IT'S NOT THE HEAT, BUT THE STUPIDITY: TEMPERATURE AND HUMAN CAPITAL FORMATION

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PRELIMINARY & INCOMPLETE - DO NOT CITE

ABSTRACT. In this paper, we provide the first evidence to our knowledge that in utero exposure to warm environmental temperatures has long-lasting impacts on human capital formation. In particular, we find that exposure to warmer temperatures in the third trimester of pregnancy leads to diminished performance in school and on standardized tests 6 to 12 years later. While much smaller in magnitude, we also find a beneficial impact of warmer temperatures in the first trimester, under certain model specifications. These effects are not driven by birthweight and parents appear to do little to alter their trajectory. Thus, rising temperatures under climate change may significantly decrease labor force quality in the future. Our results may also provide insights into the mechanisms underpinning the negative association between temperature and economic prosperity in the macroeconomic literature.

1. INTRODUCTION

Human capital, through its influence on the creation and adoption of improved technologies, has long been recognized as an important contributor to aggregate income (Nelson and Phelps 1966, Schultz 1961). Moreover, growing literatures in public health and economics suggest that initial conditions play an important role in human capital formation over the lifecycle (e.g. Heckman, 2007; Almond and Currie, 2011). One set of initial conditions that has received surprisingly limited attention in the literature is ambient temperature. Elucidating this relationship is particularly important as temperature extremes are pervasive throughout the world and climate change is expected to increase their frequency in the coming decades.

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In this paper, we extend recent work by Deschenes et al. (2009) on temperature and birthweight[1] to provide the first evidence to our knowledge that in utero exposure to climatic extremes has long-lasting impacts on human capital formation.[2] In particular, we exploit a unique panel dataset from Chile, South America that allows us to assess the impacts of fetal temperature exposure on school performance between the ages of 6 and 12. Such performance has been found to exert a significant and large impact on employment and wages in adulthood (Currie and Thomas, 1999). Our paper is unique in at least two additional regards.

First, our data allows us to, at least partially, unpack the mechanisms that underlie the fetal origins hypothesis. The majority of the literature in this area uses birthweight as a proxy for fetal health in order to assess later life outcomes (see Almond and Currie, 2011 for a nice discussion of this literature and its limitations), but this simple anthropometric measure at birth is unlikely to capture important epigenetic effects that can negatively impact intellectual growth and maturity (Petronis, 2010). Conversely, the handful of papers that directly assess the impacts of environmental shocks on later life outcomes (Almond, Edlund, and Palme 2009, Almond 2006, Sanders 2011, Maccini and Yang, 2009, Barreca, 2010), have not been able to determine the degree to which those outcomes were driven by fetal nutrition and thus birthweight. Our analysis will combine both types of measures in a single framework to evaluate the impacts of each channel independently.

Second, regardless of the channels through which fetal programming might take place, the long latency period between exposure and the outcomes of interest provides ample opportunity for parents to amplify or mitigate such effects through (dis)investments during early childhood. Whether parents compensate for poor endowments at birth by increasing investments in those children or reinforce poor endowments by directing their efforts toward children with better prospects is an open question in the literature (Behrman et al., 1994; Datar et al., 2010; Almond and Currie, 2011). Using data on siblings, we will examine these parental investments, shedding light on important intrahoushold behavior in response to child health and human capital endowments.[3]

[1] As discussed in the next section, there is also a sizable public health literature that has examined the relationship between in utero temperature exposure and birth outcomes.

[2] Two related studies that focus on different climatic exposures are worth noting. Maccini and Yang (2009) examined the impact of exposure to rainfall early in life (although not necessarily in utero) on long term outcomes. They find that higher than average rainfall during one's birth year increases educational attainment and asset holdings for adults in Indonesia. Barreca (2010) uses "malaria-ideal" temperatures as an instrument for early life exposure to malaria in the US and finds sizable impacts on educational attainment and poverty rates later in life.

[3] As such, our research is also closely related to the rich literature that uses twins to examine the human capital impacts of birth outcomes, as opposed to in utero exposure to environmental stressors (Behrman and Rosenzweig, 2001; Conley et al., 2003; Black et al., 2007; Oreopoulos et al., 2008, and Royer, 2009).

Moreover, our empirical focus on Chile is noteworthy in its own right. The geography of the country is such - it spans 38 degrees in latitude and more than 22,000 feet in altitude - that its territory includes seven major climatic subtypes, increasing the generalizability of our results. The principal pollution season occurs in winter, reducing concerns that our estimates of the impacts of hot temperature are confounded by exposure to high levels of pollution. Finally, national air conditioning penetration is approximately 1% (Chile Department of Energy, 2010), greatly reducing concerns about unmeasured avoidance behavior in response to temperature extremes (Deschenes and Greenstone, 2011).

We begin our analysis by estimating the impacts of temperature on school performance using individual level data from the SIMCE and RECH database that consists of administrative data on the grades and test scores of every student in Chile between 2002 and 2008 linked to daily weather data from the National Climatic Data Center. Our base econometric model includes year of birth and week of conception dummies as well as controls for a vector of mother characteristics. This specification enables us to identify the effects of temperature using the plausibly exogenous variation in temperature over time within a given year while controlling for seasonality in fertility outcomes. Temperature is modeled using a series of indicator variables for temperature bins by quintile to flexibly capture the relationship of interest. The analysis is then repeated with controls for birthweight to identify the impacts of temperature on school performance that are independent of fetal nutrition. Finally, we modify our specification to include sibling fixed effects to disentangle the biological effects of temperature from those arising due to parental investments during early childhood. Comparing OLS and sibling FE estimates allows us to determine whether such investments are compensating or reinforcing.

Our results suggest that rising temperatures in the third trimester of pregnancy can lead to lower test scores, both in math and language. Being in the hottest quintile of average third trimester temperatures (relative to the coolest quintile) results in test scores that are 0.07SD less in math, and a similar sized effect for language scores. The effect appears to be linear across the temperature quintiles and we compute a per degree effect of 0.004 SD. While this might appear to be a small effect, consider that the average third trimester in 2008 experienced temperatures that were 5 degrees warmer than the average third trimester in 2007. Hence, simply because of the fact that children born in 2008 experienced a warmer trimester, they likely performed 0.02 SD worse on math test scores. To put this magnitude in context, most education based interventions in developing countries result in test score improvements between 0.15-0.4 SD. What these effects look like under different forecasts for temperature by 2050 will be explored in future versions of this paper. Our fixed effects estimators suggest similar magnitudes, suggesting that long run confounders, such as parental investments, do not play a very important role in this context.

Unlike Deschenes et al (2009) who focus on climate extremes in the US, we find no statistically significant impact of temperature on birth outcomes in the somewhat temperate climate of central Chile. Nonetheless the sign and magnitudes of all coefficients are consistent with hotter temperatures leading to worse birth outcomes. When we control for birth outcomes in our school performance regressions, all coefficients becomes slightly smaller but remain significant, underscoring the role of non-nutritional channels in generating these temperature impacts.

Our analysis reveals an economically relevant and heretofore hidden cost of warmer temperatures and thus climate change. In particular, our work suggests that rising temperatures under climate change may significantly decrease labor force quality in the future. Our understanding of this relationship is also important because it sheds light on one potentially important underpinning for the macroeconomic literature that has focused on climate and economic prosperity (Sachs and Warner, 1996; Nordhaus, 2006, Dell et al., 2008).

2. Background on Climate and Human Capital

Heat stress can negatively influence a wide range of human health endpoints. Pregnant women are especially susceptible to exposure to high temperatures for several reasons, including an increased core temperature due to increased fat deposition, diminished capacity to sweat, and additional thermal stress associated with fetal maintenance (Prentice et al., 1989; Wells and Cole, 2002). A large literature has shown that warmer temperatures increase the rate of preterm births as well as the incidence of low birth weight babies (see Strand et al., 2012 and 2001, respectively for good reviews).[4] While the exact mechanisms that underlie these effects remain unknown, diminished nutrition to the fetus due to dehydration, increased uterine function, and placental enlargement have all received attention in the literature (Tegethoff et al., 2010; Strand et al., 2012).

[4]As noted in these reviews, studies vary widely in their methodological approach and their attention to potential confounders. In the interest of completeness, we also note that two correlational studies have found that cold weather leads to increases in low birth weight.

Importantly for our work, birthweight has also been shown to significantly impact educational and labor outcomes later in life. In pioneering work, Currie and Hyson (1999) found that low birthweight children were significantly less likely to pass standardized tests as teenagers in Britain. Currie and Moretti (2007) find similar effects on school attainment and adult poverty for a sample of Californians. A host of twin studies that better control for genetic endowments and other family characteristics have also consistently found negative effects from low birthweight on educational attainment, IQ, and even earnings (Behrman and Rosenzweig, 2001; Conley et al., 2003; Black et al., 2007; Oreopoulos et al., 2008, and Royer, 2009).

