# The Fetal Origins of Cognitive Aging*

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**Abstract**

Despite its enormous individual and social costs; the fundamental and long-run causes of cognitive aging remain understudied. We study the causal effect of in-utero temperature exposure on cognition during old age. Combining unique data on South African adults between 40 and 99 years of age with geospatial information on historical temperatures, our identification strategy exploits exogenous, within-municipality-of-birth, month-to-month variations in temperature, and controls for contemporaneous weather and location at the time of survey administration. We find that temperature in the first trimester of pregnancy negatively affects the cognitive function score later in life, but temperature in the second and third trimesters has a positive effect on adults cognitive function score. These differing effects result in an overall U-shaped relationship between prenatal exposure to temperature and cognition. This non-linear relationship is robust across measures of memory, reasoning, and information processing speed. Our findings are consistent with the fetal programming theory, which holds that the first trimester of pregnancy is the most crucial window of brain formation. In accordance with this theory, brain development occurring in the first trimester of pregnancy would therefore have the highest vulnerability to external shocks. Heterogeneity analysis reveals that the effect of prenatal temperature on cognition is larger for men, individuals over 75 years of age, and individuals with low social capital. Analyzing causal mechanisms, we find that prenatal temperature affects key determinants of individuals' cognitive reserve. We also find that exposure to drought during the first trimester of pregnancy and reduced sleep during adulthood are other potential channels through which the effects of prenatal exposure to temperature operate.

**Keywords:**: Fetal origins; Cognitive aging; Memory; Reasoning; Information processing; Prenatal temperature; South Africa.

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# 1 Introduction

Age-related impairments in memory, reasoning, and information processing speed are rising globally due to population aging. Cognitive aging increases psychological and emotional dependency and reduces economic productivity in the elderly, resulting in numerous individual and societal level challenges. In a context of increasing life expectancy in most countries, understanding the factors that contribute to cognitive aging is important. While there is an abundant economic literature on the short-term and contemporaneous determinants of cognitive performance in children and young adults, very few studies focus on older adults. Moreover, very little is known about the fundamental and long-term determinants of cognitive performance in this latter group. Addressing this knowledge gap is essential in designing policies aimed at promoting successful aging and supporting the economic productivity of older adults.

In this paper, we study for the first time the long-run effects of prenatal temperature anomalies on cognitive aging and document possible mechanisms governing this relationship. Our interest in early-life influences is in part motivated by the growing literature that argues that adverse environmental conditions, experienced during critical windows of fetal development, can lead to physiologic responses that are irreversible for a wide range of important outcomes later in life. (Heckman, 2006, 2007; Almond and Currie, 2011; Heckman et al., 2013; Currie and Vogl, 2013)). We focus on cognition, defined as the set of mental processes related to knowledge and understanding (Cutler and Lleras-Muney, 2010). Cognitive function is essential for communication (through speech and language), decision making (through the integration of new and existing knowledge), reasoning, and executive functioning. Moreover, cognition underpins the decision making processes that lead to certain behaviours (Riddle, 2007). It is important to note that, medically speaking, cognitive impairment differs from mental health disorders. Although cognitive dysfunction had previously been considered a secondary symptom of some diagnosed mental illnesses (Trivedi, 2006), in a broad sense, cognition denotes a 'relatively high level of information processing of specific information including thinking, memory, perception, motivation, skilled movements and language' (Trivedi, 2006). Previous literature documents the effect of climate shocks on cognitive performance using measures such as students' test scores and educational attainment (Park, 2016; Zivin et al., 2020; Cook and Heyes, 2020), labor productivity (Somanathan et al., 2015), emotional states (Noelke et al., 2016; Baylis et al., 2018), judges' decision making in court (Heyes and Saberian, 2019), amongst others. These studies examine the *contemporaneous* impacts of climate shocks on cognitive outputs, and primarily focuses on children and young adults.

Our study differs from previous contributions to the literature, by focusing on cognitive aging and by considering shocks that may affect brain formation in different stages of fetal development (Charil et al., 2010). Indeed, our study is the first to document prenatal shocks as a key driver of cognitive aging and underlying outcomes such as memory, reasoning, and information processing. We also distinguish the effect by timing of exposure to temperature anomalies, that is, by trimester of pregnancy. This makes it possible to identify the most sensitive window of fetal development for cognitive aging. In so doing, we provide new evidence in support of the so-called fetal programming theory, which underlines the importance of the first trimester of pregnancy in successful fetal brain development. (Myers, 1975; Weinstock, 2008; Ramírez-Vélez, 2012). However, our analysis goes beyond testing this latter hypothesis, as we also investigate the effect of temperature in the second and third trimesters of pregnancy, in the trimester before conception and in the first trimester following birth. In addition, to obtain a better understanding of the possible mechanisms underlying our main finding, we first document heterogeneity in the effect of prenatal temperature on later life cognitive performance by gender,age group, season, and family attributes (such as within-family social capital). We also examine the impacts of prenatal temperature on key determinants of individuals' cognitive reserve such as their literacy rate, sleep quantity, and sleep quality.[1]

We examine the relationship between ambient temperature during different stages of pregnancy and cognitive performance in the context of older South African adults. We use the "Health and Aging in Africa: A longitudinal Study of an INDEPTH Community in South Africa, 2015" (HAALSI) dataset, a unique and rich population-based cohort study of 5,059 adults aged 40 years or older.[2] HAALSI provides information on a battery of cognitive measurements along with individual level information on place of birth (municipality, district, or town), month of birth and year of birth. The HAALSI also provides individual level information on a range of socioeconomic and demographic characteristics including, but not limited

[1]Cognitive reserve is the brain's ability to change the way it operates and thus make added resources available to cope with challenges. It is developed by a lifetime of education and curiosity to help the brain better cope with any failure or decline it faces (Stern, 2002).

[2]HAALSI consists of five main projects. Each project use the same household survey and assessment tools to draw on collective information from HAALSI waves 1, 2, and 3. We focus on HAALSI's Cognition and Dementia project for which in-person interviews were conducted in order to *(i)* determine the incidence and prevalence of dementia and mild cognitive impairment; *(ii)* identify social and economic risk and resilience factors affecting cognitive decline and dementia; and *(iii)* evaluate association of markers of biological aging related to telomeres with cognitive decline. For details, see: https://haalsi.org/projects-cores

to, gender, age, religion, ethnicity, education level, and children and grandchildren. Because HAALSI does not provide geographic information (latitude and longitude) on place of birth, we collected this information from online resources using the name of each place of birth provided in the survey.

We complement this primary source of data with multiple rounds of Demographic and Health Survey (DHS) data collected in South Africa. The DHS provides geographic information from mothers aged 15-49 years old and their children. We use DHS to examine the plausible mechanisms behind the effects of prenatal temperature on the later-life cognitive outcomes we study. Specifically, we take advantage of DHS data in three ways. First, we investigate the impact of temperature shocks on maternal health and maternal behaviors which may impact fetal health. To this end, and following Adhvaryu et al. (2015), our variables include duration of breastfeeding, early life vaccination, prenatal doctor visits, and whether the birth was a home delivery. Second, we use information on parents occupation during the gestation period to check whether our effects operate via a change in agricultural yields. Lastly, we use DHS data to address some threats to our identification strategy, such as selective mortality and fertility in response to a change in weather conditions.

Together, HAALSI and DHS datasets are combined with historical gridded monthly air temperature and precipitation data from the University of Delaware air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). We identify weather conditions experienced during the prenatal period for the subsample of respondents born in South Africa. This subsample represents 3,232 individuals out of the 5,059 adults surveyed.[3] Our identification strategy exploits exogenous within-municipality-of-birth and month-to-month variations in temperature and controls for contemporaneous weather and location at the time of the survey. The remaining exogenous distribution of temperatures allows us to interpret our estimates as the causal effects of in-utero temperature on cognitive aging. In supplementary analyses, we validate our main results by examining *(i)* non-linear effects of prenatal temperature bins, and *(ii)* the effects of prenatal drought exposure on cognition. Moreover, we show that our results are not sensitive to alternative specifications including additional controls or using alternative clustering.

Our main finding is that prenatal temperature has lasting effects on cognitive performance during aging. Specifically, we find that temperature in the first trimester of pregnancy nega-

[3]We are only able to analyze the subsample of respondents born in South Africa because information on place of birth was either missing or inaccurate for respondents born in other countries. As such, we could not collect geographical coordinates on place of birth for this forign-born subsample.

tively affects the cognitive function score, but temperature in the second and third trimesters has a positive effect on this score. These differing effects result in an overall U-shaped relationship between prenatal temperature and cognition. This non-linear relationship carries over to underlying variables of the cognitive function score, including memory, reasoning, and information processing speed.

Our findings provide novel evidence in support of the fetal programming hypothesis. The prenatal period is a time of rapid change during which fetal organs and organ systems form. As such, these organs are vulnerable to both organizing and disorganizing influences (Weinstock, 2008; Charil et al., 2010). These influences on fetal development have been described as fetal programming —the process by which a stimulus or insult experienced during a vulnerable developmental period has long-lasting or permanent effects. According to this theory, the effect of programming is sensitive to the timing of the exposure and to the developmental stage of organ systems, with the first trimester described as the most crucial window of pregnancy. Indeed, our analysis reveals that the direction of the effect of prenatal temperature on cognitive aging depends on the trimester of pregnancy.

Next, we identify possible mechanisms behind the lasting effects of prenatal temperature on cognition during aging. According to the literature, there could be both direct and indirect channels through which this effect might operate, as shown in figure 1. Prenatal exposure to a temperature anomaly has a direct effect on fetal development and brain formation through altering the functioning of the hypothalamo-pituitary-adrenal (HPA) axis (Weinstock, 2008). Prenatal exposure to these temperature shocks could also have lasting effects on key determinants of individuals' cognitive reserve, including their health and capacity for human capital formation. Cognitive reserve positively affects cognitive performance during aging.

To test these mechanisms, we first examine heterogeneity in the effect of prenatal temperature on cognition. We find that the effect is more harmful for individuals over 75 years of age, for men, and for individuals who do not have siblings or grandchildren. The fact that a lack of social capital exacerbates the harmful effect of temperature anomalies is an indication that family support can help mitigate the long-term effect of adverse shocks experienced in early life. Our findings on gender's sensitivity to early-life environmental insults are consistent with those from previous studies suggesting that males are more vulnerable to prenatal environmental shocks than females (Almond and Mazumder, 2011; Almond and Edlund, 2007).[4] Second,

[4]However, there are few exceptions in the existing literature. For instance, analyzing the impact of rainfall levels experienced during early age in Indonesia, Maccini and Yang (2019) find that females are more harmed more relative to males.

we investigate whether exposure to prenatal temperature anomalies affects key determinants of individuals' cognitive reserve. We find that prenatal temperature has a non-linear effect on literacy and quality of sleep similar to its effect on the cognitive function score.[5] We also identify drought exposure during the first trimester of pregnancy as a potential channel through which the effect of prenatal exposure to temperature operates.

The remainder of the paper proceeds as follows. Section 2 discusses the related literature and outlines the paper's main contributions to this literature. Section 3 presents biological pathways linking ambient prenatal temperature to the brain's efficiency. Section 4 describes the data and variables pertaining to this study. Section 5 outlines the empirical strategy. Our findings are presented in section 6, while sections 7 presents robustness checks. Section 8 and 9 test and discuss possible mechanisms. We conclude in section 10.

## 2 Related Literature

A growing literature documents the links between long-term outcomes and early life circumstances. Early studies have documented the long-term consequences of early life exposure to conditions, events, and diseases including malaria (Barreca, 2010), rainfall (Maccini and Yang, 2019), religious fasting (Almond and Mazumder, 2011), drought (Dinkelman, 2017), and pollution (Persico, 2020), among several others. We provide a list of studies in Appendix Table A1. It is clear from this table that the focus in the prior literature has been on children and young adults, and that these studies have primarily focused on mental health as their main outcome of interest. There has been very little research done on what effect early life exposure to these conditions has on cognitive performance. Additionally, the few existing papers on this subject focus primarily on younger individuals. Prenatal stress has been linked to abnormal cognitive, behavioral and psychosocial outcomes in both animals and humans (Charil et al., 2010). While it has been well established in animal studies that prenatal stress affects the offspring's brain, this relationship remains understudied in humans.

