gestation below 12.5C had tangible effects on fuel choice during adulthood. This is likely a consequence of the effects of in-utero weather conditions on income. Changes along this margin of behavior contribute to the household's entrapment in poverty, through effects on health and productivity, but in addition they also contribute to further climate change. The analysis presented here suggests that female income-generating interventions can ameliorate these effects, at least to an extent.

[20] The Demographic and Health Survey provides a finer disaggregation of illnesses and symptoms, but does not include information on place of birth.

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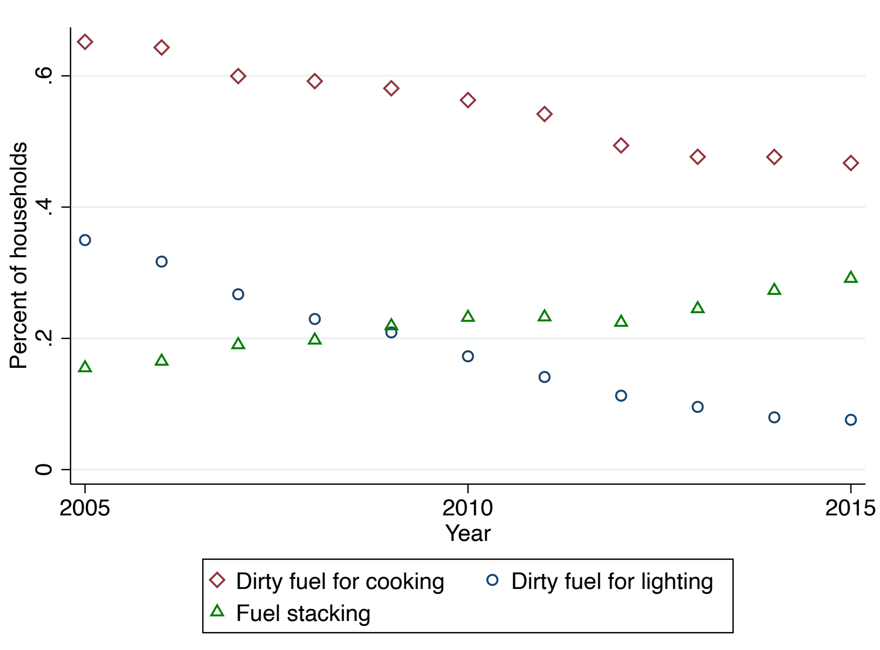
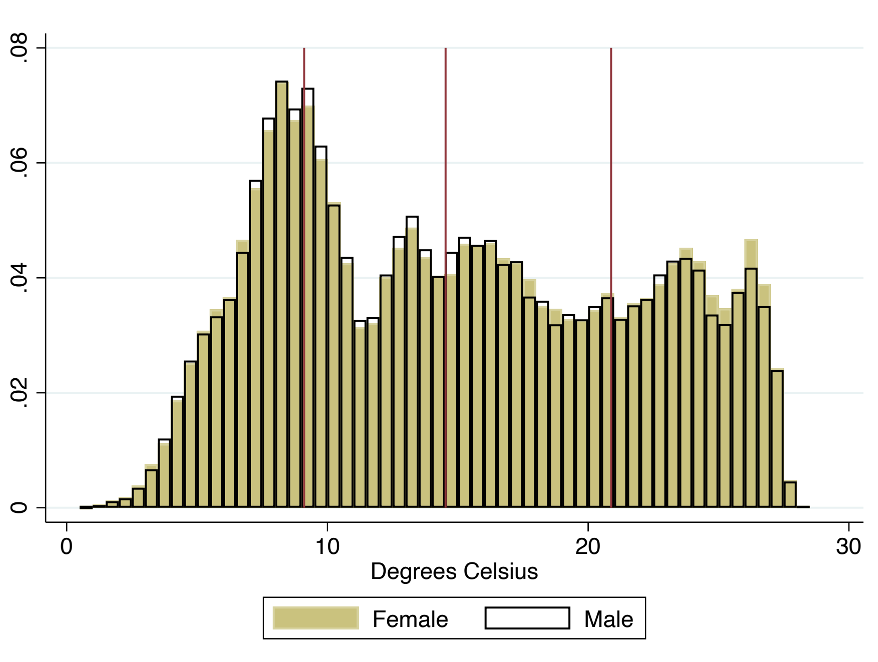
Figure 1: Use of dirty fuels for cooking and lighting, 2005-2015



Notes: Source: 2005-2015 National Household Surveys.