In addition to the effects of temperature on birthweight, temperature may play an important role in gene expression in humans. A growing body of literature in epigenetics suggests that environmental stressors can alter DNA methylation and that the gestational period may be a particularly susceptible period for such effects Feil and Fraga, 2012). Exposure to high temperatures has been implicated as such a stressor in a wide range of plants and animals (Feil and Fraga, 2012). That neuroanatomical structures in vertebrates are particularly sensitive to epigenetic regulation (Jones et al., 2011), suggests that cognitive development may be particularly vulnerable to these exposures. Thus, it appears that in utero temperature exposure can influence human capital formation in adults through fetal nutrition as captured by birth outcomes as well as epigenetic channels that are unlikely to be captured by simple anthropometric measures at birth (Petronis, 2010). As noted in the introduction, our analysis will utilize a unified framework that will allow us to begin to disentangle these mechanisms while providing the first estimates of the long-lasting effects of in utero heat stress.

3. Data

3.1. **Birth Data**

The data on the birth weight and background information on parents come from a dataset provided by the Health Ministry of the government of Chile. This dataset includes information on all the children born in the year 1992-2002. It provides data on the sex, birth weight, length, weeks of gestation and several demographics of the parents such as age, education and occupational status. In addition, the dataset provides a variable describing the type of birth, be it a single birth, double (twins), triple (triplets), etc. A unique variable identifying the mother enables us to match sibling pairs. A similar unique identifier at the individual child level allows us to match children to their school and SIMCE records.

3.2. **Education Data**

The data on school achievement comes from the SIMCE and RECH database that consists of administrative data on the grades and test scores of every student in the country between 2002 and 2008. This database was kindly provided by the Ministry of Education of Chile (MINEDUC).

3.2.1. *RECH - Registro de Estudiantes de Chile.* This database consists of the grades by subject of each student in a given year and is a census of the entire student population. The data comes in the form of individual level transcripts with grades on each subject that ranges from 1 to 7, with 7 being the highest grade. A passing grade is typically a 4. Scores appear with one decimal place (for example a student could have obtained a 6.3 in math in grade 4). A potential concern with classroom level grades is that grades *across* classrooms might not be comparable - a 4 in one classroom might be a 6 in another classroom. To avoid this complication, we utilize the fact that we observe every student in the class to standardize scores at the class level. In that sense, we consider these "scores" to be reflective of relative rankings of students within a classroom.

3.2.2. *SIMCE.* The SIMCE test covers three main subjects: Mathematics, Science and Language Arts and is administered to every student in grade 4 as well as 8 and 10 depending on the year. It is used to evaluate the progress of students regarding the national curriculum goals set out by MINEDUC. The test is constructed to be comparable across schools and time. We have data on the 4th grade SIMCE administered in 2002 and then yearly from 2005-2008. We normalize the SIMCE scores at the national level since its a nationally administered test.

3.3. **Temperature Data**

Daily temperature data is drawn from the National Climatic Data Center's Global Surface Summary of the Day database. The NCDC, a division of the US National Oceanic and Atmospheric Administration, is the world's largest achieve of climate and weather data. The Global Surface Summary of the Day database, which complies surface meteorological observations from roughly 9,000 weather stations worldwide, includes daily mean temperature, mean dew point, mean sea level pressure, mean station pressure, mean visibility, mean wind speed, maximum sustained wind speed, maximum wind gust speed, maximum temperature, minimum temperature, and precipitation daily data. The summary is collected from the NCDC's Integrated Surface Database (ISD), a global database compiled from the USAF Climatology Center and foreign agencies. The Global Surface Summary of the Day and ISD are both available to the public through the NCDC. This data covers the entire range of birth and schooling data from 1992-2002. From this data we create relevant lagged temperature variables as needed for estimation. In this current version we only use temperature data related to stations located in or near Santiago, the capital city of Chile. Santiago has 4 stations associated with it, however, for the years we examine, only one station appears to have the required data. In subsequent versions, we plan on including other regions, although it should be noted that more than a third of the population lives in Santiago, and hence, is one of the most important areas to study. In addition, the Santiago metropolitan area is a relatively small area serviced by a weather station. Hence, temperature measurements from the station assigned to residents will likely contain less noise in Santiago as opposed to other regions in the country.

4. ECONOMETRIC APPROACH

We begin by specifying a simple production function for school achievement, in spirit similar to Todd and Wolpin (2007). In this rather simplified version, test score achievement of student i born to mother j in region r born at time t[5] is a function of early childhood health (H), investments made from birth to time of test taking (P) and parental characteristics (X).

$$S_{ijrt} = f(H_{ijrt}, \sum_{k=t}^{k=T} P_{ijrk}, X_j) \tag{1}$$

Early childhood health is a function of in utero environmental conditions E (e.g. temperature, pollution), and parental characteristics. Environmental conditions experienced by the *individual* is a function of aggregate environmental conditions measured at the regional level at time t but is mitigated by individual level avoidance behavior (A).

[5]In our specification, t always refers to time of birth, not time of test taking since we use an aggregate measure of test score. Time of test taking is defined as T.

$$H_{ijrt} = h(E_{ijrt}, X_j) \tag{2}$$

$$E_{ijrt} = e(E_{rt}, A_{ijrt}) \tag{3}$$

Investments in education in turn, are a function of parental characteristics, early childhood health and an exogenous shock (e.g. parental income shocks, between birth and time of test taking). We do not make assumptions about how this relationship works; whether parents invest more in children with poorer health or the reverse is something we allow the data to reveal under certain assumptions made clear in section 4.2.

$$P_{ijrk} = m(H_{ijrt}, X_j, \eta_k) \tag{4}$$

for all k between t and T. This parsimonious specification is useful in highlighting the assumptions needed and the interpretation of the coefficients in a setting where we are interested in long run impacts of in utero environmental stressors.

Taking linear approach to estimating equation 1, we can re-express student performance as:

$$S_{ijrt} = \beta H_{ijrt} + \gamma \sum_{k=t}^{k=T} P_{ijrt} + X_j + \epsilon_{ijrt} \tag{5}$$

Since the goal here is to understand the role of in utero environmental shocks, in particular temperature on eventual test scores, we can take linear functions of equations 2 and 3 to derive:

$$S_{ijrt} = \beta E_{rt} + \beta A_{ijrt} + \gamma \sum_{k=t}^{k=T} P_{ijrt} + X_j + \epsilon_{ijrt} \tag{6}$$

Of course, not all components of are observable to researchers. In particular, investments and avoidance behavior are rarely observed. Hence:

$$S_{ijrt} = \beta E_{rt} + X_j + \underbrace{\beta A_{ijrt} + \gamma \sum_{k=t}^{k=T} P_{ijrt}}_{unobserved} + \epsilon_{ijrt} \tag{7}$$

Equation 7 is the typical estimating equation available to researchers. Estimating β is complicated for two reasons. First, avoidance behavior A is likely correlated with aggregate environmental agents E (in this case temperature). A can be viewed as part of the investments that parents make in children, which is presumably correlated with parental characteristics X. Hence, not observing avoidance behavior is problematic since it is correlated with the independent variable of interest and could affect test scores through means other than early childhood health. A common approach in the literature to deal with avoidance behavior is to find an instrument for E that is uncorrelated with A. Essentially a change in environmental conditions that behavior cannot respond to is needed for unbiased estimation of β.

A second problem is due to the long run aspect of the problem at hand - the correlation between parental investments P and E. This correlation is not obvious, but arises essentially through the impact of environmental conditions on early childhood health, and parental responses to early childhood health. The difference between these and avoidance behavior is that while avoidance behavior is necessarily a short run phenomenon in our framework, the correlation with parental investments leads to biased estimation of β for long run outcomes *even if* we were to control accurately for avoidance behavior. This is true not just of our framework but any analysis of long term effects of fetal stress. Whether the health impacts due to environment is large enough for parents to respond to or whether such responses have an impact on test scores is an open question. The point here is that for interpreting what β means in the context of long run impacts of in utero temperature, we have to consider two sources of behavior - avoidance and parental investments.

4.1. **Avoidance**

The literature examining short run impacts of environmental exposure has implemented instrument variable techniques to get around the issue of avoidance behavior. Examples include Currie and Neidell (2006), Moretti and Neidell (2007) among others. To find an instrument for temperature exposure, we require a variable that changes temperature but against which people are unable to change their behavior towards. This seems inherently problematic in the context of temperature, since temperature fluctuations, unlike ozone or other unobserved pollutants, are easily experienced as opposed to ozone or other "unobserved" pollutants.

Our approach to handling avoidance behavior is to consider two sources of avoidance. Given Chile's extraordinary range of climates, an obvious way of avoiding extreme temperatures it to locate in areas where these extremes are less likely to occur. Hence, sorting by region or location is one way to practice avoidance. Essentially, we think of the avoidance term as having two pieces of the following form:

$$A_{ijrt} = A_r^1 + A_{ijrt}^2 \tag{8}$$

We can easily account for sorting by using a region fixed effect in our regressions. We consider dealing with the individual avoidance term A_{ijrt}^2 by considering air conditioning use in Chile. The most common way to avoid temperature is to have air conditioning. Deschenes and Greenstone (2011) examine this in detail in the US and find that people do indeed adapt and practice avoidance towards temperature by increasing their energy consumption. In the Chilean context this source of avoidance seems minimal. The Chilean Ministry of Energy reports that only around 1% of households in 2010 had air conditioning. Since our data examines cohorts born between 1992-2002, we think the mitigating role of air-conditioning is even smaller for our sample. We are aware that other forms of avoidance like the use of fans or other behaviors could still confound the overall analysis. However to the extent that accounting for regional sorting and lack of air conditioning in this context *minimizes* the extent of avoidance behavior, the estimate of β will not be biased by avoidance activity.