Very few studies have examined the effects of prenatal conditions on cognitive function in late adulthood, and almost all existing studies focus on developed countries. Using data from the western region of the Netherlands, De Rooij et al. (2010) analyze the effect of maternal malnutrition (due to famine experienced during World War II), experienced during pregnancy,

[5]The direction of its effect on sleep quantity is not consistent with its effect on cognition, which suggests that sleep quantity is not a channel through which prenatal temperature affects cognitive aging. We do not find childhood health to be a channel either.

on the cognitive function of their children later in life. They find that maternal malnutrition, experienced during pregnancy, negatively effected some aspects of their children's cognitive function later in life. One possible objection to this study is that the prenatal exposure to famine was not an exogenous event. Instead, the famine in the Netherlands was a direct result of the Second World War, raising the possibility that some other negative impact of the war, besides the famine, was responsible for the negative association with cognition. In order to account for this, the authors also compare the cognitive scores of those born before the famine (but during the war) to those conceived after the famine. They do not find any difference in cognitive function between these two groups, despite the stressful war-time conditions experienced before the famine. Another study, Wilde et al. (2017) test whether temperature spikes in-utero, at conception, and immediately after birth causally affect long-run educational attainment, literacy, and disability of adults in Sub-Saharan Africa. They find that educational attainment and literacy rise for individuals who were conceived during periods of elevated temperatures. Findings from this study suggest a possible mechanism through which prenatal exposure to temperature may affect cognition, in light of the fact that higher levels of education have been found to predict better cognitive performance (Guerra-Carrillo et al., 2017). These studies, however, focus on much younger age groups than our analysis. Our study also differs from this literature in so far as it examines a wider range of cognition-related variables such as reasoning, learning efficacy, and memory.

Unlike previous studies, our paper studies the effect of early life exposure to temperature shocks on cognitive performance during aging. Our study also uses data from a developing country, specifically South Africa. South Africa is currently experiencing simultaneous demographic and epidemiologic transitions, and the country is experiencing growing rates of cognitive impairment related to aging.[6] We build upon the neurological literature that documents the sensitivity of children's brain to temperature (Bowler and Tirri, 1974; Schiff and Somjen, 1985; Hocking et al., 2001) and contribute to this literature at the intersection of medicine and economics in two main ways. First, we highlight the importance of temperature anomalies experienced at different stages of fetal development on later life outcomes. Specifically, we find that temperature in the first trimester of pregnancy negatively affects the cognitive function score in older adults, whereas temperature in the second and third trimesters has a positive effect. Our results are consistent with the fetal programming theory which holds that the first trimester of

[6]The share of South Africa's population over 65 years old is now larger than the share of individuals under 5. With this shift in demographics, South Africa has also seen an increase in age related cognitive impairment (see https://www.indexmundi.com/south_africa/demographics_profile.html).

pregnancy is the most crucial window of brain formation and has the highest vulnerability to external shocks.

Secondly, we document possible mechanisms behind the uncovered effects of prenatal temperature on cognitive aging. Building upon a unique dataset and the DHS has allowed us to test whether or not there is adaptation or mitigation to weather shocks. Specifically, we use information on child investments along with information on quality of sleep in adulthood to document operating channels. We also document significant heterogeneties in the long-term impacts of fetal shocks, showing that these impacts are higher for men, individuals over 75 years of age, and individuals with low social capital. Lastly, while much of the existing literature focuses only on rich countries, our paper takes advantage of new sources of data and novel ways of measuring cognitive performance to study the long reach of fetal exposure to changes in temperature in rural South Africa. In addition, our analysis suggests that adverse shocks experienced during fetal development may be a more significant determinant of adult outcomes in developing countries, as the capacity to offset the negative effects of these shocks is more limited in developing countries.

# 3 Conceptual Framework: Linking Temperature to Fetal Brain Formation and Cognitive Aging

In Figure 1, we summarize our conceptual framework, which describes possible channels through which prenatal temperature anomalies may affect cognitive function during aging. Biology is an important channel through which prenatal temperature is likely to affect cognitive aging. As argued below, a negative prenatal temperature shock has a direct effect on fetal development and brain formation. Additionally exposure to temperature shocks may also have an indirect effect through key determinants of individuals' cognitive reserve, such as the health of the mother and the child, and parental income & socioeconomic status.

The relationship between climate conditions, including ambient temperature experienced during pregnancy and early childhood, and cognitive development has been well-documented in the medical literature (Bowler and Tirri, 1974; Schiff and Somjen, 1985; Hocking et al., 2001). Broadly speaking, this relationship operates through biological pathways, either directly impacting the fetus or indirectly impacting the fetus via the maternal response to heat stress. According to the so-called fetal programming hypothesis, the whole fetus's nervous system and cognitive function are built in the early period of the pregnancy. Some literature points to the first trimester of pregnancy as the most crucial window for a successful and complete brain formation (Ramírez-Vélez, 2012). While the exact nature of the physiological processes leading to impaired fetal brain formation are still subject to debate, there is growing consensus that these processes may involve hormonal imbalances in early pregnancy, decreased fetal nutritional intake in late pregnancy (whether due to low maternal nutritional intake, sub-optimal placental size, or blood flow or function), and low fetal oxygen supply throughout gestation (Mousa et al., 2019). It is argued that these processes can be triggered by conditions as diverse as maternal malnutrition, stress, disease, substance abuse, and exposure to adverse environmental conditions including high altitude and extreme ambient temperature (Fowden et al., 2006). exposure to these conditions during fetal development may have irreversible effects on brain formation. Corroborating this view, existing studies show that cognitive function at age five is negatively associated with poor socioeconomic conditions at home and in the surrounding neighborhood, poor maternal education, paternal absence, low birth weight, and stunting (Stern, 2002; M Tucker and Stern, 2011). It has also been found that the effect of poor socioeconomic conditions on cognitive performance is partly mediated by a lack of psychosocial stimulation.

Prenatal climate shocks might also affect cognitive performance during aging by affecting key determinants of the cognitive reserve, such as human capital accumulation and socioeconomic status. The cognitive reserve is the brain's ability to change the way it operates and thus make added resources available to cope with challenges. [7] The cognitive reserve is developed through a lifetime of education and curiosity. Individuals with higher cognitive reserves are able more easily able to cope with any failures or declines the brain faces. Prior studies have shown that people with greater cognitive reserves are better able to stave off symptoms of degenerative brain changes associated with dementia, Parkinson's disease, multiple sclerosis, and strokes. A more robust cognitive reserve can also help function better for longer if exposed to unexpected life events, such as stress, surgery, or toxins in the environment (M Tucker and Stern, 2011; Nyberg et al., 2012). Individuals' cognitive reserve therefore affects their cognitive performance during aging.

Based on findings in the existing literature documenting the long-term effects of prenatal climate shocks on human capital accumulation, we argue that prenatal temperature has ambiguous theoretical effects on cognitive aging. For example, Wilde et al. (2017) document positive effects on education, while Dinkelman (2017) and Almond and Currie (2011) docu-

[7] See more details at the following link: https://www.health.harvard.edu/mind-and-mood/what-is-cognitive-reserve

ment negative effects on child and adult health. The opposing effects of prenatal temperature on these outcomes, which are themselves important determinants of individuals' cognitive reserve, explain this ambiguous effect on cognitive aging. It is also possible that the effect varies by the stage of pregnancy in which a fetus is exposed to temperature shocks. For example, exposure during the first trimester of pregnancy is likely to be negative, as the first trimester of pregnancy corresponds to a crucial period of fetal brain formation. If the positive effect of prenatal temperature shocks on education documented in Wilde et al. (2017) is driven by exposure at later stages of pregnancy, then one would expect temperature shocks experienced during the second or third trimester of pregnancy to have a positive effect on cognition. It is also possible that the negative effects of prenatal temperature shocks dominate the positive effects when exposure occurs in certain pregnancy periods, while the positive effects may dominate the negative effects when exposure occurs in different periods. For this reason, we distinguish between periods of fetal development when studying the long-term effect of fetal temperature anomalies on cognitive aging.

# 4 Data and Measurement of Key Variables

Data is taken from three primary sources: The first source of data used is the "Health and Aging in Africa: A Longitudinal Study of an INDEPTH Community" (HAALSI), a population-based study of 5,059 male and female residents of in rural municipalities of the Agincourt sub-district, South Africa. The survey was only administered to individuals who were 40 years of age or older at the time of the survey's administration in 2015. This is a population that lived under Apartheid through midlife. HAALSI provides information on various measures of cognition outcomes, as well as several socio-demographic and economic characteristics of surveyed individuals such as age, sex, birth order, childhood health, father's occupation, country of birth, and years of education. The second source of data used is the 2016 round of Demographic and Health Surveys (DHS) conducted for South Africa. We primarily use child and birth re-code files in order to study children's responses to weather shocks. The third data source used in this study is the University of Delaware air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). These data sources are described below.

## 4.1 Data sources

**Health and Aging in Africa: A longitudinal Study of an INDEPTH Community (HAALSI)**. HAALSI is a longitudinal population-based study of 5,059 adults aged 40 years or older.Among the five main projects of HAALSI, we focus on the "Cognition and Dementia" project for which in-person interviews were conducted. Participants completed a battery of assessments designed to evaluate their ability to learn, remember, and make judgments. Cognitive functioning was assessed in the survey using validated measures such as: orientation (ability to state the present year, month, date, and name of the current South African president); immediate word recall (the number of words correctly recalled, out of ten, from a list read aloud by the interviewer); delayed word recall (the number of words correctly recalled from the original list of ten words after a 1 min delay during which the respondent was asked unrelated questions); forward count (the ability to count correctly from 1 to 20); and number skip pattern (the ability to complete the final digit of the number skip pattern beginning with 2, 4, 6, administered if the participant was able to correctly count from 1 to 20). Confirmatory factor analysis with a robust weighted least squares estimator was used to obtain a single factor model incorporating these different measures of cognitive functioning (Muthén and Muthén, 2017). This single factor model is reported as a continuous, z-standardized latent variable, denoted "cognitive function score". This method allows for non-linear relationships between the test scores & overall cognitive function and only utilizes common co-variation between the tests to construct the variable, reducing measurement error (Muthén and Muthén, 2017).[8] A higher cognitive function z-score reflects better cognitive performance.

We collect information on the geographical coordinates of the district and municipality of birth for each respondent born in South Africa.[9] Using this information, we produce Figure 2, which shows the spatial distribution of self-reported municipalities of birth for respondents born in South Africa. We remark that, although the survey was only conducted on individuals living in the rural Agincourt sub-district, the municipalities of birth cover several regions of South Africa as described in figure A1.

**Demographic and Health Surveys** collect information on demographic, health, and so-

[8]The cognitive measures used in this study are strong predictors of not only dementia risk but also of the physical health and wellbeing of older adults (Folstein et al., 1975; Mitchell, 2009). Although the latent variable approach means that the scale of the outcome variable does not translate to a clinically defined outcome of cognitive impairment or dementia, it captures the full range of inter-individual variations in cognitive function covered by any item in the battery. The latent variable approach reduces measurement error in the individual cognitive items by using their co-variation to inform the latent cognitive function variable.

[9]Some respondents were born in Mozambique. Information on place of birth was missing for most of these respondents, and so we remove them from the analysis.

cioeconomic characteristics and outcomes in low-income and middle-income countries. These surveys are representative at the national and subnational level, and are comparable across countries and years for most variables. The surveys use a two-stage sampling technique, selecting clusters (or census enumeration zones) at the first stage and households at the second stage. The focus in these surveys is primarily on women and their children, but several surveys also collect information on men.

We use the 2016 round of DHS of South African data to explore some of the mechanisms through which prenatal temperature shocks affect cognition during aging. In particular, we examine mechanisms that show how maternal and early life investments in children adjust to prenatal temperature shocks, using information on place of residence and date of birth for each child in the DHS. For each child, we define the prenatal period as the nine-month period preceding the month of birth. The whole period is divided in three trimesters, as we are interested in how the timing of exposure to temperature shocks affects outcomes. The analysis relies on DHS data to control for birth interval in months, and number of prior children (or child birth order). We also used DHS data to obtain mothers'socio-demographic characteristics, including age at delivery, marital status, household wealth asset index[10], and educational attainment. We extract this information from both the Child and Birth recode files.