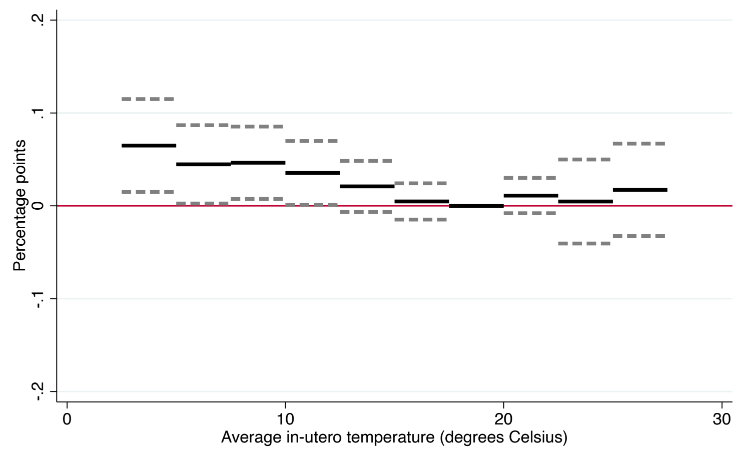
Figure 2: Average in-utero temperature



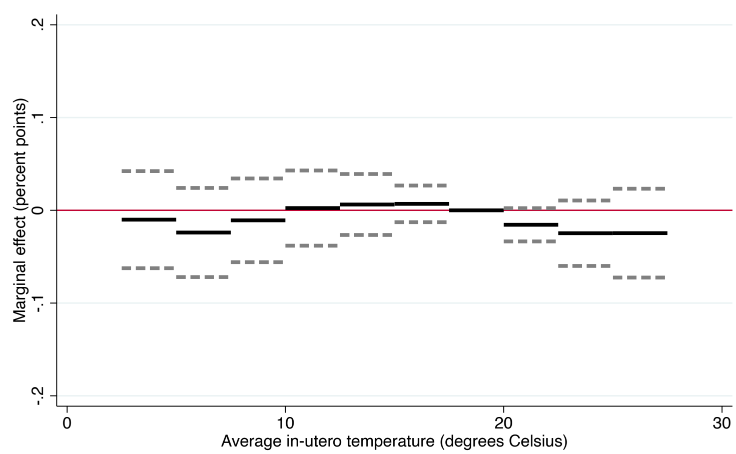
Notes: The red lines indicate the 25^{th}, 50^{th}, and 75^{th} percentiles of the pooled sample. Source: 2005-2015 National Household Surveys and Climatic Research Unit, University of East Anglia.

Figure 3: Main results, females

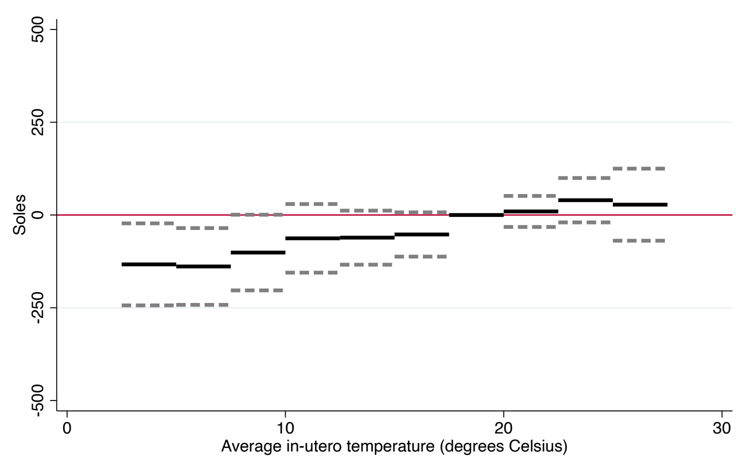
(a) Use of dirty fuels for cooking in the household



(b) Fuel stacking



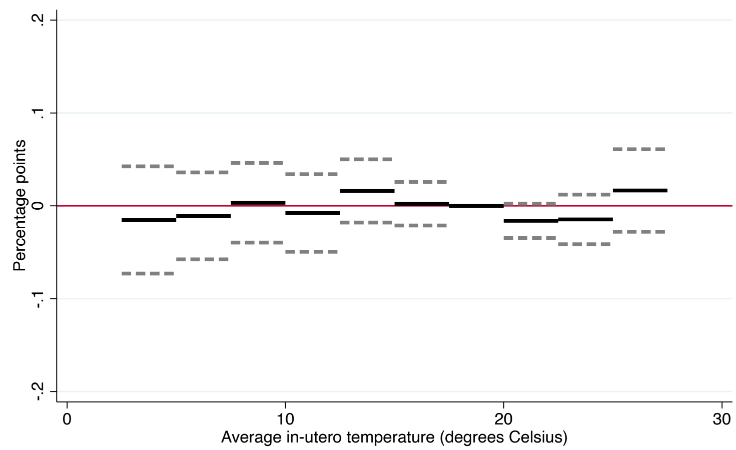
(c) Income



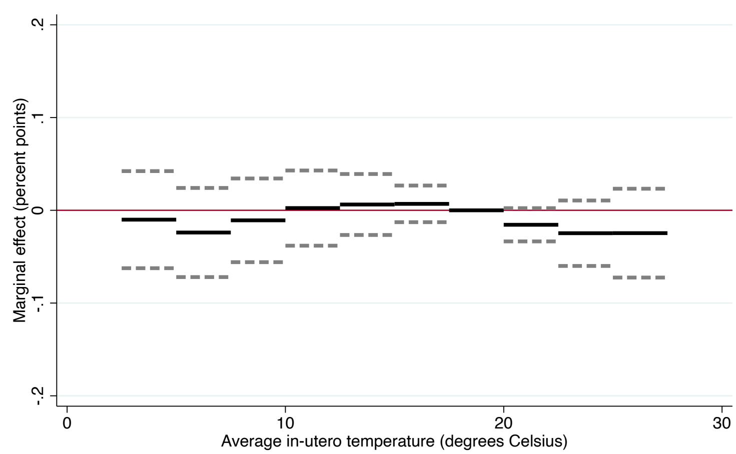
These figures plot the coefficients results of equation (1). Dashed lines represent the 95% confidence intervals. The comparison category is *temp* between 17.5 and 20C. See main text, and tables 2 and 4 for details. Source: INEI and CRU.