4.2. **Investments**

When examining long run outcomes of early childhood health, an important consideration is parental investments. However, accounting for this is complicated by lack of data and the wide range of investments or investment related behavior in which parents might engage. From a research perspective, it is crucial to understand the extent to which parental investments confound long run interpretations of β. In our context, we make some progress on this idea by controlling for early childhood health measures and by examining siblings and estimating equation 7 using a sibling fixed effects approach.

4.2.1. *Controlling for early childhood health.* Equation 4 suggests that parental investments are correlated with temperature shocks via its effect on early childhood health. To the extent we think parents react to measured components of early childhood health like gestational age and birth weight (Bharadwaj, Eberhard and Neilson (2011) explicitly show that this is the case), controlling for early childhood health should, at least partially, control for unobserved parental investments. Hence, one approach is to simply use birth weight and gestational age as control variables while estimating equation 7.

4.2.2. *Siblings approach.* To the extent that measured birth outcomes are only proxies for early childhood health, we should expect parental investments to play a role even after controlling for early childhood health measures. To dig deeper, we investigate a siblings fixed effects approach.

Consider a child i' born to mother j at time t'. Taking differences across siblings (we suppress avoidance behavior for now) we estimate:

$$\Delta S_{ijrt-i'jrt'} = \beta E_{rt-rt'} + \gamma \sum_{k=t,t'}^{k=T} (P_{ijrt} - P_{i'jrt'}) + v_{ijrt-i'rjt'} \tag{9}$$

A strict siblings model as used in the labor literature assumes that parental investments are the same within a sibling pair, and hence completely eliminates parental investments from the estimating equation. This seems largely unreasonable given the literature on how allocation of resources within the household are determined and the idea that parents might value equality and thus engage in compensating behavior towards the child who has weaker endowments (the opposite, reinforcing behavior is also certainly possible). Rather than assume that parental investments are netted out in equation 9, we rely on a weaker assumption to derive informative differences between siblings fixed effects estimates and OLS estimates.

The crucial assumption about the nature of parental investments within a household that we employ is that parental investments have some public good component within the household - recall that the sibling fixed effects literature in general assumes *perfect* public goods within the household. With this weaker assumption, we are able to compare fixed effects estimates to OLS estimates and suggest scenarios under which OLS will be less than or larger than the fixed effects estimates.

For example, suppose that parents in general compensate, i.e. provide greater resources to the child harmed by in utero environmental exposure. In this case, if parental investments are effective, we should observe that long run effects of temperature on test scores are understated. There should be a convergence in test scores across children affected and not affected by in utero temperature exposure. However, if parental investments *within* the household have *some* public good aspects, then the fixed effects estimates should be larger than OLS simply because compensation is not complete in this case. Under compensation, $OLS^c \leq FE$.

Consider the opposite, a case where parents reinforce, i.e. provide greater resources to a child not affected by in utero temperature. In this case, over the long run, we should find that children not affected by temperature do *even better* than children affected by temperature. In a sibling fixed effects setting however, the extent of reinforcement is mitigated by the public good aspect of parental investments and a sibling who receives excess investments does *less better* compared to his sibling than he otherwise might have. Under reinforcement, $OLS^r \geq FE$.

To sum up, the conceptual model above is used to identify potential sources of bias and our attempts at accounting for them. Long run outcomes are biased due to avoidance behavior as well as parental investments which react to detrimental effects of in utero temperature shocks. We attempt to account for avoidance behavior by controlling for residential choice and noting that air conditioning penetration is minimal in Chile. If parental investments in a household with multiple children have a public good component, then sibling fixed effects strategy allows to understand whether parents investments matter in the long run. In particular, depending on whether parents compensate or reinforce early childhood endowments, fixed effects estimates will likely be in between these estimates. I.e. $OLS^c \leq FE \leq OLS^r$.

4.3. **Estimating equation**

In general, our estimating equations are similar to equation 7 with some added details specific to the case of in utero temperature.

For example, to better isolate the effect of temperature from general season specific effects we use the approach of Deschenes, Greenstone and Guryan (2009) by accounting for week (or day/month/quarter) of conception fixed effects. Moreover, the in utero period is long at nine months, and we generally think of it as being divided into three equally spaced periods, largely based on rates of growth and changes to fetus during these different trimesters. Hence, rather than use a single measure of temperature for the entire pregnancy, we use temperature at the trimester level. We also flexibly account for the effects of temperature by using non linear bins of average temperature by trimester. That is to say, we use quintiles of temperature within each trimester and use these as our preferred measures of temperature. Certainly there are other ways of measuring temperature like number of "hot" days (see Deschenes, Greenstone and Guryan (2009)), and we discuss these approaches in the results section. Our basic estimating equation follows the form:

$$Y_{ijrt} = \sum_{k=1,T=1}^{k=5,T=3} \beta_k^T Temp_{rtTk} + \gamma \mathbf{X_j} + \sum_{g=1}^{g=52} \alpha_g C_{ijrt} + \eta_r + Year_t + \epsilon_{ijrt} \tag{10}$$

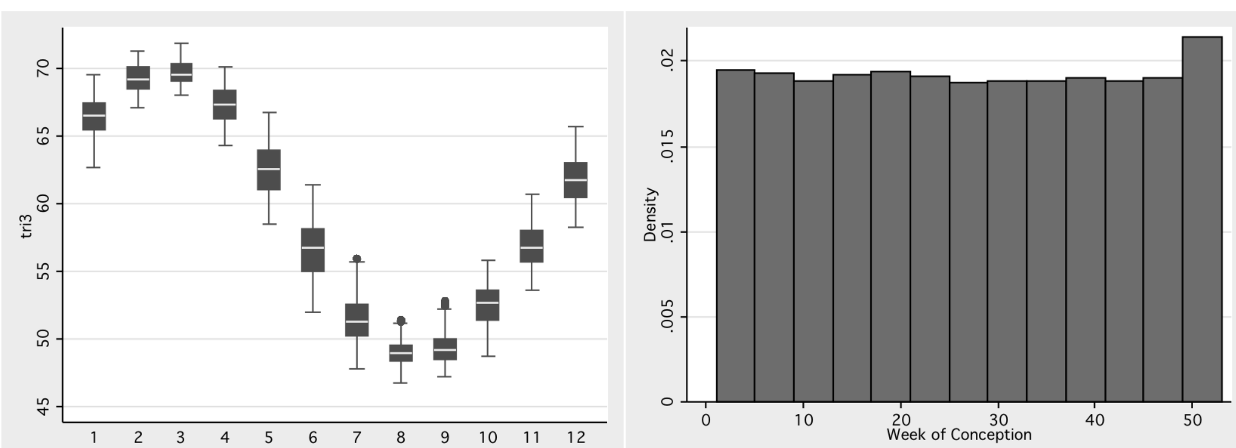
Where Y is the outcome (health at birth, or test scores) of child i, born to mother j, in region r, at time t. The coefficients of interest are the β_k^T which is the effect of being in temperature quintile k in trimester T. The omitted category is always the coldest quintile, so for example, the coefficient β_5^3 measures the impact of being in the hottest quintile relative to the coldest quintile in the third trimester. X's are family specific controls. Regressions use mother's education and age. C_{ijrt} is the week of conception dummy. For a child born on day t the week of conception is different based on different gestational age. Indeed, we compute week of conception based on gestational age of the child. In the results section we show robustness to approximate day of conception, month and quarter of conception as well. Finally, η_r and $Year_t$ are region and time (birth year) fixed effects.

5. Results

5.1. **Preliminaries**

Within Santiago, there appears to be considerable variation in trimester temperatures based on month of birth. As figure 1 suggests, not only is the month to month variation in temperature significant in Santiago, but also that there appears to be no systematic planning of births by week in the year. Graph B of Figure 1 shows a relatively smooth histogram for the week of conception with only a slight increase towards the end of the year. Hence, at a very preliminary level, we are not worried about unobservables of the fertility decision driving exposure to temperature and outcomes of interest.