**Weather variables.** Historical weather data is obtained from the University of Delaware air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). UDEL data is gridded at the $0.5 \times 0.5$ ° spatial resolution with monthly average measures of temperature and precipitation derived from a large number of stations, both from the Global Historical Climate Network (GHCN) and the archives of Legates and Willmott.

Using our collected data on the geographical coordinates of place and date of birth, we merge the HAALSI dataset with historical gridded monthly air temperature and precipitation data from the University of Delaware air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). The merging consists of assigning to each individual the weather conditions of the grid point closest to their municipality in a particular month and year. By doing so we were able to match 3,212 out of 5,059 individuals, born in 213 municipalities between 1915 and 1975.[11] Similarly, we merge the 2016 DHS for South Africa with UDEL temperature data

[10]This index is made available in the DHS data and is not constructed by the authors. It aggregates the assets owned by the household using factor analysis. A greater score on the index indicates ownership of more items such as radios or motorcycles. We lose sample size in this specification because it is missing for a large number of observations

[11]We were able to match all the respondents born in South Africa. The only respondents not matched were born in Mozambique or elsewhere.

using the year and month of birth of each child in the DHS and the geographical coordinates of the cluster in which the child's mother resides. In some specifications, account for non-linearity by binning monthly temperatures into five bins: $< 20$ °C, 20-22 °C, 22-24 °C, $> 24$ °C, with $<$20 °C considered as the reference category.

### 4.2 Summary statistics

Our main sample consists of 3,212 individuals (all born in South Africa). Figure A2 describes the change in average temperature and precipitation by year of birth. Unlike precipitation trends, which appear to be constant, temperature trends upwards over time. This finding is consistent with most climate models. This increase started around 1940, a year after which most births occurred in our sample (as shown in figure A3).

We examine whether the distribution of total births follows a certain seasonality. Put differently, we would like to check whether there is a certain pattern in fertility across months in a year. Figure 3 plots the total distribution of births by month (see upper graph of Figure 3), combined with change of average temperature by trimester of pregnancy by month of birth (see lower graph of Figure 3). Figure 3 reveals that, apart from June where we notice a peak in total births, births are equally distributed between months. In addition, the upper graph of figure 3 represents the distribution of temperature on a given trimester of pregnancy by month of birth. As mentioned earlier, this analysis intends to examine the seasonality in average temperature by trimester of pregnancy.

Figure 4 shows the distribution of the cognition z-score in the sample. The average cognition z-score ranks at 0.2 with a standard deviation of around 0.95. A higher the cognition score corresponds with better cognitive performance. Figure 4 represents the cognition score as a function of age. As expected, the data shows that cognition decreases with age. This downward trend in cognitive performance over time reveals that age related cognitive decline is a natural phenomenon. However, we want to know if, for the same cohort, differences in temperature shocks experienced during the period of pregnancy affect this variation in cognitive performance during aging. To do so, we start the analysis by looking at the correlation between average prenatal temperature and later life cognition z-score at the year of birth level, as represented in figure 5. Each dot in figure 5 represents the cognition z-score associated with the average temperature experienced during the nine months of pregnancy. This graph suggests a non-linear relationship with a quadratic shape between prenatal temperature and cognition z-score.[12] Note

[12]The quadratic shape can be seen in the temperature range corresponding to most observations, that is

that we can not derive a causal interpretation from this relationship given that it does not account for spatial and temporal variations in birth. However, the shape of this relationship suggests a functional form for the regression analysis.

Finally, table 1 summarizes the key variables pertaining to this study. In our sample, 48.2 % of individuals are male, and almost half of the respondents are single (48.5%). The average age, height, and weight of individuals in the sample is 61 years, 163.5 cm, and 27.6 kg/$m^2$, respectively. An average individual has 6.9 years of education. Most individuals (87.4%) self-reported experiencing good health during childhood. Around 83% reported being religious. Regarding weather conditions experienced during the pregnancy period, an average individual was exposed to an average monthly temperature of 21.45 °C, and an average of 5.7 mm of monthly precipitation.

# 5 Methodology

## 5.1 Identification Strategy

We estimate the impact of ambient temperature at different stages of pregnancy on adult cognitive function score using reduced form fixed-effects models. Our identification strategy exploits exogenous within-municipality-of-birth and month-to-month variations in temperature and controls for contemporaneous weather and location at the time of interview. The remaining exogenous distribution of temperatures allows us to interpret the effects of temperature shocks as causal.

Our following baseline model is estimated using ordinary least squares regressions.

$$Cognition_{ijmt} = \alpha Temp_{ijmt} + \rho * (Temp_{ijmt})^2 + CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \tag{1}$$

We regress the cognition z-score of each individual on the average temperature experienced during the nine-month period of pregnancy ($Temp$). Our specification allows us to interpret temperature shocks experienced in a given municipality and month of birth to be the difference between the long-run average temperature and the actual monthly temperature. We also include a quadratic term for this average temperature to capture potential non-linearity. $Cognition_{ijmt}$ is a measure of cognitive performance of individual $i$ born in municipality $j$ in month $m$ of year $t$. $\alpha$ and $\rho$ are the coefficients of interest associated with $Temp_{ijmt}$ and $(Temp_{ijmt})^2$,

temperature between 16 and 24 degrees.

respectively. $\mu_j$ and $\lambda_m$ correspond to municipality of birth and month of birth fixed effects, respectively. $\eta_t$ is a year of birth fixed effect, and $X_i$ is a vector of individual-specific control variables (such as gender, marital status, age group, sex, and birth order).[13] $CW_i$ refers to contemporaneous weather indicators experienced by individuals around the time of interview. $CW_i$ include temperature and precipitation. The error term, $\epsilon_{ijt}$, represents unobserved shocks and is assumed to be uncorrelated with temperature given the controls.

We are also interested in accessing what impact the timing of temperature shocks, in the course of pregnancy, has on cognition during aging. To do this, we estimate the following equation:

$$Cognition_{ijmt} = \sum_{k=0}^{4} \left[\alpha_k * Temp^k_{ijmt} + \rho_k * (Temp^k_{ijmt})^2\right] + CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \quad (2)$$

In this specification, we intend to capture the trimester effect on later life cognition z-score. We regress the cognition z-score of each individual on the average temperature for each of five following trimesters $k$: the trimester before the conception, the first, second, and third trimesters of pregnancy, and the trimester after birth.

We perform several additional exercises to confirm the robustness of our results. We begin by extending the period of shock by considering one year before the time of conception and one year after the date of birth. This exercise aims to distinguish between the effect of shocks experienced during pregnancy from shocks experienced before or after pregnancy. We also estimate our equation (1) while using different fixed-effects, different controls, and altering the average temperature variable such that it measured at the year of birth level. In this specification, we add municipality of birth quadratic times trend to the set of fixed-effects from equation (1)., in order to account for structural changes in municipalities over time. In this specification, we also control for average precipitation level specific to a location observed during year of birth. Many individuals in rural South Africa rely on agricultural yields for their livelihoods, and given that these yields are greatly affected by precipitation levels, the inclusion of this control variable is relevant. Specifically, the inclusion of this control provides an indirect way of capturing income shocks in rural areas. Finally, we add in an additional control for father's occupation during childhood. This control is likely to be relevant since father's occupation is a major determinant of birth outcomes, as suggested by (Chahnazarian, 1988).

[13]In our preferred specification, we either control for individuals age or add year of birth fixed effects.

In a supplementary analysis, we explore the possibility of a non-linear relationship between prenatal temperature shocks and adults cognitive score, across a range of temperature bins. Formally, we categorize temperature into five bins $b \in <20$ °C, 20-22 °C, 22-24 °C, $>24$ °C, with $<20$ °C being as the reference category.[14] Our main regressor, $Temp^b$, is an indicator variable equal 1 if average temperature during the entire pregnancy period falls into a bin $b$ and 0 otherwise.[15] We estimate the following binned model:

$$Cognition_{ijmt} = \sum_b \alpha_b * Temp^b_{ijmt} + CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \tag{3}$$

Our estimates identify the effect of a given prenatal average temperature bin relative to $<20$ °C.

## 5.2 Concerns about Coefficient Bias

It is important to point out some potential sources of coefficient bias. One threat to our identification strategy is the imprecise measurement of the nine-month pregnancy period. Indeed, a woman might ignore the exact time of conception, and the gestational period may be longer or shorter than nine months.[16] It follows that, if there is a conception effect, it will be difficult to determine whether the coefficient associated with average temperature before conception is capturing part of average temperature during the first trimester's effect. To address this concern, we consider a linear version of our preferred specification using the average temperature of the 3 months preceding the conception, the 9 months in utero, and the 3 months after birth. The result of this analysis is presented in Appendix table A3. This specification allows us to identify the contribution of a temperature shock associated with a given month.

Next, we discuss two other possible threats to our identification strategy: migration, and selective fertility and mortality.

**Migration.** While our database provides information on place of birth, we do not know if individuals' parents, in particular their mother, moved at some point over the pregnancy period. In the case of migration our estimates would be biased, as the temperature shocks in the

[14] We are therefore interested in examining how a temperature deviation from this reference category impacts our primary outcome, the cognitive function score.

[15] In the most recent literature studying the effects of temperature, temperature spikes are not measured using average monthly temperature as in this paper, but rather use daily measures of temperature which are then aggregated to the monthly level. We do not employ such methods, since historical daily temperature data for South Africa is scarce and more unreliable than any other region in the world (see Dell et al. (2014) for a more detailed discussion).

[16] Wilde et al. (2017) discuss similar threats to their identification strategy.

location of birth would no longer correspond to the temperature shocks actually experienced by the fetus. This problem is important in the historical context of pre- and post-apartheid South Africa, which has experienced a wave of displaced people from Mozambique. However, with the onset of apartheid, many communities, especially those in rural areas, saw their movement restricted.[17] Since the majority of respondents in our dataset were born during the apartheid, migration is a minor concern in identifying our main effect.

**Selective fertility and mortality.** Prior studies in the literature on the long-term human consequences of early-life environmental circumstances have pointed-out that selective fertility or mortality, reflected by skewed sex ratios (Catalano et al., 2008; Adhvaryu et al., 2015; Wilde et al., 2017). Addressing these issues may require information on fertility history or mortality rates during childbearing ages, which will allow to test whether women adjust to temperature shocks measured at the year of birth level. Because HAALSI does not contain this information, we use the 2016 child and birth recode files of DHS data for South Africa to address this potential source of bias. We test for selective fertility and mortality concerns by examining the impacts of prenatal temperature shocks on a range of biological markers at birth and a range of early life health outcomes. The analysis examining the impact on biological markers at birth is shown in Appendix table A5 and the analysis examining the impact on early life heath outcomes is shown in A6.

# 6 Results

We start with the analysis of the impact of average temperature during the whole pregnancy period on cognitive function during aging. This finding is interpreted as a cumulative effect and provides an idea on how fetal development responds to environmental insults. We then discuss the results of our analysis on the impacts of temperature shocks at different stages (trimesters) of pregnancy on cognitive function score and on the underlying measures of cognitive function in adulthood. We also present some additional results which examine the possibility of alternative explanations besides stress in our analyses, and test the robustness of our main findings.

[17] To illustrate this idea of individual migration restrictions, Dinkelman (2017) quotes this citation from the Secretary for Bantu Administration and Development General Circular No. 25 (1967): "It is accepted Government policy that the Bantu are only temporarily resident in the European areas of the Republic, for as long as they offer their labour there. As soon as they become, for some reason or other, no longer fit for work or superfluous in the labour market, they are expected to return to their country of origin or the territory of the national unit where they fit in ethnically if they were not born and bred in the homeland."