Figure 4: Main results, males

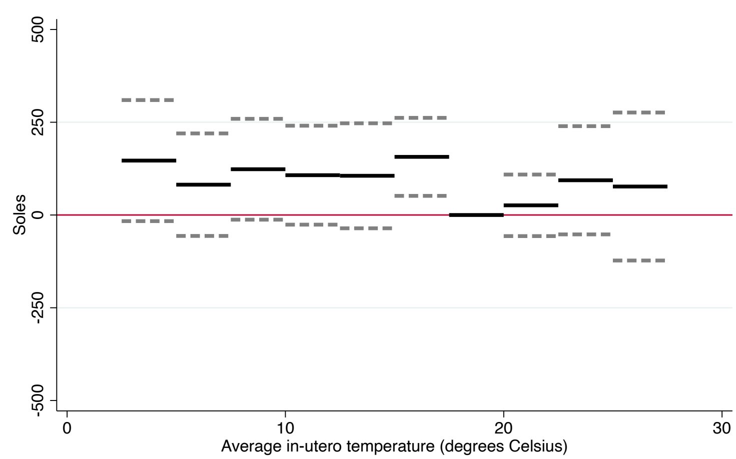
(a) Use of dirty fuels for cooking in the household



(b) Fuel stacking

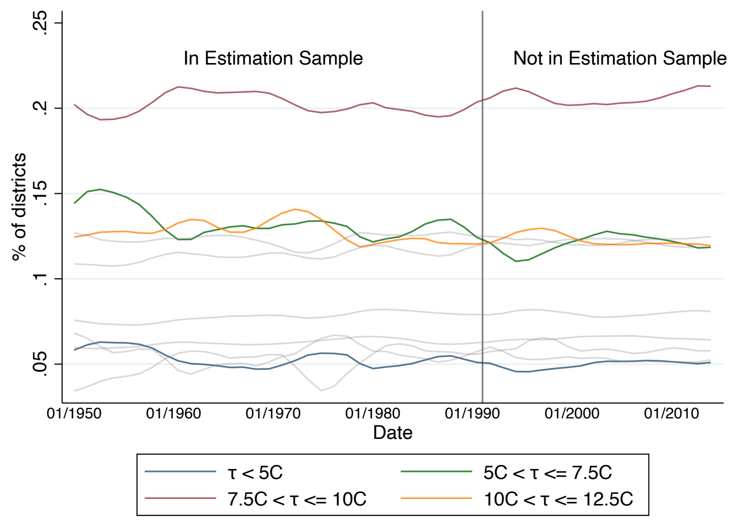


(c) Income



These figures plot the coefficients results of equation (1). Dashed lines represent the 95% confidence intervals. The comparison category is *temp* between 17.5 and 20C. See main text, and tables 2 and 4 for details. Source: INEI and CRU.

Figure 5: Nine-month average temperature (τ) per district, 1950-2015



Notes: τ is the nine-month average temperature up to the date indicated in the horizontal axis. The vertical axis measures the share of districts where τ fell in each bin. The gray lines denote bins above 12.5C.

Table 1: Descriptive statistics

Variable	(1) Observations	(2) Mean	(3) Standard deviation
Panel A - Females			
Age (years)	178,214	42.0	10.9
Two-headed household(1/0)	178,214	.71	.45
Schooling (years)	178,202	7.3	5.0
Monthly individual income (2015 Soles)	123,903	607.4	967.5
Pooor (1/0)	178,214	.33	.47
Born in rural district (1/0)	174,282	.65	.48
Average temperature during gestation (C)	176,232	15.1	6.7
Panel B - Males			
Age (years)	152,653	43.4	10.4
Two-headed household (1/0)	152,653	.83	.37
Schooling (years)	152,640	8.8	4.4
Monthly individual income (2015 Soles)	145,869	1,109.1	1,609.9
Poor (1/0)	152,653	.33	.47
Born in rural district(1/0))	149,260	.66	.47
Average temperature during gestation (C)	150,595	15.0	6.6
Panel C - Fuel use in the household			
Fuel stacking (1/0)	203,510	.22	.41
Dirty fuel for lighting (1/0)	203,510	.16	.37
Dirty fuel for cooking (1/0)	203,510	.52	.50
Kerosene for cooking (1/0)	203,510	.02	.13
Charcoal for cooking (1/0)	203,510	.14	.35
Wood for cooking (1/0)	203,510	.39	.49
Other fuel for cooking (1/0)	203,510	.25	.43

Notes: The sample includes the principal couple, or the household head in case he or she doesn't have a spouse. Source: 2005-2015 ENAHO and CRU.