FIGURE 1. Temperature and Conception in Santiago

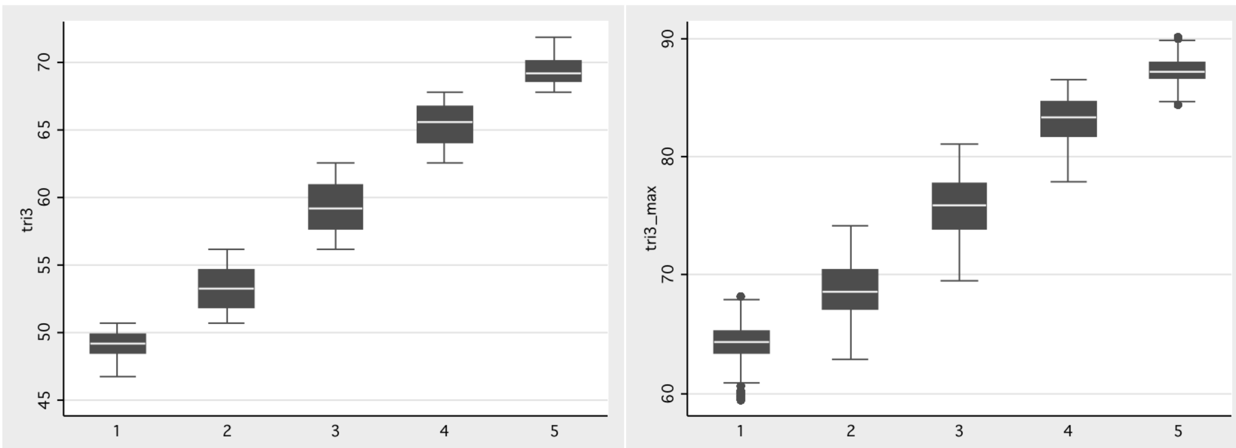


(A) 3rd Trimester Temperature by Month of Birth

(B) Density of Week of Conception

Since the regressions use quintiles of temperature in the third trimester as the independent variable, it is useful to see what the average temperature in these quintiles look like, as well as the variation within each one. Figure 2 reveals considerable variation across and to a lesser degree within each quintile.

FIGURE 2. Temperature Quintiles in Santiago



(A) Average daily temperature (B) Average daily maximum

5.2. **Temperature and Test Scores**

The impact of in utero temperature on test scores is presented in Tables 1 (math scores) and 2 (language scores). As specified in section 4.3, we estimate equation 10 using temperature quintiles by trimester. This table analyzes performance in math in the classroom as well as on the SIMCE, a national test administered in 4th grade. Note that the observations in column 4-6 are smaller than the observations in columns 1-3 since we observe the SIMCE only for 4th graders. All effects are interpreted in standard deviations of the test score, since scores are standardized at the classroom level or at the national level in the case of SIMCE.

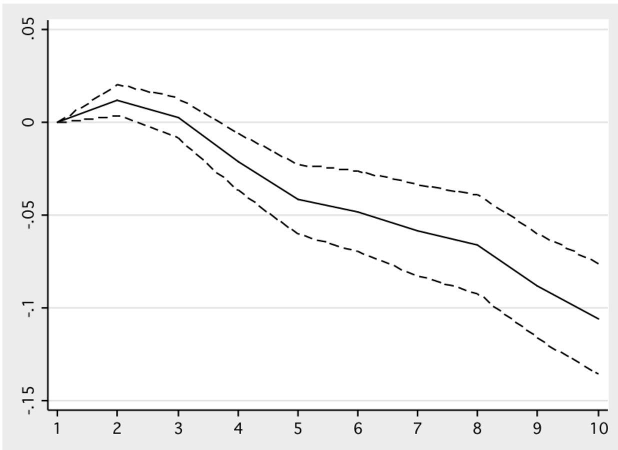
From Table 1 it is apparent that hotter quintiles in utero are worse for school outcomes in the third trimester. The omitted category in each trimester is the coldest quintile. Hence, Table 1, column 2 suggests that relative to the coldest quintile, being in the 4th quintile of the temperature distribution in the third trimester reduces test scores by 0.04SD. The impact of being in the hottest quintile in the third trimester is 0.076SD. This represents an approximate 20 degree difference in temperature compared to the coolest quintile. Since the effect of temperature appears to be linear across the quantiles, the results suggest a per degree increase in temperature associated with a decline of 0.0038SD in math.

Temperature variation in the second trimester appear to not matter for test scores as much when we examine the classroom based scores; however, when using the SIMCE there is a strong negative impact on test scores. In the first trimester, there appears to be a small but *positive* impact of hotter weather in some specifications. For SIMCE results the positive effects of first trimester appear more persistent; in aggregate though, this positive effect is tempered by the negative impacts in the third trimester, while overall effect remains negative.

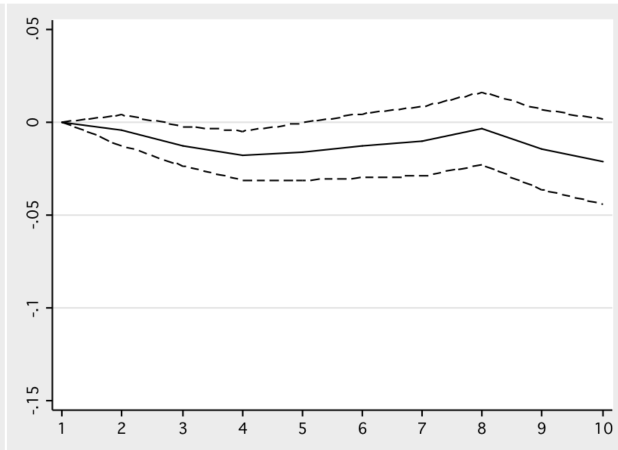
Table 1 also shows the sensitivity of the estimation to the addition of various covariates. Adding week of conception and year of birth makes a big difference to the estimates (column 2 or 5). This is to be expected since we wish to purge the estimates of the *general* effects of temperature and seasonality. The addition of mother specific characteristics like education and age appears to not change the estimates further. Since week of conception appears to be an important control, in Appendix Table 1 we show the effects are robust to other variables aimed at capturing seasonality. Table 2, in a format identical to Table 1 shows the impact of in utero temperature on language scores. The results are largely similar to those found for math.

To facilitate interpretation, Figure 3 provides a visual representation of the math score regression for Table 1, Column 2, using a more flexible specification for temperature. The impact of warmer temperatures in the third trimester have a pronounced negative effect on school performance. In contrast the second and third trimesters reveal negligible effects.

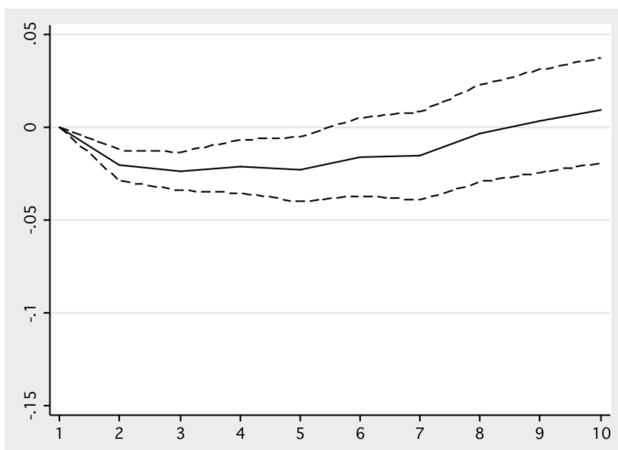
FIGURE 3. Math Test scores and in utero temperature: Santiago



(A) Third Trimester



(B) Second Trimester



(C) First Trimester

Figure notes: X axis is temperature deciles, Y axis is standardized classroom math score. Solid lines are coefficients from decile dummies estimated from a regression similar to equation 10, dashed lines are 95% CI.

To explore whether the effects of temperature on test scores come from their impact on health, we control for observables like birth weight and gestational age. Table 3 shows that controlling for these birth outcome measures does little to change the impact of in utero temperature on test outcomes. Perhaps this is not altogether unsurprising given the findings in the next section - we find small impacts on birth outcomes, and more importantly, any impact we might see appear to be concentrated in the second trimester.

5.3. **Sibling Fixed Effects**

There appears to be substantial variation in temperatures experienced within siblings. Figure 4 suggests that the average in utero difference in temperature experienced within siblings is around 8F.

FIGURE 4. Temperature differences within siblings: Santiago

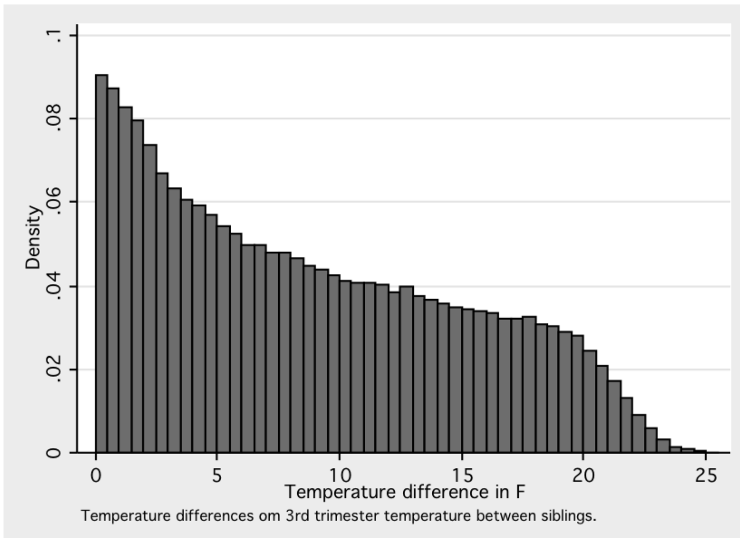
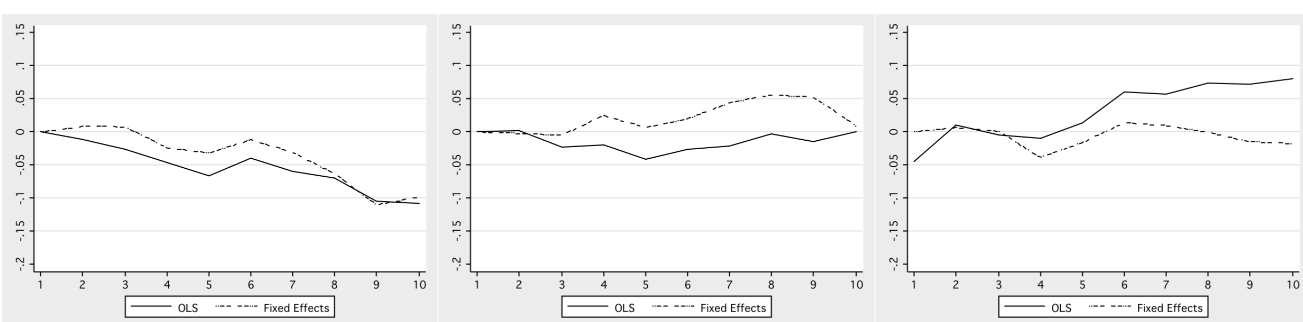


Figure notes: Temperature differences in Farenheit.