## 6.1 Cognition score

We begin by investigating the effects of prenatal ambient temperature during the nine month pregnancy period, and during the trimesters before the conception and after birth, on adult cognitive function z-score by estimating equation (1). The dependent variable used for this set of regressions is the adult cognitive function z-score. Equation (1) also includes a quadratic term of average temperature to capture potential non-linearity in the effects. The results are presented in Table 2 with standard errors presented in the brackets. In column (1) we present estimates of equation 1 that include only municipality of birth fixed effects, month of birth fixed effects, and individual level controls. The individual controls included are gender, ethnicity, age, and religion. Column (2) adds in additional controls for month of interview fixed effects to capture time-specific conditions or events occurring at the time of the interview, which may affect individuals' cognitive function z-scores. Column (3) controls for all variables and fixed effects included in Column (2), while adding an additional controls contemporaneous weather conditions at the time of the interview. Specifically, Column (3), includes additional controls for average temperature at the time of the interview and precipitation in the month of interview. Finally, Column (4) considers all the set of controls. For all these specifications, we cluster standard errors at the municipality of birth level. This is done to account for serial correlation in the error term, as well as to account for correlation between individuals born in the same municipality.

Our results suggest that average prenatal temperature anomalies have persistent effects on cognitive performance during aging. This estimate are consistent across all specifications. We find that temperature in the first trimester of pregnancy negatively affects individuals' cognitive function score later in life, but temperature in the second and third trimesters has a positive effect. We confirm these results by estimating a linear version of equation (1) in which we examine the impact of average temperature by each month of the pregnancy period. The results for this latter specification are reported in Table A3 and are consistent with our main findings. These differing effects result in an overall U-shaped relationship between prenatal temperature and cognition. This non-linear relationship is robust across measures of memory, reasoning, and information processing speed. Our findings are consistent with the biological theory positing that the prenatal period is a time of rapid change during which fetal organs and organ systems form and are more vulnerable to both organizing and disorganizing influences (Weinstock, 2008; Charil et al., 2010). These influences on the fetus have been described as programming —the process by which a stimulus or insult during a vulnerable developmental period has long-lasting or permanent effects. Furthermore, the biology theory indicates that the effects of programming depend on the timing of exposure and the developmental stage of fetuses' organ systems, with the first trimester described as the window of pregnancy most vulnerable to external shocks.

Figure 6 shows the distribution of residuals from our preferred specification removing all controls and fixed effects. This figure shows the remaining variation in individuals' cognition z-scores. The absence of a clear pattern in the distribution of residuals indicates that our model does not ignore any observable variables susceptible to explain the variation of individual's cognitive z-score.

For ease of understanding of our effects, we represent in figure 7 the variation in cognition z-score driven by change in average prenatal temperature. This figure shows that moderate temperatures are associated with poor results in cognition z-score while higher ones lead to better outcomes in cognitive performance. It is important to mention that the results refer to the cumulative effects of temperature on cognitive performance over the course of pregnancy. The main finding of our paper indicates that the most pleasant temperatures are associated with the worst outcomes, while the most extreme temperatures are associated with the best outcomes. This result seems counter-intuitive. Later, we try a set of alternative specifications to help understand this finding and examine whether there is a selection effect.

We now estimate the effect of temperature by trimester of pregnancy using equation (2). Table 3 reports the coefficient estimates of equation (2). We focus on the first trimester given that it is well established that it corresponds to the fetal programming period (Barker, 1997). Fetal programming occurs in a critical period of embryonic and fetal development in which tissues and organs are created. Environmental-insults or shocks such as extreme weather during fetal programming results in permanent alterations to certain structural and physiological metabolic functions of the fetus. Column (3) corresponds to our preferred specification. Our results suggest that a one degree deviation from average temperature experienced in the first trimester of pregnancy decreases an adult's cognitive z-score by 0.08 SD. Our coefficient estimates are consistent across all specifications, and all coefficients are statistically significant at the 10 percent level. Using average marginal effects associated to temperature and its quadratic term, we represent the predicted change of cognition z-score as shown in figure 8. Moreover, our findings indicate that, after the first trimester, ambient temperature during pregnancy does not negatively affect cognition in adulthood. In order to validate our results, we test the effect of ambient temperature on cognitive z-score for the 3 months prior to conception and the 3 months after birth. While there is no effect of temperature before conception, we find that ambient temperature experienced during the 3 months after birth decreases the adult cognitive function score by 0.12 SD. Therefore, our results underline the persistent effects of prenatal temperature shocks on adult cognitive skills.

### 6.2 Effects of Prenatal Temperature on other Measures of Cognition

We next estimate the effects of prenatal temperature on the ability to count, the ability to list words, and the ability to concentrate or recall, using equation (2). For expositional purposes, we show the results graphically.

Figure 9 represents the effects of temperature shocks on various measures of adults' cognition function, by trimester of exposure. To produce these estimates, we use the specification expressed in column (3) from table 3 in which we replace the dependent variable with one of the underlying measures of cognitive performance. Overall, our results for the first trimester of pregnancy indicate that a one degree deviation from average monthly temperature is associated with a decrease in each measure of cognitive performance. However, as in the main results 3, we notice a switch in sign of these effects for the second and third trimesters of pregnancy. These estimates are consistent with the effects on cognition z-score and suggest that fetal conditions, especially those occurring at the time of fetal programming, are harmful for individuals' cognition later in life. Our paper provides the first evidence on the persistent impacts of ambient temperature, experienced at different stages of pregnancy, on cognitive function during aging.

## 7 Robustness Checks

### 7.1 Alternative specifications

The results are robust to a number of sensitivity checks. We consider two groups of robustness checks. First, we examine the effect of temperature using various sets of specifications. Second, we repeat this exercise by extending the window to one year before conception and one year after birth (that is, 12 months before conception and after birth).

Table 4 reports results for the first set of robustness checks. Column (1) shows the results of our primary specification obtained using equation (1). Columns (2) through (4) include a variety of alternative specifications intended to check the robustness of our findings. We subsequently control for interaction terms of municipalities and month of birth, level of precipitation during the nine-month pregnancy period, and father's occupation. Column (2) adds additional interaction terms between municipality of birth and month of birth to our main specification. This specification allows us to capture any seasonality or activities specific to a municipality which are likely to affect the prenatal care received by the mother. Column (3) adds controls for the average precipitation level experienced during the pregnancy period to our primary specification. Existing literature (Wilde et al., 2017; Adhvaryu et al., 2015; Almond and Mazumder, 2011) points out the importance of rainfall variation for maternal health, as abnormally low rainfall can be a source of negative income shocks and infectious diseases. Therefore, controlling for precipitation allows us to obtain the net effect of ambient temperature on adult cognition. The regression specification used for Column (4) includes additional controls for fathers' occupation and obtain the same result as in column (3). Our results are consistent across different specifications.

We perform a similar analysis for the second set of robustness checks. Coefficient estimates from this second set of robustness checks are available in Table 5. In this table, we extend the window of the pre-pregnancy and post-pregnancy periods to one year before conception and 1 year after birth, respectively. By doing so, we intend to examine whether the effects are driven by short or medium conditions apart from temperatures that have occurred around the pregnancy period. Our results are consistent with those obtained in the main specification.

## 7.2 Accounting for Non-linearity

So far, we have estimated the effect of prenatal temperature using a continuous treatment variable. However, given the spatial and temporal disparities in exposure to climatic conditions, a one degree deviation in a region where the average outdoor temperature is 5 °C is not the same as in a region where the average temperature is 20 °C. An appropriate way to solve this issue is to examine how sensitive our results are to a given temperature threshold.

Our robustness checks examine how the cognitive function score varies with different temperature bins. We categorize individuals in our sample by exposure to prenatal temperature bins. We consider four temperature bins $< 20$°C; 20-22°C; 22-24°C; and $>$24° C, with $< 20$°C being the reference category. The results are reported in table 6. For ease in the exposition, we present these point estimates, along with their 95% confidence intervals, graphically in figure 10. Again, our results suggest that relative to $< 20$°C, individuals exposed to a temperature range of $20 - 22$°C in-utero are more likely to suffer from cognitive impairment later in life. However, this negative effect is likely to decrease as temperature increases.

# 8 Heterogeneity in the impacts of prenatal temperature on cognition

In this section, we attempt to explore the heterogeneous effects of ambient temperature during pregnancy on cognition by adult specific characteristics. These characteristics include individuals' sex/gender, age group, family social capital, and season (dry or rainy) of birth. Formally, we estimate the following equation:

$$\begin{aligned} Cognition_{ijmt} &= \alpha Temp_{ijmt} + \rho (Temp_{ijmt})^2 + \beta Temp_{ijmt} * H + \gamma (Temp_{ijmt})^2 * H \\ &+ CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \end{aligned} \tag{4}$$

where $H$ denotes each of the aforementioned individual specific characteristics. Table 7 reports the results for this regression specification. Each column of Table 7 reports the coefficient for the interaction term between temperature and the relevant characteristic. We also summarize these point estimates in figure 11.

**Gender.** Column (1) of table 7 below reports the coefficient estimate for the interaction term between temperature and being male. Although not statistically significant, our findings indicate that compared to a female, deviation from average temperature during the entire pregnancy decreases by a male's cognitive function score 0.081 SD. This result is obtained after controlling for ethnicity and religion, with standards errors clustered at the municipality level. Our findings parallel those from prior studies (Catalano et al., 2008; Adhvaryu et al., 2015; Dinkelman, 2017; Carrillo, 2020; Pongou et al., 2017) suggesting that males are more vulnerable to environmental insults compared to females. Part of this literature attributes male fragility to a combination of biological and environmental factors (Pongou, 2013), and to sex differences in the ability to produce nutrients in the placenta (Ross and Desai, 2005). Our analysis is the first to show that prenatal temperature affects men's and women's cognition differently during aging.

**Season.** We are also interested in understanding how the long-term effect of prenatal temperature on cognition differs by season of birth (dry or rainy). Column (2) of table 7 reports the estimated coefficient for the interaction term between prenatal temperature and being born in a hot or dry season. Our results indicate that the impacts of temperature shocks experienced during dry seasons are more harmful than those experienced in rainy seasons. Our findings complement prior studies that have shown seasonality is a key factor in explaining some mental health disorders such as depression or suicide (Mullins and White, 2019). However, we differ from these studies by focusing on cognition.

**Age group.** We examine how the long-term effect of prenatal temperature on cognition during aging differs by age group. We consider four age groups: $40-55$, $55-65$, $65-75$,. and $>75$, with $40-55$ being used as the reference category. Column (3) of table 7 reports the estimated coefficients on the age group times prenatal temperature interaction terms. Only the interaction term between prenatal temperature and being over 75 years of age was found to be statistically significant. We find that a one SD departure from average prenatal temperature reduces the cognition score of a person aged $>75$ years by 0.2 SD more than individuals aged $40-55$. the statistical insignificance of the other age group interactions terms is an interesting result, as it suggests that younger individuals are more likely to offset the adverse effects of prenatal temperature shocks.

**Family social capital.** We examine how the long-term impacts of prenatal temperature shocks vary by family social capital. We consider two aspects of family social capital: having siblings, and having grandchildren. The rationale behind this analysis is that being in a large family might negatively affect the amount of parental investment in the human capital of each child, which would negatively affect cognition during aging. At the same time, it is possible that this effect may act in the opposite direction, as having siblings or grandchildren might increase an individuals' level of social interactions. Having more social interactions could help individuals' mitigate the adverse long-term effects of negative temperature shocks by maintaining a certain level of brain activities including learning and memory.

Column (4) of table 7 reports the estimated coefficient on an interaction term between prenatal temperature and a binary variable for not having siblings. We find that, compared to individuals with siblings, those without siblings are less likely to experience a decline in cognitive performance as a result of exposure to prenatal temperature. Column (5) of table 7 reports the estimated coefficient on an interaction term between prenatal temperature and a binary variable for having grandchildren. Our results suggest that, relative to individuals with grandchildren, those without grandchildren are more likely to suffer from the negative effects of prenatal temperature on cognition score. These findings suggest that social interactions in older adults help to offset the effects of adverse temperature shocks experienced in-utero.