Table 2: Effect on use of dirty fuels

	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
	Lighting	Cooking	Fuel Stacking	Lighting	Cooking	Fuel Stacking
temp $\leq$5.0	0.008	0.065**	-0.010	-0.035	-0.015	0.026
	(0.021)	(0.025)	(0.027)	(0.023)	(0.029)	(0.027)
5.0< temp $\leq$7.5	0.015	0.045**	-0.024	-0.003	-0.011	0.025
	(0.018)	(0.021)	(0.024)	(0.019)	(0.024)	(0.023)
7.5< temp $\leq$10.0	0.020	0.046**	-0.011	0.005	0.003	0.021
	(0.018)	(0.020)	(0.023)	(0.017)	(0.022)	(0.021)
10.0< temp $\leq$12.5	-0.000	0.035**	0.002	-0.004	-0.008	0.009
	(0.016)	(0.017)	(0.021)	(0.017)	(0.021)	(0.020)
12.5< temp $\leq$15.0	0.005	0.021	0.006	-0.013	0.016	0.012
	(0.012)	(0.014)	(0.017)	(0.013)	(0.017)	(0.016)
15.0< temp $\leq$17.5	0.001	0.005	0.007	-0.004	0.002	-0.002
	(0.006)	(0.010)	(0.010)	(0.007)	(0.012)	(0.010)
20.0< temp $\leq$22.5	0.016*	0.011	-0.016*	0.019**	-0.016*	-0.008
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.012)
22.5< temp $\leq$25.0	0.011	0.005	-0.025	0.015	-0.015	0.004
	(0.013)	(0.023)	(0.018)	(0.011)	(0.014)	(0.016)
temp >25.0	0.016	0.017	-0.025	-0.011	0.017	0.032
	(0.015)	(0.025)	(0.024)	(0.014)	(0.023)	(0.020)
Mean of Dep Variable	0.164	0.544	0.234	0.178	0.539	0.220
Number of Observations	175105	175105	175105	149776	149776	149776
Number of Clusters	193	193	193	193	193	193
R squared	0.350	0.333	0.154	0.361	0.343	0.166

Notes: The sample is the principal couple, aged 18 or more. Dependent variables are indicators of use of dirty fuels for lighting (columns 1, 4), cooking (columns 2, 5), or fuel stacking (columns 3, 6). *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year), district of birth-by-year fixed effects, and a count of months in each temperature bin 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: 2005-2015 ENAHO and CRU.

Table 3: Effect by fuel, females

	Fuel Type			Area		Age	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Firewood	Charcoal	Kerosene	Rural	Urban	18 to 42	Over 42
temp ≤5.0	0.093***	-0.016	0.000	0.077**	0.052	0.135***	0.037
	(0.026)	(0.014)	(0.007)	(0.031)	(0.063)	(0.048)	(0.032)
5.0< temp ≤7.5	0.071***	-0.017	-0.003	0.057**	0.028	0.061*	0.060**
	(0.021)	(0.014)	(0.006)	(0.027)	(0.053)	(0.036)	(0.030)
7.5< temp ≤10.0	0.065***	-0.010	-0.002	0.057**	0.029	0.052*	0.065**
	(0.019)	(0.013)	(0.005)	(0.025)	(0.044)	(0.031)	(0.028)
10.0< temp ≤12.5	0.047**	-0.005	-0.003	0.042*	0.024	0.036	0.048*
	(0.018)	(0.011)	(0.004)	(0.022)	(0.042)	(0.027)	(0.025)
12.5< temp ≤15.0	0.025*	0.004	-0.002	0.025	0.021	0.009	0.043*
	(0.014)	(0.008)	(0.004)	(0.019)	(0.023)	(0.021)	(0.023)
15.0< temp ≤17.5	0.004	0.004	-0.001	0.004	0.007	-0.013	0.017
	(0.009)	(0.005)	(0.002)	(0.016)	(0.013)	(0.015)	(0.013)
20.0< temp ≤22.5	0.019**	-0.008	-0.000	0.014	0.008	0.011	0.015
	(0.008)	(0.006)	(0.004)	(0.014)	(0.013)	(0.016)	(0.017)
22.5< temp ≤25.0	-0.002	-0.000	0.001	0.015	0.002	-0.010	0.035
	(0.016)	(0.014)	(0.004)	(0.021)	(0.035)	(0.028)	(0.032)
temp >25.0	-0.008	0.022	0.008*	0.018	0.025	0.025	0.014
	(0.021)	(0.025)	(0.005)	(0.025)	(0.043)	(0.037)	(0.032)
Mean of Dep Variable	0.406	0.151	0.018	0.639	0.370	0.551	0.536
Number of Observations	175105	175105	175105	112090	60570	87692	83033
Number of Clusters	193	193	193	191	64	193	193
R squared	0.393	0.395	0.202	0.338	0.193	0.370	0.363

Notes: The sample is the principal couple, aged 18 or more. Dependent variables in columns (1)-(3) are indicators of dirty fuels for cooking, in columns (4)-(7) is an indicator of dirty fuel use, but the sample is split by area of birth (columns 4, 5) or age (columns 6, 7). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year), district of birth-by-year fixed effects, and a count of months in each temperature bin 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: 2005-2015 ENAHO and CRU.