Sibling fixed effects estimates are reported in Table 4. In this table we only report OLS estimates for the sample of siblings to make comparisons between OLS and FE meaningful. For classroom scores in math and language, OLS and FE estimates appear remarkably similar. FE estimates are similar to the larger OLS sample too. However, when examining SIMCE scores, we begin to see some differences.

FIGURE 5. Sibling FE: SIMCE scores and in utero temperature: Santiago



(A) Third Trimester (B) Second Trimester (C) First Trimester

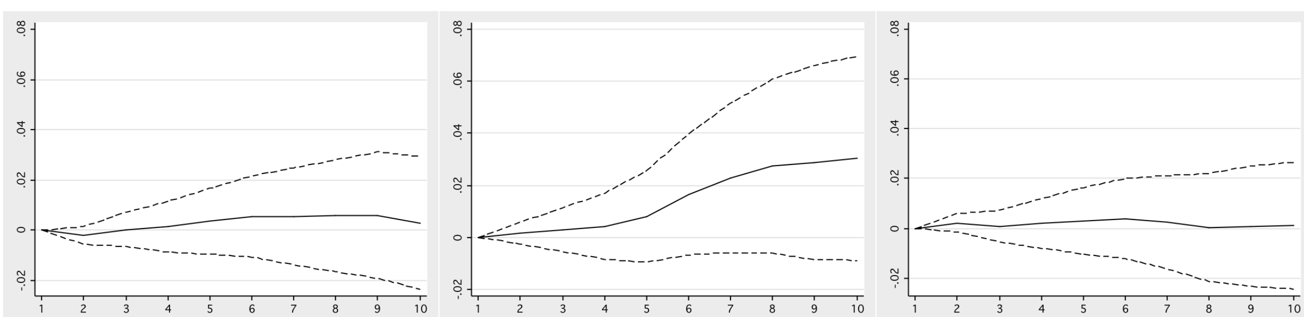
Figure notes: X axis is temperature deciles, Y axis is standardized SIMCE math score. OLS estimates from the same sample as the FE. Coefficients represent decile dummies estimated from a regression similar to equation 10.

The differences between OLS and FE while not significant, appear to show that FE estimates are smaller than OLS estimates. Since OLS and FE are largely similar, we conclude that parents do not appear to respond to health or other detriments caused by temperature. Hence, the long run OLS estimates of in utero temperature shocks are likely not tempered or exacerbated by parental investments. This conclusion is not surprising in light of the small and statistically insignificant effects we find on direct early childhood health outcomes.

5.4. **Temperature and Birth Outcomes**

Table 5 shows that across a wide range of birth outcomes, we find very little effects of temperature. This is in contrast to the results of Deschenes et al 2009, who find significant effects of in utero temperature on birth weight; this is possibly due to the fact that we simply do not observe the temperature extremes in Santiago that they do for states across the US. Figure 6 illustrates, despite large standard errors, the positive impact of warmer climate on the probability of low birth weight.

FIGURE 6. Test scores and Low Birth Weight



(A) Third Trimester (B) Second Trimester (C) First Trimester

Figure notes: X axis is temperature deciles, Y axis is probability of low birth weight. Solid lines are coefficients from decile dummies estimated from a regression similar to equation 10, dashed lines are 95% CI.

5.5. **Robustness checks**

If temperature is correlated with other environmental stressors, particularly pollution, then we might be concerned that the observed relationship between temperature and outcomes is the result of other environmental exposure. To address this, in Table 6 we show that controlling for humidity (as measured by dew point) and pollution (PM10) does not affect our results.

Table 7 explores whether other ways of measuring exposure to in utero temperature affects the results. We explore three ways of measuring temperature. In Column 1, we use the average temperature in each trimester. Since the results from the previous section suggested largely linear impacts, it is not surprising to see that the coefficient for third trimester temperature is close to the per degree effect we computed earlier.

FIGURE 7. Number of days with Max Temp>90: 3rd Trimester

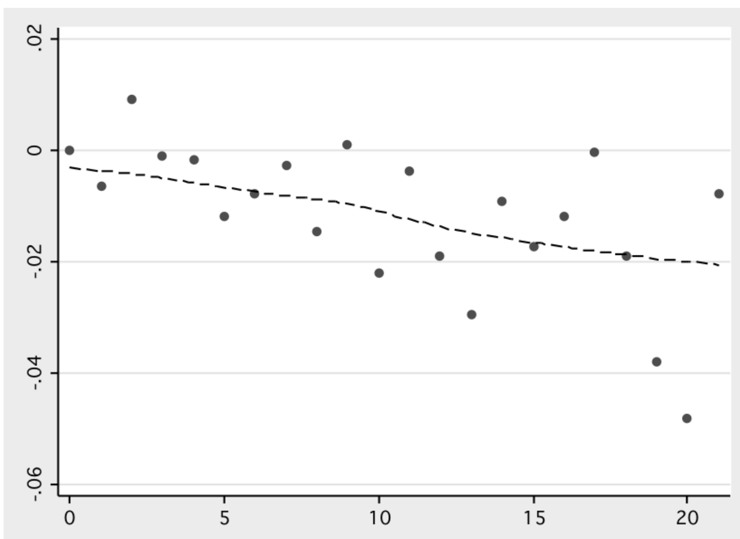


Figure notes: X axis is number of days in the 3rd trimester where the maximum temperature exceeds 90F, Y axis is standardized classroom score. Coefficients come from a regression similar to equation 10, with dummies for number of days above 90F in the third trimester. Excluded category is zero days above 90F in the third trimester. Regression controls for quintiles of average temperature in each trimester and average maximum in the second and third trimester.

In columns 2 and 3, we move away from direct temperature measures to measuring days above and below certain temperatures by trimester. This is similar to the approach used by Deschenes et al 2009.

Column 2 suggests that for every day in the third trimester when the average temperature is above 70F, test scores decrease by 0.001 SD. Column 3 measures temperatures days based on the daily maximum. For every day in the third trimester when the daily maximum is above 90F, we see a decline in test scores of 0.001 SD. A small, marginally significant increase is seen for days in the first trimester. Thus, these alternate ways of measuring temperature effects point to significant negative impacts of in utero temperature exposure on cognitive outcomes in school. These results are consistent with those found in our base model specifications.

6. Conclusion

The importance of early life endowments and conditions on later life outcomes has been increasingly recognized within the fields of public health and economics. In this paper, we extend recent work by Deschenes et al. (2009) on climatic extremes and birthweight to provide the first evidence to our knowledge that in utero exposure to warm environmental temperatures has long-lasting impacts on human capital formation. In particular, we find that exposure to warmer temperatures in the third trimester lead to diminished performance in school and on standardized tests 6 to 12 years later. While much smaller in magnitude, we also find a beneficial impact of warmer temperatures in the first trimester, under certain model specifications. The magnitude of these effects appears sizable relative to those found in the literature that examines performance improvements attributable to education based interventions in LDCs. In addition to their relevance to any assessment of the impacts of climate change, these results may provide an important foundation for our understanding of macroeconomic literature that has focused on climate and economic prosperity.

Two other features of our analysis are particularly noteworthy. First, our measured impacts of temperature on school performance do not appear to be driven by birth outcomes. Thus, it appears that fetal programming is occurring, at least partially, through non-nutritional channels. Second, our analysis of impacts across siblings provides little evidence that parental investments are responding to child endowments. Parents neither invest nor divest in disadvantaged children, perhaps because the subtly of poor endowments are difficult to measure in our setting.

Future versions of this paper will extend the analysis in several directions. First, we will add additional regions from Chile to encompass a wider range of climates and climatic extremes. Second, we will use our limited data on self-reported parental investments in children to further probe whether the minimal differences using our sibling fixed effects specification was due to a lack of parental investments or the ineffectiveness of such investments. Third, we will use statistically downscaled forecasts of climate change to assess the impacts of the predicted temperature distribution in Chile on human capital formation and thus labor force quality in 2050.

7. References

Almond, Douglas, and Janet Currie (2011). "Human Capital Development Before Age 5." In Handbook of Labor Economics, Vol. 4b, pp. 1315Ð1486. Elsevier.