# 9 Possible mechanisms and discussion

So far, we have shown that prenatal ambient temperature affects later-life cognitive performance. We have also examined how these effects vary with individual's characteristics. In this section, we attempt to understand the possible mechanisms behind these relationships. There are several mechanisms through which prenatal temperature shocks could plausibly affect later-life cognition. The existing literature suggests two main channels, a direct channel and an indirect channel (Berry et al., 2010). The direct channel relates to the impact of temperature on fetal development. Heat stress affects fetal and placenta growth which significantly alters the functioning of the hypothalamopituitary-adrenal (HPA) axis (Weinstock, 2008), a major source of mental disorders such as schizophrenia, and depression (Adhvaryu et al., 2015). Indirect effects operate through the impacts of temperature on the mother's health and her behavioral responses to abnormal temperature. One possible indirect pathway though which this effect might operate is through higher malaria infection rates, as previous studies have shown that increases in temperature are more likely to favour the transmission of malaria (Barreca, 2010). Figure 1 summarizes the possible channels through which temperature shocks experienced during pregnancy may impact later life determinants of the cognitive reserve such as educational attainment and health outcomes.

## 9.1 Temperature effects on related human capital outcomes

Figure 1 along with the published literature suggests that these effects of prenatal temperature on human capital operate via fetal brain sensitivity to temperature, impacts on birth outcomes, impairment of childhood health, and change in early-life investments in children. We therefore test the effect of in-utero temperature shock on three categories of outcomes: Childhood health, literacy rate, and sleep quality in adulthood. Table 8 as well as figure 12 report our coefficient estimates.

**Childhood health.** Column (1) of Table 8 reports the estimated effect of temperature on individuals' self-reported childhood health. The dependent variable is a dummy equal to 1 if an individual reported that their childhood health was good and equal to 0 otherwise. Our findings suggest that higher prenatal temperature negatively affects childhood health, but the effect is not statistically significant.

**Literacy rate.** Column (2) of Table 8 reports the estimated effect of temperature on individual's literacy. We find that a higher prenatal temperature negatively affects literacy, but this effect is not linear. This result corroborates findings by Wilde et al. (2017) on the relationship between temperatures experienced at different stages of pregnancy and later-life educational attainment.

**Sleep quantity and quality.** Columns (3) and (4) of Table 8 examine prenatal temperature effects on hours of sleep and quality of sleep during adulthood. Our findings suggest that, while greater prenatal temperature positively affects the quantity of sleep, it has a negative effect on its quality. Given the documented importance of sleep for cognitive productivity (Berry et al., 2010; Mullins and White, 2019), our findings suggest that quality of sleep is a key channel through which prenatal temperature negatively effects cognition during aging.

## 9.2 Discussion

**Drought exposure during the first trimester.** Maternal exposure to temperature shocks during pregnancy can affect fetal death and offspring's outcomes through three potential mechanisms that impact the fetus either directly or indirectly through mother's responses. These include *(i)* biological effects induced by heat stress which may result in health issues including placental abruption (He et al., 2018), premature birth or stillbirth (Carolan-Olah and Frankowska, 2014; Strand et al., 2011), and pregnancy loss (Beltran et al., 2014); *(ii)* behavioral mechanisms involving a change in consumption habits (food selection, appetite loss); and *(iii)* income, owing to the negative impacts of extreme temperature on agricultural yields. In addition, according to the biological and neurological literature, the first trimester of pregnancy has been identified as the most critical window of pregnancy. This is due to fetal programming occurring in the first trimester of pregnancy. Therefore, we hypothesize that any adverse shock experienced during the first trimester of pregnancy could have detrimental effects on cognition. Such adverse shocks are not necessarily limited to temperature shocks, as droughts experienced during the first trimester of pregnancy could also have detrimental effects on brain formation and early childhood cognitive development. This effect could plausibly operate through nutritional deprivation to the mother. We investigate this hypothesis in our framework by comparing the cognition z-score of individuals for two groups of individuals: those who were exposed to the dry season during the first trimester of pregnancy, and those who were exposed to the wet season during the first trimester of pregnancy. Table 9 reports the results for this set of regressions.

Column (1) shows the results for the relationship between prenatal temperature and cognitive performance during aging conditional on first trimester of pregnancy happening in the hot season. Column (2) presents the results for the relationship between prenatal temperature and cognitive performance during aging conditional on the first trimester of pregnancy occurred during the rainy season. Our findings indicate that, relative to individuals who experienced a rainy season during the first trimester of pregnancy, those exposed to dry season are more likely to suffer from cognitive impairment. These results are supportive of the drought channel as a possible mechanism explaining the relationship between early life temperature shocks and cognitive performance during aging.

**Natural selection.** The effect of prenatal temperature on cognition during aging could be biased by the fact that adverse climate conditions impair fetal health and early life outcomes (Deschênes et al., 2009), implying that individuals experiencing such exposure might have gone before reaching adulthood. Put differently, there is a selection over the course of life from the pregnancy period until later in life with implication that only individuals with better cognitive performance survive. If we believe this hypothesis, our sample is selective with most of individuals having good health. We propose to test the selection effect by examining the impact of prenatal temperature on cognition performance of individuals conditional on their (i) self-report health during childhood; (ii) whether or not they belong to high-income family, and (iii) by parent occupation. The results of the latter analysis are reported in table XX.

# 10 Conclusion

This paper answers the question of whether and how prenatal temperature shocks occurring at different stages of the pregnancy period affect cognition during aging. We take advantage of a unique South African dataset. Our results suggest that average prenatal temperatures anomalies have persistent effects on cognitive performance during aging. Specifically, we find that temperature in the first trimester of pregnancy negatively effects cognitive function score later in life, but temperature in the second and third trimesters has a positive effect. These differing effects result in an overall U-shaped relationship between prenatal temperature and cognition. This non-linear relationship extends to measures of memory, reasoning, and information processing speed. We analyze causal mechanisms, and find that the effects of prenatal average temperature on cognition during aging is larger for men, individuals above 75 years of age, and individuals without siblings or grandchildren. Finally, we identify drought exposure during the first trimester of pregnancy and reduced sleep quality during adulthood as the potential channels through which the effect of prenatal temperature might operate.

In a context of rising concerns surrounding climate change, coupled with the aging of the population, our paper offers several policy recommendations. First, our findings show that the period of pregnancy is a crucial window for long-term cognition. Therefore, it suggests that policies aimed at improving cognitive skills and productivity in old age should target mothers during early pregnancy periods. Second, this study is relevant for policies which support the labor market and draws attention to the importance of investing in the cognition of older workers. Finally, from a climate change perspective, this study speaks to the broad literature seeking to provide methods though which humanity might adapt to, and mitigate the harmful effects of, climate change on human capital.

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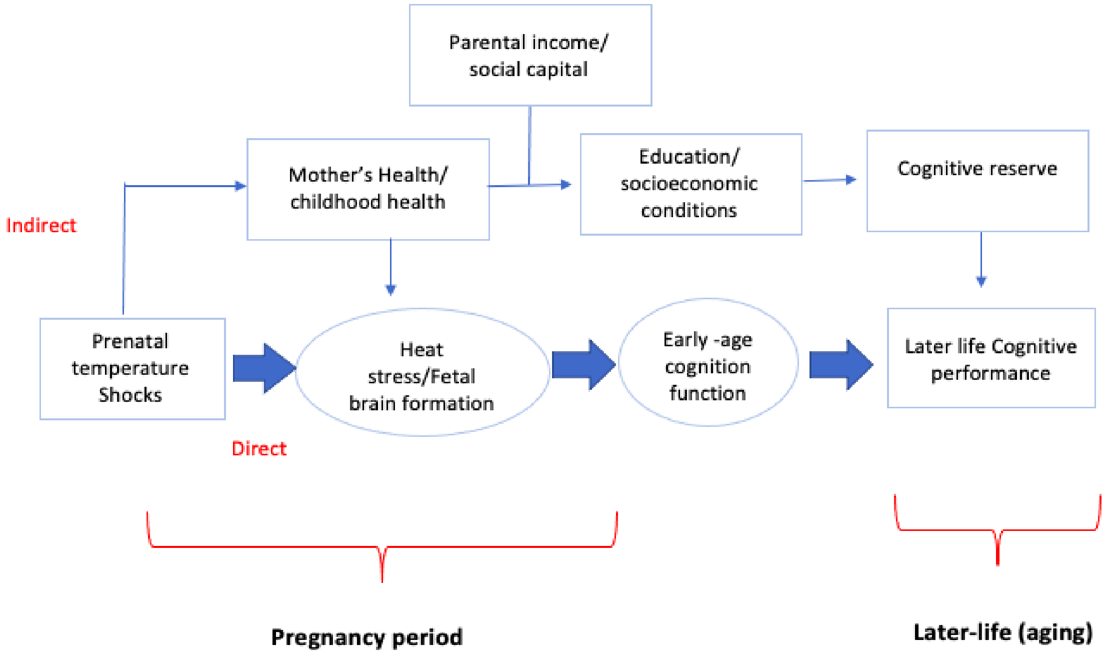
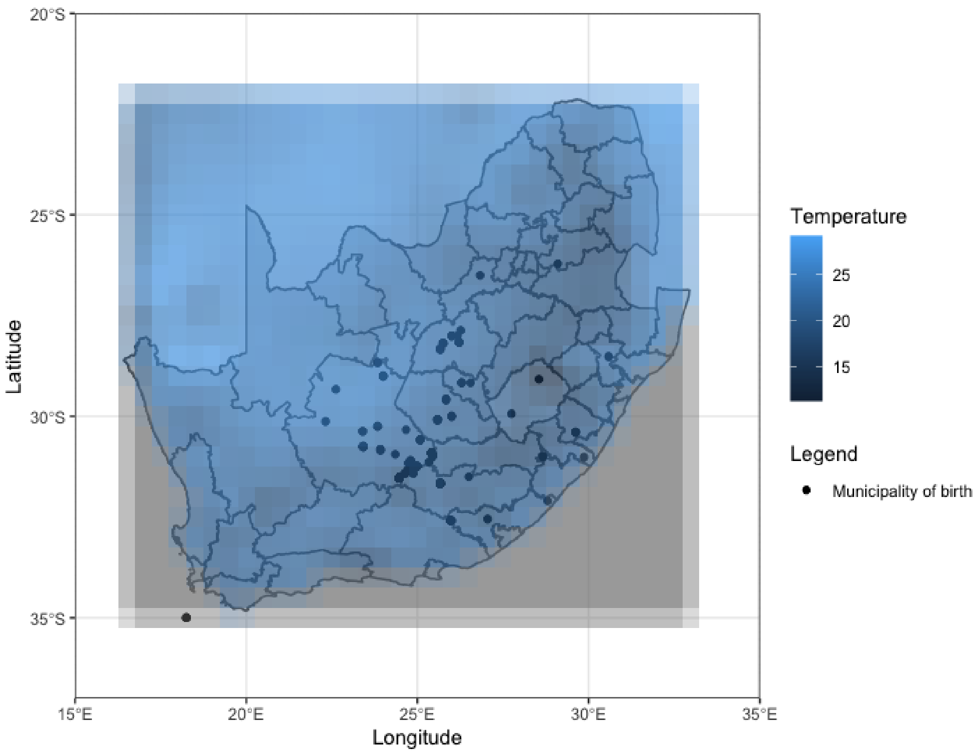
# Figures and Tables

Figure 1: Conceptual framework: how does prenatal temperature shocks affect cognitive performance during aging?