Table 4: Mechanisms: Schooling and income

	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
	Schooling	Income	HH is poor	Schooling	Income	HH is poor
temp ≤5.0	-0.018	-199.238***	0.043	0.054	163.776*	0.001
	(0.034)	(69.302)	(0.027)	(0.036)	(87.735)	(0.030)
5.0< temp ≤7.5	-0.026	-189.172***	0.036	0.050*	102.752	0.006
	(0.029)	(66.811)	(0.023)	(0.028)	(75.791)	(0.026)
7.5< temp ≤10.0	-0.039	-134.258**	0.043**	0.024	145.644*	0.008
	(0.026)	(66.606)	(0.020)	(0.025)	(73.967)	(0.023)
10.0< temp ≤12.5	-0.010	-89.909	0.036*	0.015	128.267*	0.015
	(0.024)	(60.692)	(0.020)	(0.023)	(72.769)	(0.020)
12.5< temp ≤15.0	0.003	-70.993	0.036***	0.008	100.000	0.024
	(0.021)	(49.475)	(0.013)	(0.021)	(74.298)	(0.017)
15.0< temp ≤17.5	0.011	-60.059	0.018***	0.017	160.352***	0.016
	(0.017)	(41.240)	(0.007)	(0.011)	(52.108)	(0.010)
20.0< temp ≤22.5	-0.020*	14.585	0.015	0.002	25.711	-0.001
	(0.012)	(25.900)	(0.010)	(0.011)	(43.051)	(0.011)
22.5< temp ≤25.0	-0.020	48.729	0.023*	0.009	90.699	0.006
	(0.018)	(36.747)	(0.013)	(0.019)	(75.862)	(0.015)
temp >25.0	-0.031	59.382	0.045**	0.025	65.416	0.003
	(0.022)	(67.475)	(0.021)	(0.025)	(104.168)	(0.019)
Mean of Dep Variable	0.489	607.763	0.331	0.632	1108.845	0.331
Number of Observations	175092	120584	175105	149764	142970	149776
Number of Clusters	193	193	193	193	193	193
R squared	0.345	0.162	0.296	0.312	0.161	0.301

Notes: The sample is the principal couple, aged 18 or more. Dependent variable: in columns (1) and (4) is years of schooling; in columns (2) and (5) is income in Soles of 2015-Lima; in columns (3) and (6) is an indicator that takes the value of 1 if the household is classified as poor. *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year), district of birth-by-year fixed effects, and a count of months in each temperature bin 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: 2005-2015 ENAHO and CRU.

Table 5: Mechanisms: Partner characteristics and intra-household bargaining power

		Intrahousehold Barganing		Partner Characteristics	
	(1)	(2)	(3)	(4)	(5)
	Two-headed household	Difference in schooling	Income share	Post-Primary	Income
temp ≤5.0	0.059*	0.131	-0.014	-0.074*	-142.724
	(0.031)	(0.307)	(0.028)	(0.044)	(99.278)
5.0< temp ≤7.5	0.045	-0.017	-0.022	-0.074*	-96.387
	(0.029)	(0.258)	(0.022)	(0.040)	(91.843)
7.5< temp ≤10.0	0.029	-0.093	-0.021	-0.069*	-82.426
	(0.027)	(0.219)	(0.020)	(0.036)	(89.398)
10.0< temp ≤12.5	0.020	0.088	-0.017	-0.085***	-104.691
	(0.025)	(0.194)	(0.017)	(0.033)	(76.349)
12.5< temp ≤15.0	0.017	0.172	-0.007	-0.063**	4.138
	(0.019)	(0.167)	(0.016)	(0.030)	(61.511)
15.0< temp ≤17.5	0.007	0.026	0.003	-0.005	21.313
	(0.014)	(0.100)	(0.011)	(0.025)	(42.213)
20.0< temp ≤22.5	-0.005	-0.369***	0.005	0.017	-34.716
	(0.012)	(0.110)	(0.010)	(0.023)	(38.242)
22.5< temp ≤25.0	-0.007	-0.360**	0.000	0.027	-2.595
	(0.016)	(0.149)	(0.018)	(0.033)	(68.632)
temp >25.0	-0.014	-0.413	-0.007	0.017	-24.381
	(0.022)	(0.251)	(0.019)	(0.046)	(92.474)
Mean of Dep Variable	0.715	-1.469	0.356	0.763	1086.116
Number of Observations	175105	123947	77435	81056	118216
Number of Clusters	193	193	193	191	193
R squared	0.218	0.169	0.176	0.257	0.178

Notes: The sample consists of female heads or spouses of the head aged 18 or over. Dependent variable: in column (1) is an indicator that the household has male and female head; in column (2) is female head's schooling minus male head's schooling, in column (3) is female income as share of the principal couple's income, in column (4) is an indicator that her partner has post-primary studies, and in column (6) is partner's income. *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year), district of birth-by-year fixed effects, and a count of months in each temperature bin 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: 2005-2015 ENAHO and CRU.