Barreca, Alan (2010). "The Long-Term Economic Impact of In Utero and Postnatal Exposure to Malaria," Journal of Human Resources, 45: 865-892.

Behrman, Jere R., Mark R. Rosenzweig, and Paul Taubman (1994). "Endowments and the Allocation of Schooling in the Family and in the Marriage Market: The Twins Experiment." Journal of Political Economy, 102: 1131Ð1174.

Black, S.E., P.J. Devereux, and K.G. Salvanes (2007) "From the Cradle to the Grave? The Effect of Birth Weight on Adult Outcomes," Quarterly Journal of Economics, 122: 409-439.

Datar, Ashlesha, Rebecca Kilburn, and David Loughran (2010). "Endowments and Parental Investments in Infancy and Early Childhood." Demography, 470: 125Ð144.

Dell, Melissa, Benjamin Jones and Benjamin Olken (2008). "Climate Change and Economic Growth: Evidence from the Last Half Century," NBER Working Paper 14132.

DeschŘnes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." American Economic Journal: Applied Economics, 3(4): 152Ð85.

Feil, Robert and Mario F. Fraga. "Epigenetics and the environment: emerging patterns and implications." Nature Reviews Genetics 13, 97-109 (February 2012)

Jones A, Osmond C, Godfrey KM, Phillips DI. "Evidence for developmental programming of cerebral laterality in humans." PLoS One. 2011 Feb 16;6(2):e17071.

Maccini Sharon and Dean Yang (2009). "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall," American Economic Review, 99: 1006-1026.

Nordhaus, William (2006). "Geography and Macroeconomics: New Data and Findings," Proceedings of the National Academy of Science, 103: 3510-3517.

Oreopoulos, Phil, Mark Stabile, Randy Walld, and Leslie Roos, "Short, Medium, and Long Term Consequences of Poor Infant Health: An Analysis using Siblings and Twins," NBER Working Paper (2006).

Petronis, Arturas (2010). "Epigenetics as a Unifying Principle in the Aetiology of Complex Traits and Diseases." Nature, 465: 721Ð727.

Prentice, A.M., et al.,1989. Energy-sparing adaptations in human pregnancy assessed by whole-body calorimetry. Br.J.Nutr.62,5Ð22.

Sachs, Jeffrey and Andrew Warner (1997). "Sources of Slow Growth in African Economies," Journal of African Economies, 6: 335-376.

Strand LB, Barnett AG, Tong S. "Maternal exposure to ambient temperature and the risks of preterm birth and stillbirth in Brisbane, Australia." Am J Epidemiol. 2012 Jan 15;175(2):99-107.

Strand LB, Barnett AG, Tong S. "The influence of season and ambient temperature on birth outcomes: a review of the epidemiological literature." Environ Res. 2011 Apr;111(3):451-62.

Tegethoff M, Greene N, Olsen J, Meyer AH, Meinlschmidt G, 2010 Maternal Psychosocial Stress during Pregnancy and Placenta Weight: Evidence from a National Cohort Study. PLoS ONE 5(12): e14478. doi:10.1371/journal.pone.0014478

Wells, J.C.K., Cole, T.J., 2002. Birth weight and environmental heat load: a between- population analysis. Am. J. Phys. Anthropol. 119, 276Ð282.

TABLE 1: In utero temperature and Math Scores

	Temperature by trimester and quintile	(1)	(2)	(3)	(4)	(5)	(6)
		Classroom Math Scores			SIMCE Math Scores		
Third trimester: Temperature relative to coldest quintile	Quintile 2	-0.0220***	-0.00738*	-0.00731*	-0.0270***	-0.0107	-0.0134**
		(0.00339)	(0.00414)	(0.00413)	(0.00574)	(0.00781)	(0.00655)
	Quintile 3	-0.0675***	-0.0332***	-0.0322***	-0.0825***	-0.0391***	-0.0385***
		(0.00533)	(0.00668)	(0.00671)	(0.00888)	(0.0129)	(0.0112)
	Quintile 4	-0.108***	-0.0474***	-0.0443***	-0.123***	-0.0781***	-0.0739***
		(0.00650)	(0.00850)	(0.00846)	(0.0108)	(0.0171)	(0.0145)
	Quintile 5	-0.160***	-0.0766***	-0.0727***	-0.171***	-0.120***	-0.109***
		(0.00711)	(0.00975)	(0.00974)	(0.0121)	(0.0195)	(0.0164)
Second trimester: Temperature relative to coldest quintile	Quintile 2	-0.00310	-0.00554	-0.00555	-0.0185***	-0.0410***	-0.0398***
		(0.00301)	(0.00389)	(0.00392)	(0.00497)	(0.00843)	(0.00722)
	Quintile 3	0.00271	-0.00262	-0.00317	-0.0197***	-0.0511***	-0.0491***
		(0.00377)	(0.00581)	(0.00587)	(0.00626)	(0.0118)	(0.01000)
	Quintile 4	0.0142***	-0.000583	-0.00132	-0.0167***	-0.0461***	-0.0405***
		(0.00312)	(0.00722)	(0.00730)	(0.00517)	(0.0140)	(0.0122)
	Quintile 5	-0.00963***	-0.0170*	-0.0169*	-0.0521***	-0.0857***	-0.0761***
		(0.00253)	(0.00891)	(0.00902)	(0.00421)	(0.0162)	(0.0146)
First trimester: Temperature relative to coldest quintile	Quintile 2	-0.0162***	-0.00342	-0.00353	-0.0114*	-0.00340	0.00316
		(0.00339)	(0.00422)	(0.00421)	(0.00591)	(0.00866)	(0.00721)
	Quintile 3	-0.0120**	-0.000768	-0.00158	0.00399	0.0337**	0.0361***
		(0.00535)	(0.00658)	(0.00650)	(0.00904)	(0.0136)	(0.0112)
	Quintile 4	0.0120*	0.00579	0.00546	0.0213*	0.0441***	0.0494***
		(0.00659)	(0.00848)	(0.00844)	(0.0110)	(0.0165)	(0.0140)
	Quintile 5	0.0131*	0.0172*	0.0167*	0.0234*	0.0510***	0.0519***
		(0.00710)	(0.00963)	(0.00960)	(0.0122)	(0.0189)	(0.0160)
	Controls	None	Year of birth, Week of conception	2+ Sex, Mother's age and education	None	Year of birth, Week of conception	5+ Sex, Mother's age and education
	Observations	1,097,013	1,097,013	1,097,013	610,213	610,213	610,213
	R-squared	0.007	0.007	0.018	0.006	0.014	0.143

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: standard errors clustered at region-year-month-day level. Excluded quintile is the coolest temperature quintile in each trimester.

TABLE 2: In utero temperature and language test scores

	Temperature by trimester and quintile	(1)	(2)	(3)	(4)	(5)	(6)
		Classroom Language Scores			SIMCE Language Scores		
Third trimester: Temperature relative to coldest quintile	Quintile 2	-0.0186***	-0.00523	-0.00524	-0.0270***	-0.0107	-0.0134**
		(0.00339)	(0.00417)	(0.00407)	(0.00574)	(0.00781)	(0.00655)
	Quintile 3	-0.0605***	-0.0281***	-0.0271***	-0.0825***	-0.0391***	-0.0385***
		(0.00534)	(0.00672)	(0.00663)	(0.00888)	(0.0129)	(0.0112)
	Quintile 4	-0.0976***	-0.0424***	-0.0385***	-0.123***	-0.0781***	-0.0739***
		(0.00650)	(0.00838)	(0.00821)	(0.0108)	(0.0171)	(0.0145)
	Quintile 5	-0.143***	-0.0694***	-0.0640***	-0.171***	-0.120***	-0.109***
		(0.00712)	(0.00957)	(0.00942)	(0.0121)	(0.0195)	(0.0164)
Second trimester: Temperature relative to coldest quintile	Quintile 2	-0.00116	-0.00130	-0.000926	-0.0185***	-0.0410***	-0.0398***
		(0.00301)	(0.00387)	(0.00389)	(0.00497)	(0.00843)	(0.00722)
	Quintile 3	0.00552	0.00571	0.00579	-0.0197***	-0.0511***	-0.0491***
		(0.00377)	(0.00579)	(0.00574)	(0.00626)	(0.0118)	(0.01000)
	Quintile 4	0.0162***	0.00975	0.00988	-0.0167***	-0.0461***	-0.0405***
		(0.00311)	(0.00714)	(0.00708)	(0.00517)	(0.0140)	(0.0122)
	Quintile 5	-0.00619**	-0.00367	-0.00211	-0.0521***	-0.0857***	-0.0761***
		(0.00253)	(0.00871)	(0.00868)	(0.00421)	(0.0162)	(0.0146)
First trimester: Temperature relative to coldest quintile	Quintile 2	-0.0117***	0.000872	0.00107	-0.0114*	-0.00340	0.00316
		(0.00339)	(0.00399)	(0.00394)	(0.00591)	(0.00866)	(0.00721)
	Quintile 3	-0.00733	0.00605	0.00538	0.00399	0.0337**	0.0361***
		(0.00534)	(0.00638)	(0.00622)	(0.00904)	(0.0136)	(0.0112)
	Quintile 4	0.0146**	0.0121	0.0116	0.0213*	0.0441***	0.0494***
		(0.00660)	(0.00832)	(0.00816)	(0.0110)	(0.0165)	(0.0140)
	Quintile 5	0.0136*	0.0203**	0.0201**	0.0234*	0.0510***	0.0519***
		(0.00710)	(0.00953)	(0.00935)	(0.0122)	(0.0189)	(0.0160)
	Controls	None	Year of birth, Week of conception	2+ Sex, Mother's age and education	None	Year of birth, Week of conception	5+ Sex, Mother's age and education
	Observations	1,093,503	1,093,503	1,093,503	610,213	610,213	610,213
	R-squared	0.006	0.006	0.044	0.006	0.014	0.143

Robust standard errors in pai

*** p<0.01, ** p<0.05, * p<0.1

Notes: standard errors clustered at region-year-month-day level. Excluded quintile is the coolest temperature quintile in each trimester.