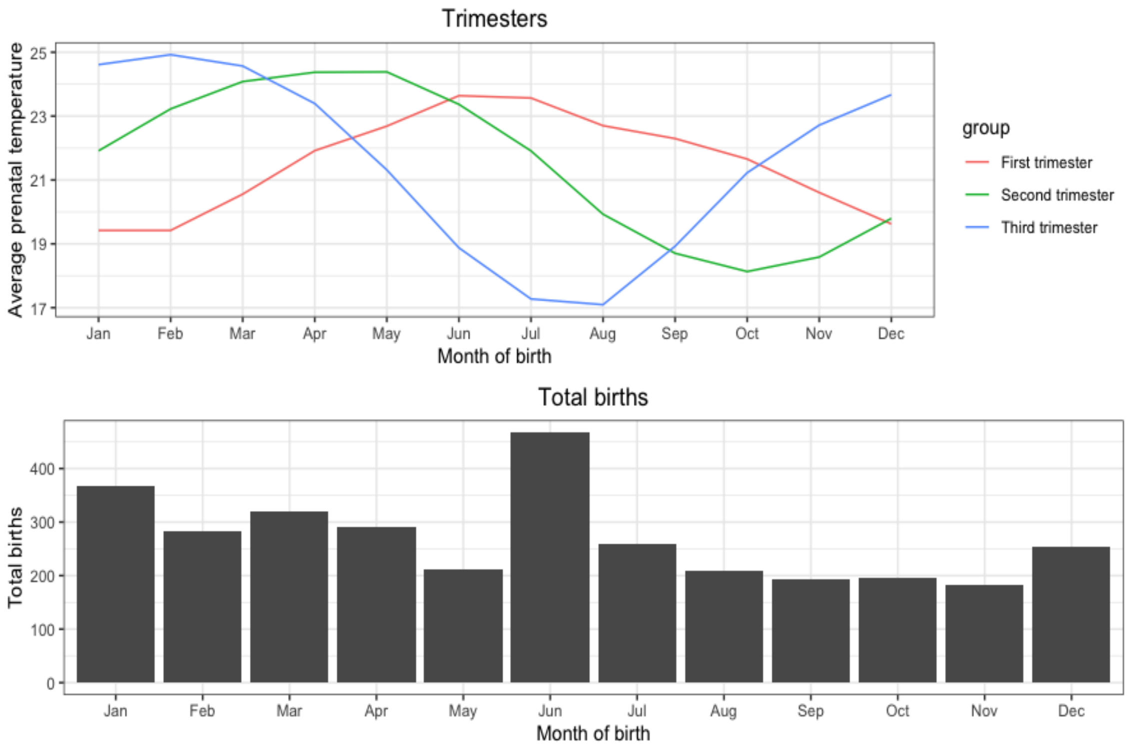

**Notes**: The figure above depicts the mechanisms through which prenatal temperature shocks affect later life cognitive performance. Broadly speaking, biology is the main channel through which prenatal temperature affects cognition during aging. A negative temperature has a direct effect on fetal development and brain formation, and an indirect effect through the health of the mother and the child.

Figure 2: Municipalities of birth in South Africa and spatial variation in average temperature



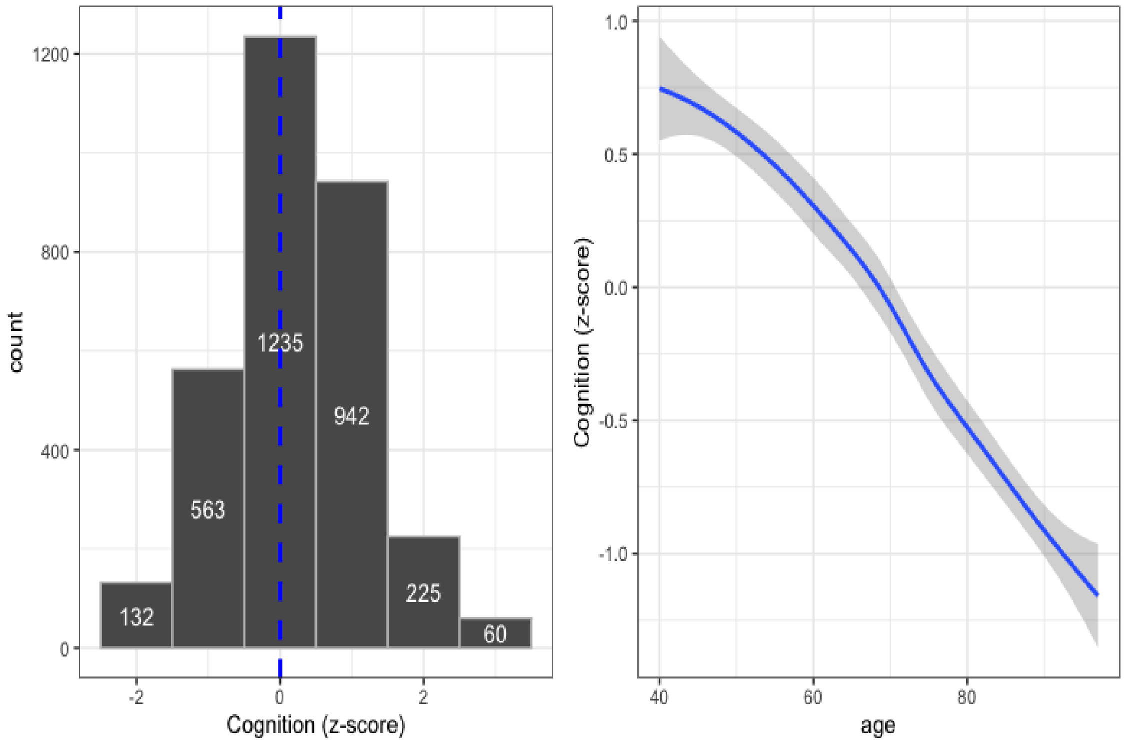

**Notes**: This chart shows the distribution of municipalities of birth in South Africa along with spatial variation of temperature on a given month. In this plot, we consider January, 1940 as an example. Each dot represents a given municipality of birth as reported by surveyed individuals.

Figure 3: Total births and temperature distribution by month of birth



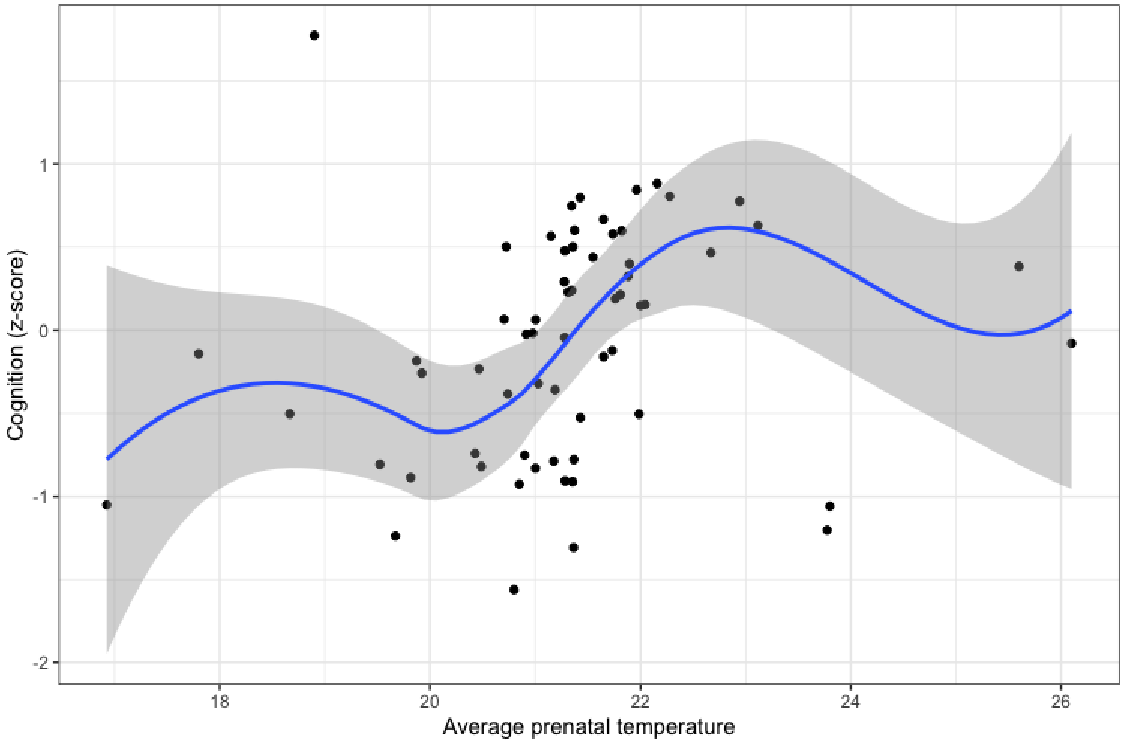

**Notes**: This chart plots together total births distribution combined with the change of average temperature by trimester of pregnancy by month of birth. It reveals that apart for June where we notice a peak in total births, they are equally distributed over the months. It suggests that individuals do not select in their timing of fertility.

Figure 4: Distribution of cognition z-score by age



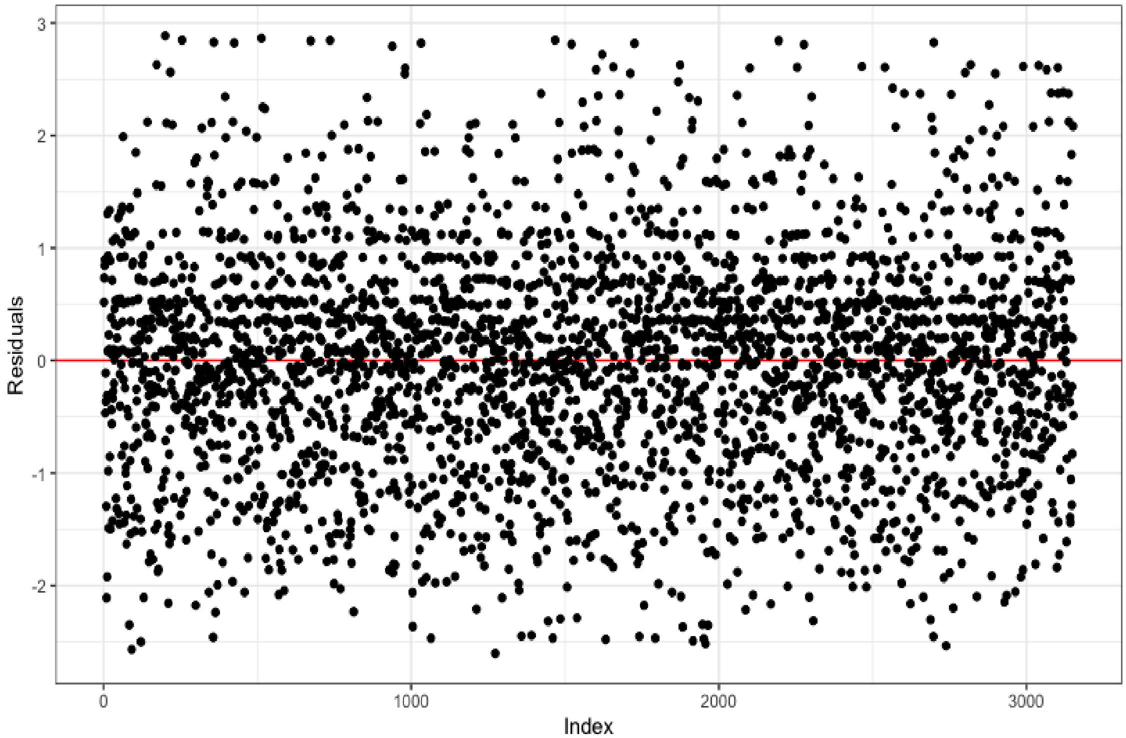

**Notes**: This figure shows the distribution of cognition z-score by age. The left panel is a histogram with a count of individuals by cognition score. On the right panel, we plot cognition z-score against individual's age. It appears that cognitive skills decline with age as expected.