Table 6: Effects by trimester

	Dirty Fuel		
	(1)	(2)	(3)
	1st Trim	2nd Trim	3rd Trim
temp $\leq$ 5.0	0.048***	0.025	0.003
	(0.017)	(0.021)	(0.019)
5.0< temp $\leq$7.5	0.027**	0.016	0.005
	(0.014)	(0.017)	(0.017)
7.5< temp $\leq$10.0	0.024**	0.006	0.004
	(0.012)	(0.015)	(0.015)
10.0< temp $\leq$12.5	0.024**	0.014	0.004
	(0.010)	(0.012)	(0.013)
12.5< temp $\leq$15.0	0.013	0.006	0.002
	(0.008)	(0.009)	(0.011)
15.0< temp $\leq$17.5	0.010	0.001	-0.005
	(0.007)	(0.006)	(0.009)
20.0< temp $\leq$22.5	-0.003	-0.002	-0.001
	(0.008)	(0.008)	(0.007)
22.5< temp $\leq$25.0	-0.009	0.010	-0.007
	(0.010)	(0.012)	(0.009)
temp > 25.0	-0.006	0.003	-0.018**
	(0.010)	(0.012)	(0.009)
Mean of Dep Variable	0.544	0.544	0.544
Number of Observations	175105	175105	175105
Number of Clusters	193	193	193
R squared	0.333	0.333	0.333

Notes: The sample consists of female heads or spouses of the head aged 18 or over. Dependent variable is an indicator of use of dirty fuels for cooking. *temp* is average in-utero temperature (in degrees Celsius) over the first trimester (column 1), second trimester (column 2), and third trimester (column 3). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year) and district of birth-by-year fixed effects 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: 2005-2015 ENAHO and CRU.

Table 7: Effects by trimester on Schooling and Income

	Schooling			Income		
	(1)	(2)	(3)	(4)	(5)	(6)
	1st Trim	2nd Trim	3rd Trim	1st Trim	2nd Trim	3rd Trim
temp $\leq$ 5.0	-0.258	0.173	0.282	-53.312	-36.615	62.552
	(0.199)	(0.222)	(0.246)	(41.542)	(38.091)	(48.767)
5.0< temp $\leq$7.5	-0.245	0.134	0.239	-46.233	-43.924	50.897
	(0.174)	(0.186)	(0.199)	(35.955)	(35.849)	(44.292)
7.5< temp $\leq$10.0	-0.231	0.046	0.302*	-40.007	-43.418	45.594
	(0.156)	(0.166)	(0.178)	(32.763)	(35.027)	(39.922)
10.0< temp $\leq$12.5	-0.261*	0.066	0.294*	-40.444	-30.545	42.842
	(0.138)	(0.138)	(0.156)	(25.766)	(30.372)	(34.273)
12.5< temp $\leq$15.0	-0.155	0.029	0.154	-38.168**	-21.385	51.064*
	(0.108)	(0.107)	(0.101)	(18.399)	(29.201)	(28.181)
15.0< temp $\leq$17.5	-0.036	-0.021	0.107*	-52.619***	7.056	55.921**
	(0.067)	(0.066)	(0.065)	(13.628)	(31.441)	(23.554)
20.0< temp $\leq$22.5	-0.165**	-0.035	-0.051	1.066	-34.424***	0.015
	(0.083)	(0.068)	(0.070)	(24.821)	(12.606)	(16.865)
22.5< temp $\leq$25.0	-0.211**	-0.212**	0.006	4.120	-39.683**	-10.156
	(0.099)	(0.084)	(0.094)	(21.286)	(18.929)	(20.413)
temp > 25.0	-0.228*	-0.244***	0.005	15.168	-49.941***	-27.575*
	(0.118)	(0.092)	(0.088)	(21.379)	(16.901)	(15.874)
Mean of Dep Variable	7.260	7.260	7.260	607.763	607.763	607.763
Number of Observations	175092	175092	175092	120584	120584	120584
Number of Clusters	193	193	193	193	193	193
R squared	0.386	0.386	0.386	0.162	0.162	0.162

Notes: The sample is female heads or spouses of the head aged 18 or over. Dependent variable: in columns (1) - (3) years of schooling; in columns (3) - (6) is income in Soles of 2015-Lima. *temp* is average in-utero temperature (in degrees Celsius) over the first trimester (columns 1 and 4), second trimester (columns 2 and 5), and third trimester (columns 3 and 6). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year), and district of birth-by-year fixed effects 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: 2005-2015 ENAHO and CRU.

Table 8: Effects of average in-utero temperature and conditional cash transfers, 2009-2015

	(1) All households	(2) Poor, Non-beneficiary	(3) Juntos Beneficiary
temp ≤5.0	0.061*	0.186**	0.047
	(0.033)	(0.079)	(0.087)
5.0< temp ≤7.5	0.059**	0.169***	-0.018
	(0.028)	(0.063)	(0.069)
7.5< temp ≤10.0	0.068***	0.117**	-0.037
	(0.024)	(0.057)	(0.060)
10.0< temp ≤12.5	0.055**	0.058	-0.056
	(0.021)	(0.049)	(0.057)
12.5< temp ≤15.0	0.034*	0.018	-0.047
	(0.018)	(0.047)	(0.051)
15.0< temp ≤17.5	0.003	-0.008	-0.049
	(0.012)	(0.035)	(0.039)
20.0< temp ≤22.5	0.006	0.024	0.010
	(0.012)	(0.041)	(0.043)
22.5< temp ≤25.0	-0.001	0.019	-0.030
	(0.030)	(0.050)	(0.059)
temp >25.0	-0.005	0.017	-0.135
	(0.031)	(0.059)	(0.100)
Mean of Dep Variable	0.511	0.697	0.806
Number of Observations	123575	20839	15193
Number of Clusters	193	192	151
R squared	0.327	0.469	0.561

Notes: The sample is female heads or spouses of the head aged 18 or over. The dependent variable is an indicator that the household uses wood, charcoal or kerosene for cooking. Column (1) contains all households in the 2009-2015 surveys. Column (2) is the subsample of poor household that are not beneficiaries of JUNTOS, a conditional cash transfer program. Column (3) is the subsample of JUNTOS beneficiaries. *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year), district of birth-by-year fixed effects, and a count of months in each temperature bin 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: 2009-2015 ENAHO and CRU.