TABLE 3: In utero temperature and test scores contorlling for birth outcomes

	Temperature by trimester and quintile	(1)	(2)	(3)	(4)	(5)	(6)
		Classroom Math Scores			SIMCE Math scores		
Third trimester: Temperature relative to coldest quintile	Quintile 2	-0.00723*	-0.00765*	-0.00714*	-0.0103	-0.0106	-0.00948
		(0.00412)	(0.00412)	(0.00411)	(0.00783)	(0.00780)	(0.00774)
	Quintile 3	-0.0330***	-0.0333***	-0.0330***	-0.0386***	-0.0390***	-0.0376***
		(0.00660)	(0.00658)	(0.00660)	(0.0129)	(0.0129)	(0.0128)
	Quintile 4	-0.0472***	-0.0474***	-0.0471***	-0.0769***	-0.0781***	-0.0763***
		(0.00836)	(0.00836)	(0.00836)	(0.0172)	(0.0171)	(0.0169)
	Quintile 5	-0.0770***	-0.0775***	-0.0768***	-0.119***	-0.120***	-0.117***
		(0.00957)	(0.00956)	(0.00956)	(0.0197)	(0.0194)	(0.0192)
Second trimester: Temperature relative to coldest quintile	Quintile 2	-0.00523	-0.00529	-0.00527	-0.0400***	-0.0412***	-0.0401***
		(0.00380)	(0.00381)	(0.00380)	(0.00852)	(0.00840)	(0.00828)
	Quintile 3	-0.000468	-0.000831	-0.000767	-0.0481***	-0.0519***	-0.0508***
		(0.00567)	(0.00567)	(0.00565)	(0.0122)	(0.0118)	(0.0116)
	Quintile 4	0.00354	0.00206	0.00318	-0.0415***	-0.0473***	-0.0449***
		(0.00705)	(0.00703)	(0.00701)	(0.0145)	(0.0139)	(0.0138)
	Quintile 5	-0.0126	-0.0144*	-0.0129	-0.0808***	-0.0869***	-0.0843***
		(0.00852)	(0.00853)	(0.00849)	(0.0168)	(0.0162)	(0.0161)
First trimester: Temperature relative to coldest quintile	Quintile 2	-0.00295	-0.00333	-0.00293	-0.00288	-0.00341	-0.00253
		(0.00422)	(0.00422)	(0.00421)	(0.00867)	(0.00864)	(0.00856)
	Quintile 3	0.000239	-0.000563	0.000274	0.0340**	0.0338**	0.0346***
		(0.00653)	(0.00654)	(0.00652)	(0.0136)	(0.0136)	(0.0134)
	Quintile 4	0.00729	0.00593	0.00739	0.0447***	0.0441***	0.0454***
		(0.00835)	(0.00835)	(0.00835)	(0.0166)	(0.0165)	(0.0163)
	Quintile 5	0.0190**	0.0174*	0.0191**	0.0519***	0.0509***	0.0523***
		(0.00943)	(0.00944)	(0.00943)	(0.0190)	(0.0188)	(0.0187)
	Controls	Log Birth Weight	Gestational Age	Log Birth Weight + Gestational Age	Log Birth Weight	Gestational Age	Log Birth Weight + Gestational Age
	Observations	1,097,013	1,097,013	1,097,013	610,213	610,213	610,213
	R-squared	0.011	0.008	0.011	0.015	0.014	0.017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: standard errors clustered at region-year-month-day level. Other controls include fixed effects for year of birth and week of conception. Excluded quintile is the coolest temperature quintile.

TABLE 4: OLS and Siblings Fixed effects models

		Score		Score Lang		SIMCE		SIMCE Lang	
	VARIABLES	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Third trimester: Temperature relative to coldest quintile	Quintile 2	-0.00867	-0.0115*	-0.0113*	-0.0145**	-0.0157*	0.00262	-0.0113	-0.00330
		(0.00573)	(0.00631)	(0.00580)	(0.00612)	(0.00937)	(0.0162)	(0.00916)	(0.0173)
	Quintile 3	-0.0311***	-0.0275***	-0.0312***	-0.0336***	-0.0458***	-0.0113	-0.0482***	-0.0246
		(0.00894)	(0.0101)	(0.00913)	(0.00998)	(0.0155)	(0.0254)	(0.0154)	(0.0271)
	Quintile 4	-0.0485***	-0.0469***	-0.0454***	-0.0496***	-0.0704***	-0.0284	-0.0783***	-0.0394
		(0.0115)	(0.0128)	(0.0116)	(0.0126)	(0.0209)	(0.0336)	(0.0198)	(0.0351)
	Quintile 5	-0.0778***	-0.0771***	-0.0772***	-0.0838***	-0.110***	-0.0648	-0.128***	-0.0822**
		(0.0132)	(0.0150)	(0.0132)	(0.0147)	(0.0246)	(0.0401)	(0.0235)	(0.0416)
Second trimester: Temperature relative to coldest quintile	Quintile 2	-0.00513	-0.00191	-0.00229	0.00283	-0.0166*	0.00776	-0.00256	0.0191
		(0.00537)	(0.00624)	(0.00539)	(0.00613)	(0.00992)	(0.0155)	(0.00980)	(0.0161)
	Quintile 3	-0.00951	-0.00377	-0.00470	0.00472	-0.0317**	-0.00465	-0.00526	0.0227
		(0.00783)	(0.00917)	(0.00795)	(0.00896)	(0.0147)	(0.0235)	(0.0143)	(0.0250)
	Quintile 4	-0.00182	0.00378	0.00498	0.0130	-0.0213	0.0314	0.00449	0.0484
		(0.00973)	(0.0114)	(0.00983)	(0.0111)	(0.0179)	(0.0292)	(0.0176)	(0.0308)
	Quintile 5	-0.0200*	-0.0200	-0.00601	-0.00449	-0.0470**	0.00993	-0.0238	0.0173
		(0.0115)	(0.0133)	(0.0116)	(0.0129)	(0.0211)	(0.0341)	(0.0206)	(0.0363)
First trimester: Temperature relative to coldest quintile	Quintile 2	-0.00161	-0.00842	-0.00269	-0.00273	-0.00923	-0.00767	-0.0147	-0.0121
		(0.00566)	(0.00672)	(0.00568)	(0.00649)	(0.0103)	(0.0167)	(0.0101)	(0.0185)
	Quintile 3	-0.000606	-0.00717	6.83e-05	-0.00160	0.0164	0.0158	0.00126	-0.0219
		(0.00899)	(0.0104)	(0.00905)	(0.0102)	(0.0167)	(0.0270)	(0.0157)	(0.0281)
	Quintile 4	0.00582	0.000294	0.00616	0.00471	0.0191	0.0140	-0.00343	-0.0393
		(0.0114)	(0.0128)	(0.0114)	(0.0126)	(0.0202)	(0.0326)	(0.0198)	(0.0345)
	Quintile 5	0.0131	-0.00129	0.00958	-0.00660	0.0237	0.0108	0.00320	-0.0494
		(0.0130)	(0.0147)	(0.0131)	(0.0145)	(0.0229)	(0.0376)	(0.0225)	(0.0399)
	Observations	581649	581649	579,379	579,379	324,596	324,596	324,596	324,596
	R-squared	0.011	0.680	0.007	0.695	0.012	0.844	0.010	0.827

Robust standard errors in pai
*** p<0.01, ** p<0.05, * p·

Notes: standard errors clustered at region-year-month-day level. Other controls include fixed effects for year of birth and week of conception. Sample includes families where number of siblings ranges from 2-5. Exluded quintile is the coolest temperature quintile.