Figure 5: Cognition z-score and average prenatal temperature



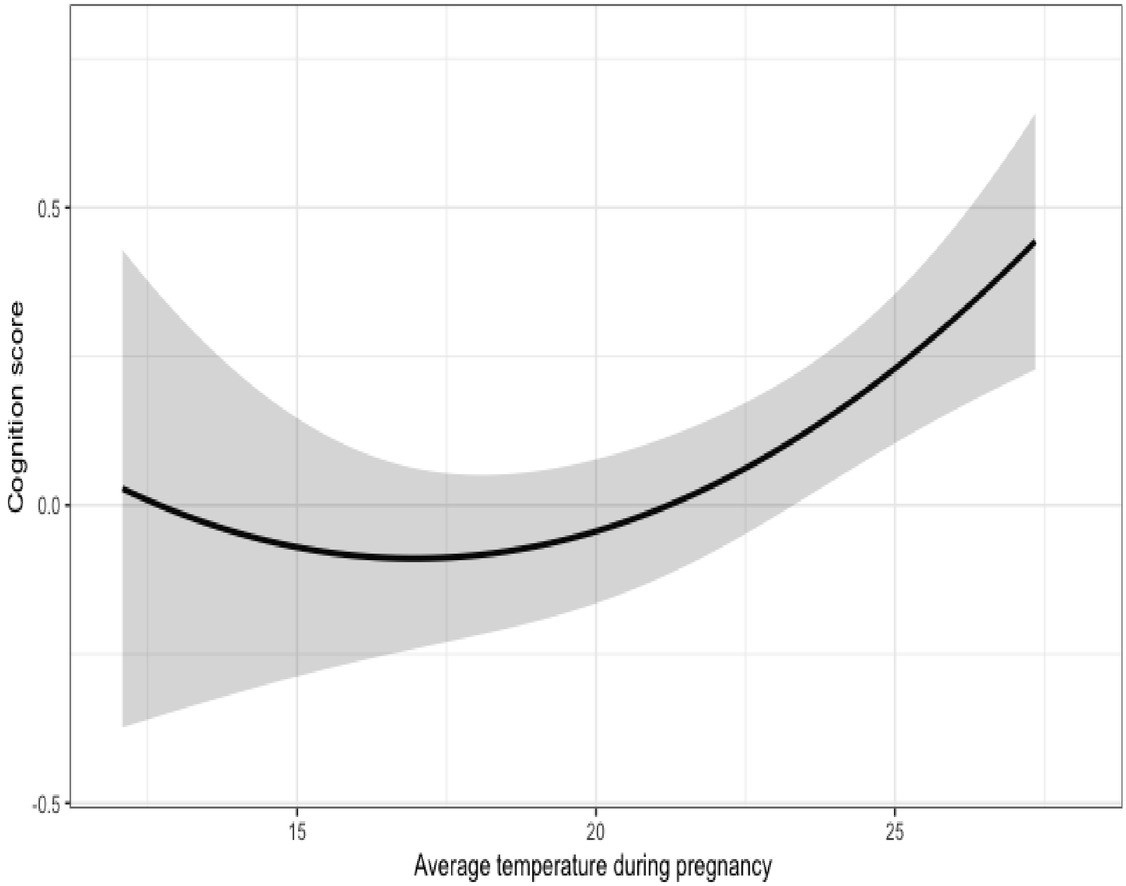

**Notes**: This figure shows the association between cognition z-score and average prenatal temperature. Each dot gives the cognition z-score at year of birth level associated to a given average temperature experienced during the nine months of pregnancy. This graph depicts a non-linear shape between these two variables.

Figure 6: Residuals from the preferred specification



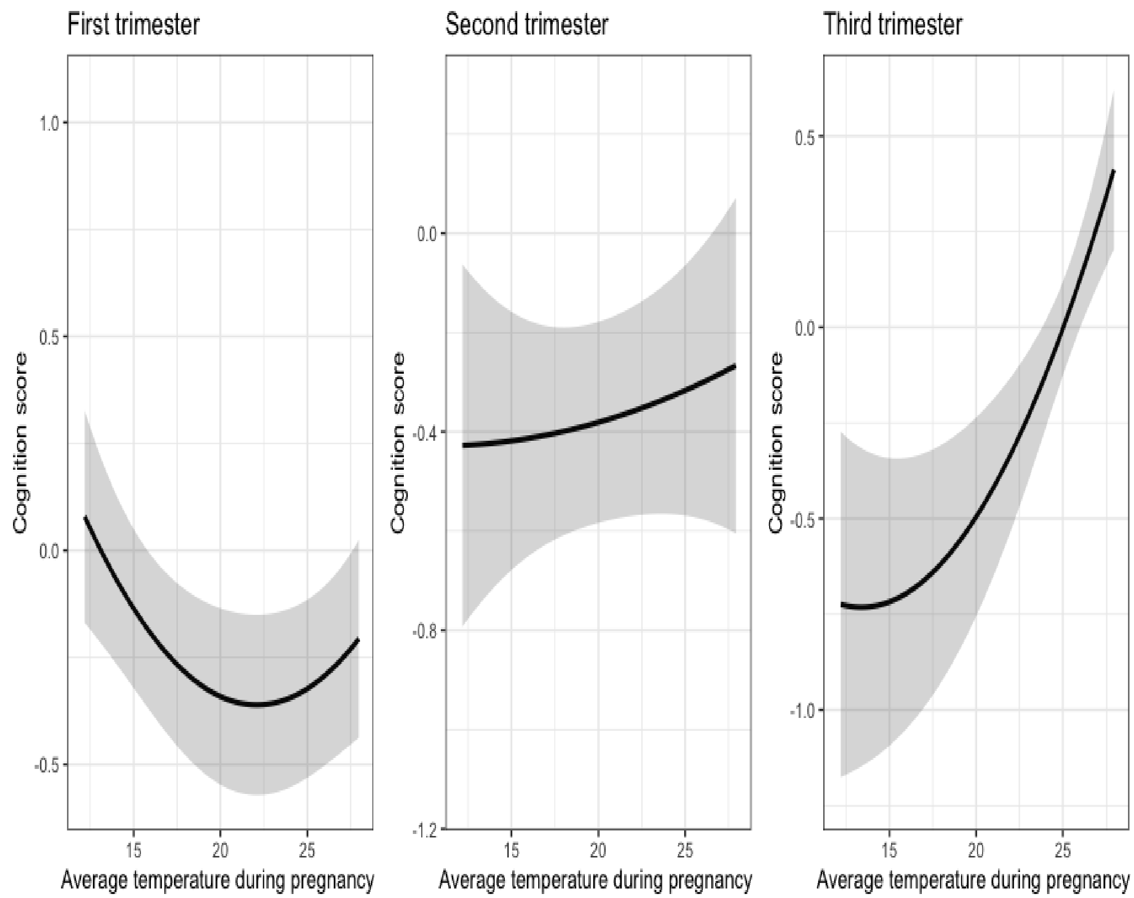

**Notes**: The figure above represents the distribution of the residuals obtained from our preferred specification in which we remove any controls and fixed effects.

Figure 7: Cognition score and change in average temperature of pregnancy



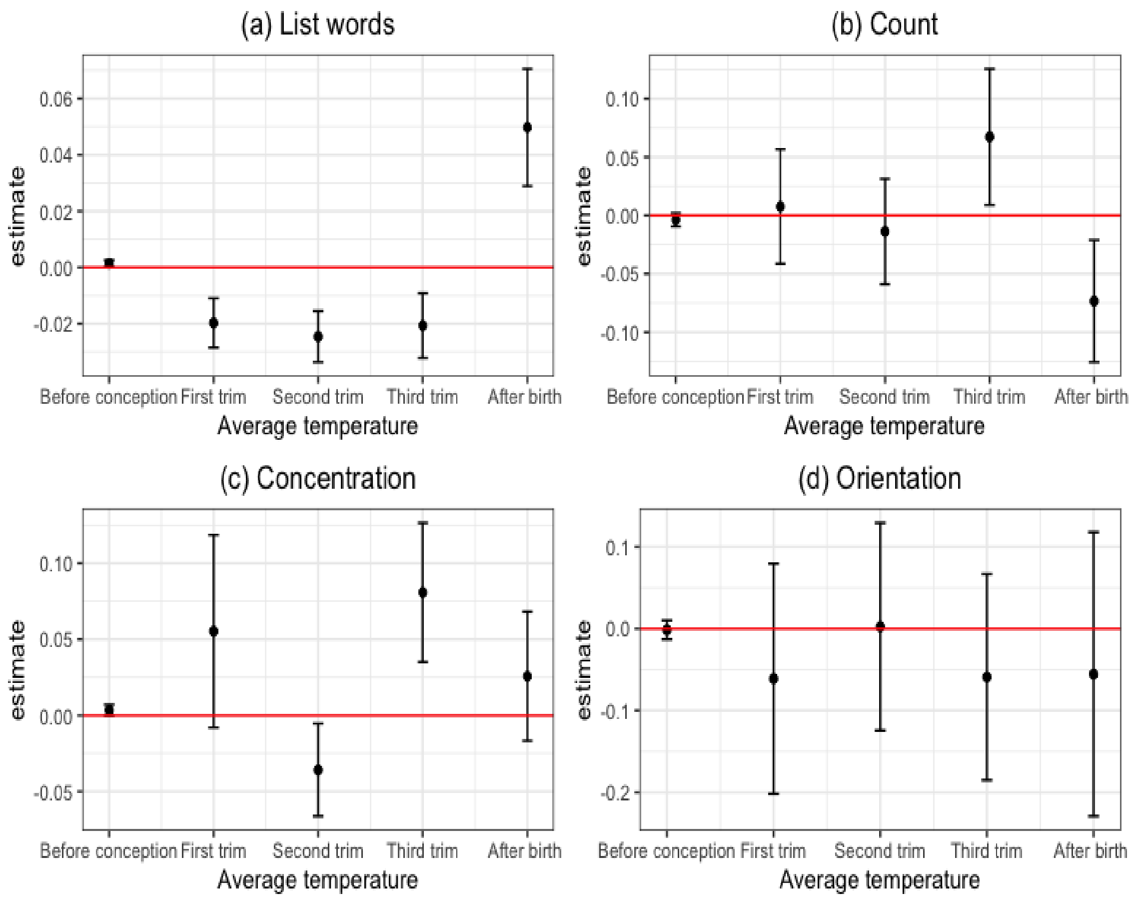

**Notes**: The figure above represents the prediction of cognition score with change of average prenatal temperature. This figure is derived form our preferred specification in which we control for individual characteristics, municipalities and month of birth fixed effects, along with a quadratic term of temperature to account for non linearity in the effects. Our findings suggest that, while moderate temperatures are worst off for cognitive abilities, the higher ones are associated with better cognitive functions.

Figure 8: Cognition score and change in average temperature by trimester of pregnancy



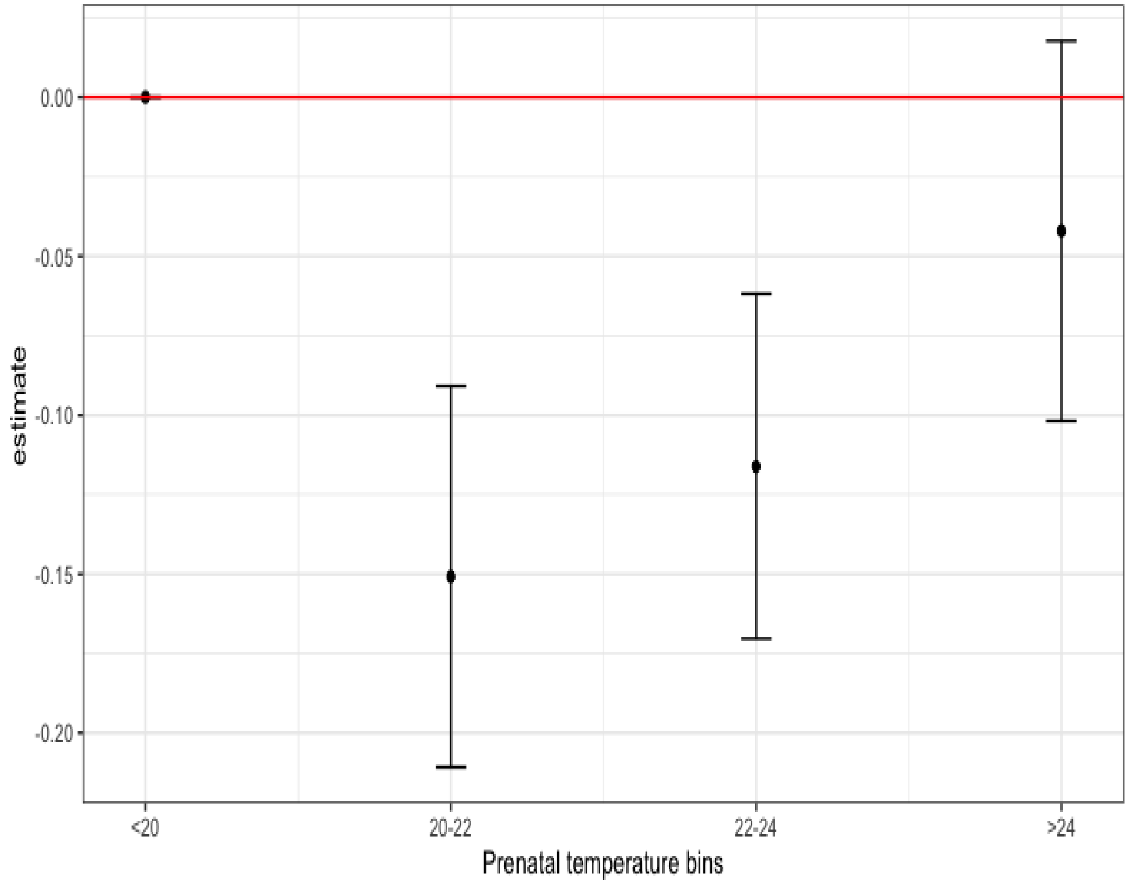

**Notes**: The figure above represents the prediction of cognition score with change of average prenatal temperature by trimester of pregnancy. This figure is derived from our preferred specification in which we control for individual characteristics, municipalities and month of birth fixed effects, along with a quadratic term of temperature to account for non linearity in the effects. Our findings suggest that, for first trimester, while moderate temperatures are worst off for cognitive abilities, the higher ones are associated with better cognitive functions.