Appendix

Table A.1: Alternative definitions

	(1) Cook Dirty 2	(2) Cook Dirty 3
temp $\leq$5.0	0.068***	0.059**
	(0.025)	(0.027)
5.0$<$ temp $\leq$7.5	0.047**	0.046**
	(0.020)	(0.021)
7.5$<$ temp $\leq$10.0	0.039**	0.035*
	(0.018)	(0.019)
10.0$<$ temp $\leq$12.5	0.034**	0.013
	(0.017)	(0.017)
12.5$<$ temp $\leq$15.0	0.012	0.006
	(0.013)	(0.014)
15.0$<$ temp $\leq$17.5	-0.006	-0.005
	(0.007)	(0.007)
20.0$<$ temp $\leq$22.5	0.027***	0.028***
	(0.008)	(0.008)
22.5$<$ temp $\leq$25.0	0.019	0.014
	(0.015)	(0.013)
temp $>$25.0	0.026	0.011
	(0.021)	(0.021)
Mean of Dep Variable	0.378	0.470
Number of Observations	173003	173003
Number of Clusters	193	193
R squared	0.374	0.370

Notes: The sample is female heads or spouses of the head aged 18 or over. Dependent variable: in columns (2) is an indicator that the household cooks with: wood, charcoal, kerosene or "other fuels" (see main text for discussion); in column (2) is an indicator that the household's main fuel for cooking is wood, charcoal, or kerosene. *temp* is average in-utero temperature (in degrees Celsius). The comparison category is 17.5-20C. All regressions include fixed effects date of birth (month and year), and district of birth-by-year fixed effects, and a count of months in each temperature bin 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: 2005-2015 ENAHO and CRU.

Table A.2: Alternative specifications

	(1) Main Specification	(2) Removing θ_j	(3) Controlling for SDT	(4) District of Residence FFEE
temp $\leq$5.0	0.065**	0.058***	0.059**	0.040*
	(0.025)	(0.020)	(0.025)	(0.022)
5.0< temp $\leq$7.5	0.045**	0.035*	0.031	0.018
	(0.021)	(0.018)	(0.022)	(0.020)
7.5< temp $\leq$10.0	0.046**	0.034**	0.025	0.023
	(0.020)	(0.016)	(0.018)	(0.018)
10.0< temp $\leq$12.5	0.035**	0.032**	0.023	0.014
	(0.017)	(0.014)	(0.016)	(0.015)
12.5< temp $\leq$15.0	0.021	0.022**	0.017	0.014
	(0.014)	(0.011)	(0.012)	(0.012)
15.0< temp $\leq$17.5	0.005	0.011	0.009	-0.001
	(0.010)	(0.007)	(0.008)	(0.009)
20.0< temp $\leq$22.5	0.011	0.011	0.013	0.009
	(0.010)	(0.008)	(0.009)	(0.009)
22.5< temp $\leq$25.0	0.005	0.005	0.007	0.014
	(0.023)	(0.013)	(0.014)	(0.022)
temp >25.0	0.017	0.009	0.012	0.026
	(0.025)	(0.016)	(0.018)	(0.026)
SD of in-utero temperature			-0.006	
			(0.005)	
Mean of Dep Variable	0.544	0.544	0.544	0.544
Number of Observations	175105	175105	173101	175101
Number of Clusters	193	193	193	193
R squared	0.333	0.333	0.333	0.449

Notes: The sample is female heads or spouses of the head aged 18 or over. Dependent variable is an indicator that the household uses wood, kerosene or charcoal for cooking. Column (1) is the main specification. In column (2) the count of months in each temperature bin was removed. In column (3) the count is replaced by the standard deviation of mean monthly temperature in the district of birth during the 9 months prior to birth. Column (4) controls for district of residence fixed effects. The comparison category is 17.5-20C. Standard errors are clustered at the province level. Statistically significant at the 90(*), 95(**) and 99(***) percent of confidence. Source: 2005-2015 ENAHO and CRU.

Table A.3: Interaction with standard deviation of in-utero temperature

	(1) Level	(2) × SDT	(3) Marginal Effect at mean SDT	(4) 95% Confidence Interval	(5)
temp ≤5.0	0.132***	-0.056***	0.068***	0.018	0.118
	(0.033)	(0.013)	(0.025)		
5.0< temp ≤7.5	0.064**	-0.025*	0.035	-0.010	0.080
	(0.031)	(0.015)	(0.023)		
7.5< temp ≤10.0	0.044*	-0.015	0.026	-0.013	0.066
	(0.025)	(0.011)	(0.018)		
10.0< temp ≤12.5	0.027	-0.001	0.026	-0.001	0.061
	(0.024)	(0.013)	(0.018)		
12.5< temp ≤15.0	0.036	-0.020	0.012	-0.016	0.040
	(0.022)	(0.013)	(0.014)		
15.0< temp ≤17.5	0.011	-0.001	0.010	-0.011	0.030
	(0.019)	(0.008)	(0.011)		
20.0< temp ≤22.5	0.033*	-0.014	0.018*	-0.002	0.038
	(0.019)	(0.009)	(0.010)		
22.5< temp ≤25.0	0.009	-0.003	0.005	-0.022	0.032
	(0.024)	(0.014)	(0.014)		
temp >25.0	-0.002	0.011	0.011	-0.027	0.048
	(0.031)	(0.018)	(0.019)		
SD in-utero temperature	0.005				
	(0.008)				
Mean of Dep Variable	0.544				
Number of Observations	173101				
Number of Clusters	193				
R squared	0.333				