TABLE 5: In utero temperature and Birth Outcomes

	Temperature by trimester and quintile	(1) Birth Weight	(2) Log Birth Weight	(3) Probability of Low Birth Weight	(4) Gestational Age (in weeks)	(5) Infant Mortality (1 year)	(6) Neonatal Mortality (28 days)	(7) 24 hr mortality
Third trimester: Temperature relative to coldest quintile	Quintile 2	-5.438	-0.00232	0.00285	-0.00448	0.00126*	0.000615	0.000475
		(7.080)	(0.00270)	(0.00300)	(0.0373)	(0.000731)	(0.000612)	(0.000367)
	Quintile 3	-7.137	-0.00319	0.00555	-0.0225	0.00181	0.000648	0.000912
		(13.09)	(0.00522)	(0.00545)	(0.0693)	(0.00143)	(0.00123)	(0.000749)
	Quintile 4	-8.869	-0.00331	0.00589	-0.0287	0.00220	0.000744	0.00101
		(18.91)	(0.00763)	(0.00780)	(0.100)	(0.00205)	(0.00178)	(0.00106)
	Quintile 5	-2.420	-0.00154	0.00480	0.0150	0.00285	0.00103	0.00134
		(23.30)	(0.00942)	(0.00956)	(0.124)	(0.00254)	(0.00219)	(0.00131)
Second trimester: Temperature relative to coldest quintile	Quintile 2	-3.426	-0.000876	0.00160	-0.0127	0.000485	-0.000122	0.000476
		(9.247)	(0.00356)	(0.00384)	(0.0488)	(0.000903)	(0.000776)	(0.000455)
	Quintile 3	-18.05	-0.00759	0.00748	-0.109	0.000994	0.000399	0.00121
		(18.84)	(0.00749)	(0.00763)	(0.0997)	(0.00188)	(0.00164)	(0.000999)
	Quintile 4	-37.49	-0.0164	0.0163	-0.178	0.00270	0.00206	0.00203
		(28.10)	(0.0113)	(0.0114)	(0.150)	(0.00281)	(0.00246)	(0.00152)
	Quintile 5	-40.39	-0.0186	0.0201	-0.190	0.00455	0.00373	0.00295
		(34.27)	(0.0139)	(0.0139)	(0.183)	(0.00348)	(0.00306)	(0.00188)
First trimester: Temperature relative to coldest quintile	Quintile 2	-5.241	-0.00237	0.000134	-0.0121	5.48e-05	0.000346	-0.000254
		(6.940)	(0.00262)	(0.00289)	(0.0362)	(0.000735)	(0.000596)	(0.000336)
	Quintile 3	-6.843	-0.00318	0.000788	-0.00691	-0.00144	-0.000492	-0.00123*
		(13.25)	(0.00523)	(0.00547)	(0.0693)	(0.00143)	(0.00122)	(0.000699)
	Quintile 4	-7.671	-0.00281	-0.000864	0.0151	-0.00252	-0.00194	-0.00144
		(18.35)	(0.00735)	(0.00750)	(0.0968)	(0.00197)	(0.00171)	(0.000997)
	Quintile 5	-11.92	-0.00400	-0.000576	0.0103	-0.00288	-0.00228	-0.00170
		(22.67)	(0.00913)	(0.00927)	(0.120)	(0.00241)	(0.00210)	(0.00125)
	Observations	1,137,189	1,137,189	1,137,189	1,137,189	1,133,975	1,129,513	1,125,543
	R-squared	0.001	0.001	0.000	0.002	0.000	0.000	0.000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: standard errors clustered at region-year-month-day level. Other controls include fixed effects for year of birth and week of conception. Excluded quintile is the coolest temperature quintile in each trimester. Excluded quintile is the coolest temperature quintile.

TABLE 6: In utero temperature and outcomes in Santiago - Controlling for PM10 and Dew Point

	Temperature by trimester and quintile	(1) Classroom Math Scores	(2) Classroom Language Scores	(3) SIMCE Math Scores	(4) SIMCE Language Scores
Third trimester: Temperature relative to coldest quintile	Quintile 2	-0.0171**	-0.0106	-0.0605***	-0.0254*
		(0.00762)	(0.00763)	(0.0151)	(0.0153)
	Quintile 3	-0.0443***	-0.0303***	-0.0829***	-0.0393*
		(0.0117)	(0.0116)	(0.0208)	(0.0203)
	Quintile 4	-0.0489***	-0.0380***	-0.100***	-0.0373
		(0.0149)	(0.0145)	(0.0271)	(0.0258)
	Quintile 5	-0.0729***	-0.0622***	-0.153***	-0.0853***
		(0.0168)	(0.0163)	(0.0316)	(0.0299)
Second trimester: Temperature relative to coldest quintile	Quintile 2	-0.00453	-0.00123	-0.0500***	-0.00239
		(0.00766)	(0.00772)	(0.0154)	(0.0130)
	Quintile 3	-0.00430	0.00505	-0.0830***	-0.0109
		(0.0107)	(0.0111)	(0.0211)	(0.0182)
	Quintile 4	-0.00246	0.00499	-0.104***	-0.0303
		(0.0131)	(0.0134)	(0.0254)	(0.0221)
	Quintile 5	-0.0158	-0.00691	-0.176***	-0.0756***
		(0.0160)	(0.0162)	(0.0311)	(0.0268)
First trimester: Temperature relative to coldest quintile	Quintile 2	0.00929	0.0124*	0.0180	-0.00298
		(0.00665)	(0.00645)	(0.0128)	(0.0126)
	Quintile 3	0.0197*	0.0225**	0.0757***	0.0320*
		(0.0104)	(0.0102)	(0.0199)	(0.0178)
	Quintile 4	0.0226*	0.0297**	0.106***	0.0467**
		(0.0137)	(0.0136)	(0.0244)	(0.0217)
	Quintile 5	0.0184	0.0222	0.0802***	0.0271
		(0.0151)	(0.0152)	(0.0292)	(0.0271)
	Observations	480705	478486	285608	285608
	R-squared	0.010	0.008	0.011	0.006

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: standard errors clustered at region-year-month-day level. Other controls include fixed effects for year of birth and week of conception. Daily PM10 information is available consistently after 1997, hence sample sizes are smaller.

TABLE 7: Different ways of measuring temperature

Impact of temperature on math classroom scores

Average across each trimester		Number of days in a given temperature bin		Number of days in a given temperature maximum	
3rd Trimester	-0.00485***	T3: t>70	-0.00115***	T3: Max>90	-0.00121***
	(0.000917)		(0.000352)		(0.000460)
2nd Trimester	-0.00100*	T2: t>70	-0.000415	T2: Max>90	-0.00148***
	(0.000562)		(0.000296)		(0.000511)
1st Trimester	0.00125	T1: t>70	-0.000361	T1: Max>90	0.000922*
	(0.000887)		(0.000356)		-0.000504
		T3: 60<t<70	-0.000852***		
			(0.000323)		
		T2: 60<t<70	-0.000362		
			(0.000254)		
		T1: 60<t<70	-0.00128***		
			(0.000318)		
		T3: 45<t<60	0.000331		
			(0.000245)		
		T2: 45<t<60	-0.000384		
			(0.000259)		
		T1: 45<t<60	-0.00158***		
			(0.000253)		
Observations	1,097,013		1,097,013		838,397
R-squared	0.007		0.007		0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: standard errors clustered at region-year-month-day level. Other controls include fixed effects for year of birth and week of conception.

APPENDIX TABLE 1: Robustness to controlling for seasonality

	Temperature by trimester and quintile	(1) Week of Conception	(2) Day of Conception	(3) Month of Conception	(4) Quarter of Conception
Third trimester: Temperature relative to coldest quintile	Quintile 2	-0.00738*	-0.00699*	-0.00966**	-0.00705*
		(0.00414)	(0.00412)	(0.00406)	(0.00411)
	Quintile 3	-0.0332***	-0.0338***	-0.0405***	-0.0425***
		(0.00668)	(0.00665)	(0.00645)	(0.00621)
	Quintile 4	-0.0474***	-0.0481***	-0.0577***	-0.0730***
		(0.00850)	(0.00846)	(0.00807)	(0.00765)
	Quintile 5	-0.0766***	-0.0774***	-0.0887***	-0.121***
		(0.00975)	(0.00971)	(0.00926)	(0.00863)
Second trimester: Temperature relative to coldest quintile	Quintile 2	-0.00554	-0.00592	-0.00392	-0.000412
		(0.00389)	(0.00386)	(0.00368)	(0.00357)
	Quintile 3	-0.00262	-0.00339	0.000256	0.00316
		(0.00581)	(0.00582)	(0.00530)	(0.00484)
	Quintile 4	-0.000583	-0.00189	0.00589	0.0207***
		(0.00722)	(0.00729)	(0.00640)	(0.00487)
	Quintile 5	-0.0170*	-0.0177**	-0.0126	0.0142**
		(0.00891)	(0.00900)	(0.00774)	(0.00562)
First trimester: Temperature relative to coldest quintile	Quintile 2	-0.00342	-0.00322	-0.00457	-0.00817**
		(0.00422)	(0.00420)	(0.00405)	(0.00410)
	Quintile 3	-0.000768	-0.00129	0.00135	-0.00186
		(0.00658)	(0.00659)	(0.00637)	(0.00619)
	Quintile 4	0.00579	0.00481	0.0134*	0.0133*
		(0.00848)	(0.00848)	(0.00816)	(0.00750)
	Quintile 5	0.0172*	0.0157	0.0249***	0.00920
		(0.00963)	(0.00965)	(0.00922)	(0.00840)
	Observations	1,097,013	1,097,013	1,097,013	1,097,013
	R-squared	0.007	0.008	0.007	0.007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: standard errors clustered at region-year-month-day level. Other controls include fixed effects for year of birth.