Notes: The sample is female heads or spouses of the head aged 18 or over. Dependent variable is an indicator that the household uses wood, charcoal or kerosene for cooking. Column (1) reports the coefficient each variable, and column (2) the coefficient of the interactions of each variable with the standard deviation of in-utero temperature. Column (3) reports the marginal effect evaluated at the mean value of SDT, and columns (4) and (5) report its 95% confidence interval. The regression includes date of birth (month and year) and district of birth-by-year fixed effects 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: 2005-2015 ENAHO and CRU.

Table A.4: Falsification test: Temperature before pregnancy

	Months 10-12 prior to birth		
	(1)	(2)	(3)
	Cook Dirty	Cook Dirty 2	Cook Dirty 3
temp $\leq$ 5.0	0.004	-0.007	-0.006
	(0.005)	(0.005)	(0.005)
5.0< temp $\leq$7.5	0.006	0.006	0.005
	(0.008)	(0.007)	(0.008)
7.5< temp $\leq$10.0	0.005	0.001	-0.007
	(0.007)	(0.007)	(0.007)
10.0< temp $\leq$12.5	-0.000	0.005	0.005
	(0.007)	(0.007)	(0.007)
12.5< temp $\leq$15.0	-0.004	-0.006	-0.008
	(0.008)	(0.008)	(0.008)
15.0< temp $\leq$17.5	-0.011	0.001	0.008
	(0.008)	(0.008)	(0.009)
20.0< temp $\leq$22.5	-0.001	-0.009	-0.010
	(0.009)	(0.009)	(0.009)
22.5< temp $\leq$25.0	0.005	-0.001	0.003
	(0.011)	(0.010)	(0.011)
temp >25.0	0.008	0.006	0.000
	(0.009)	(0.009)	(0.010)
Mean of Dep Variable	0.544	0.378	0.470
Number of Observations	175105	173003	173003
Number of Clusters	193	193	193
R squared	0.333	0.374	0.370

Notes: The sample is female heads or spouses of the head aged 18 or over. Dependent variable: in column (1) is an indicator that the household uses wood, charcoal or kerosene for cooking, in column (2) is an indicator that the household uses wood, charcoal, kerosene or other fuel for cooking, in column (3) is an indicator that the household's main cooking fuel is wood, charcoal or kerosene. *temp* is average in-utero temperature (in degrees Celsius) over months 10-12 prior to birth. The comparison category is 17.5-20C. All regressions include date of birth (month and year) and district of birth-by-year fixed effects 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: 2005-2015 ENAHO and CRU.

Table A.5: Falsification test: Temperature before pregnancy

	Months 11-13 prior to birth		
	(1)	(2)	(3)
	Cook Dirty	Cook Dirty 2	Cook Dirty 3
temp $\leq$ 5.0	0.004	-0.014	-0.028
	(0.018)	(0.016)	(0.018)
5.0$<$ temp $\leq$7.5	-0.001	-0.008	-0.023
	(0.015)	(0.014)	(0.015)
7.5$<$ temp $\leq$10.0	0.003	-0.010	-0.024**
	(0.013)	(0.011)	(0.012)
10.0$<$ temp $\leq$12.5	0.010	-0.003	-0.014
	(0.011)	(0.010)	(0.011)
12.5$<$ temp $\leq$15.0	0.001	0.004	-0.006
	(0.009)	(0.007)	(0.007)
15.0$<$ temp $\leq$17.5	-0.010	0.002	-0.002
	(0.006)	(0.005)	(0.005)
20.0$<$ temp $\leq$22.5	-0.006	-0.000	0.005
	(0.007)	(0.006)	(0.006)
22.5$<$ temp $\leq$25.0	-0.001	0.007	0.019**
	(0.008)	(0.008)	(0.009)
temp $>$25.0	-0.003	-0.005	0.005
	(0.010)	(0.010)	(0.011)
Mean of Dep Variable	0.544	0.378	0.470
Number of Observations	175105	173003	173003
Number of Clusters	193	193	193
R squared	0.333	0.374	0.370

Notes: The sample is female heads or spouses of the head aged 18 or over. Dependent variable: in column (1) is an indicator that the household uses wood, charcoal or kerosene for cooking, in column (2) is an indicator that the household uses wood, charcoal, kerosene or other fuel for cooking, in column (3) is an indicator that the household's main cooking fuel is wood, charcoal or kerosene. *temp* is average in-utero temperature (in degrees Celsius) over months 11-13 prior to birth. The comparison category is 17.5-20C. All regressions include date of birth (month and year) and district of birth-by-year fixed effects 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: 2005-2015 ENAHO and CRU.