Figure 9: Decomposition of the effect by various measures of cognition function



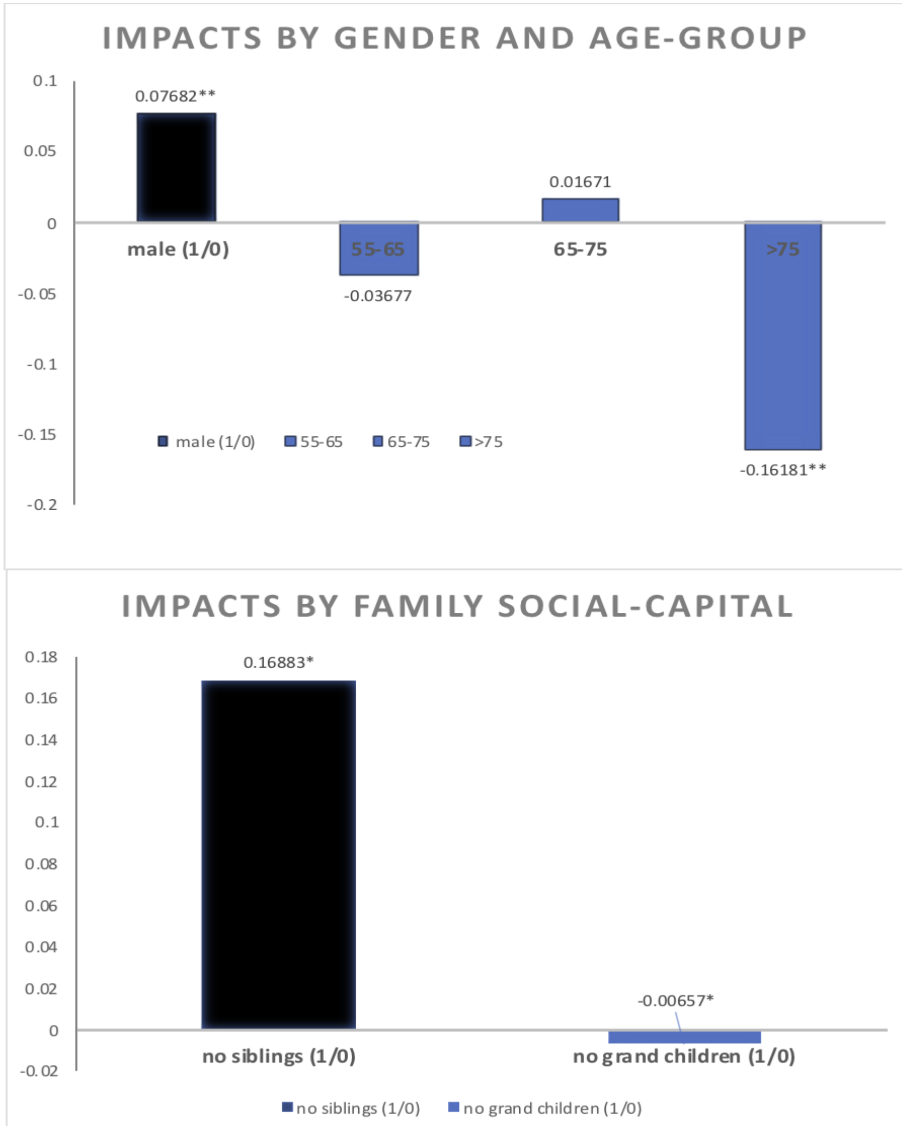

**Notes**: The figure above represents the point estimates of the effect of average temperature of a given trimester of pregnancy on cognition z-score along with various measure of cognitive performance. These measures include individual ability to list words, count, concentrate, and orientation. This figure is derived form our preferred specification in which we control for individual characteristics, municipalities and month of birth fixed effects, along with a quadratic term of temperature to account for non linearity in the effects. Our findings suggest that, while moderate temperatures are worst off for cognitive abilities, the higher ones are associated with better cognitive functions.

Figure 10: Non-linear effects on cognition score using prenatal temperature bins



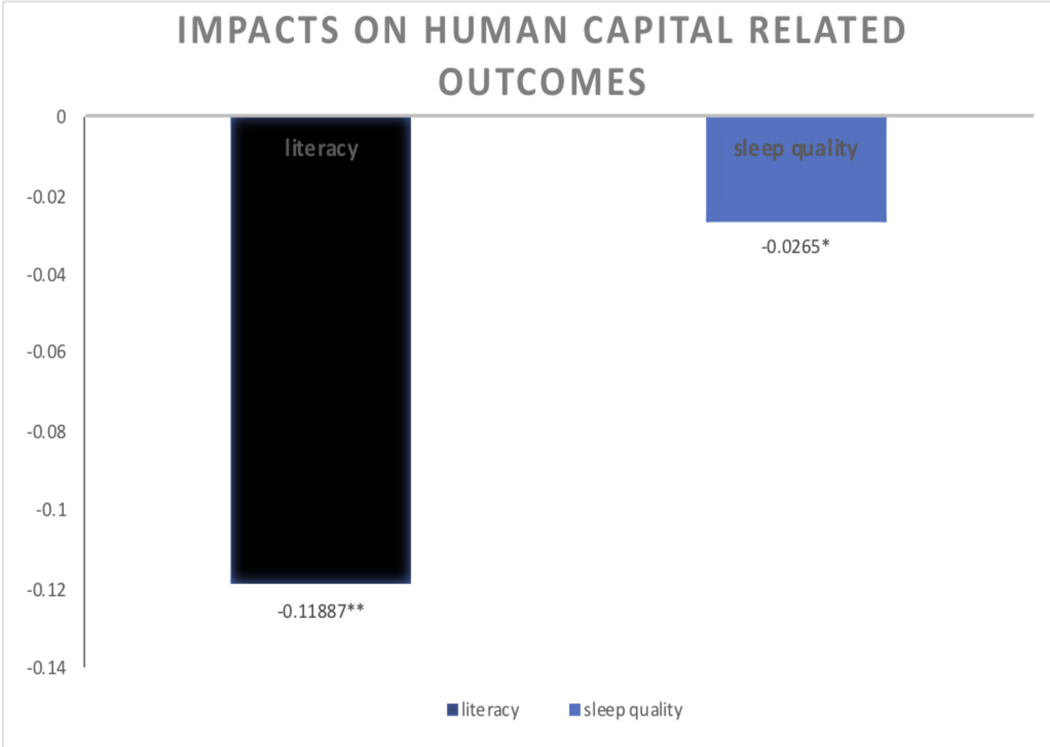

**Notes**: The figure above represents the point estimates of the effect of average prenatal temperature bins on cognition z-score along with various measure of cognitive performance. We consider four range of temperature bins < 20°C; 20-22°C; 22-24°C; >24° C with < 20°C considers as the reference category. Our point estimates are interpreted relative to <20 °C category. This figure is derived form our preferred specification in which we control for individual characteristics, municipalities and month of birth fixed effects, along with a quadratic term of temperature to account for non linearity in the effects. Our findings suggest that, while moderate temperatures are worst off for cognitive abilities, the higher ones are associated with better cognitive functions.

Figure 11: Heterogeneity in the impacts by gender, age-group and family social-capital




**Notes**: The figure above represents the point estimates of the effect of average prenatal temperature on cognition z-score by gender, age-group and within family social-capital. The upper graph shows the results by gender and age-group and indicate that the effect of in-utero temperature is larger for men and individuals over 75 years old. Regarding the family attributes, results indicate that cognitive function are better off when individual have siblings and grand children.

Figure 12: Impacts of prenatal temperature on human capital related outcomes




**Notes**: The graph above plots the point estimates of the impacts of average prenatal temperature on human capital related outcomes including literacy rate and sleep quality. Results indicate that both literacy and sleep are negatively affect by prenatal temperature shocks.

Table 1: Summary Statistics

| Variables | N | Mean | St. Dev. |
|---|---|---|---|
| **Health Outcomes** | | | |
| cognition (z-score) | 3,165 | 0.200 | 0.957 |
| depression | 3,166 | 1.418 | 1.613 |
| memory | 3,174 | 2.673 | 0.958 |
| **Weather at month of birth** | | | |
| temperature (°C) | 3,226 | 21.459 | 3.802 |
| precipitation (cm) | 3,226 | 5.756 | 6.589 |
| **Individual characteristics** | | | |
| male | 3,232 | 0.482 | 0.500 |
| age | 3,231 | 61.519 | 12.562 |
| Childhood health (good) | 3,231 | 0.874 | 0.332 |
| Childhood health (poor) | 3,231 | 0.126 | 0.332 |
| education | 3,225 | 6.899 | 5.493 |
| literacy | 3,232 | 3.198 | 0.634 |
| body mass index (bmi) | 3,005 | 27.645 | 7.311 |
| height | 3,006 | 163.538 | 8.997 |
| religious (yes) | 3,232 | 0.829 | 0.376 |
| single (yes) | 3,230 | 0.485 | 0.500 |
| wealth asset index | 3,232 | 3.295 | 1.388 |

Notes: Authors'calculations

Table 2: Temperature effects on cognition z-score during aging using quadratic model

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Cognition score** | | | |
| | (1) | (2) | (3) | (4) |
| Before conception (0-3 months) | 0.06909 | 0.11926 | 0.05798 | 0.11926 |
| | (0.06210) | (0.06538) | (0.06123) | (0.06538) |
| Before conception (0-3 months)$^2$ | -0.00158 | -0.00274 | -0.00128 | -0.00274 |
| | (0.00147) | (0.00156) | (0.00143) | (0.00156) |
| temp | -0.23901*** | -0.23787*** | -0.13969*** | -0.23787*** |
| | (0.03143) | (0.03537) | (0.02910) | (0.03537) |
| temp$^2$ | 0.00623*** | 0.00621*** | 0.00423*** | 0.00621*** |
| | (0.00072) | (0.00083) | (0.00066) | (0.00083) |
| After birth (0-3 months) | -0.29171*** | -0.23986*** | -0.27566*** | -0.23986*** |
| | (0.04888) | (0.04511) | (0.04805) | (0.04511) |
| After birth (0-3 months)$^2$ | 0.00681*** | 0.00559*** | 0.00646*** | 0.00559*** |
| | (0.00124) | (0.00111) | (0.00122) | (0.00111) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | | Y | Y | Y |
| Contemporaneous Weather | | | Y | |
| Month of Interview | | | | Y |
| Observations | 3,106 | 3,106 | 3,106 | 3,106 |
| $R^2$ | 0.16918 | 0.23662 | 0.17898 | 0.23662 |

**Notes**: $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature on later-life cognition score. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as gender, ethnicity, religion. We try a series of specifications from column (1) to (4) with different controls and fixed effects. Column (4) reports estimates from our preferred specification.

Table 3: Temperature effects on cognition score by trimesters of pregnancy period

| | *Dependent variable:* | | |
|---|---|---|---|
| | **Cognition score** | | |
| | (1) | (2) | (3) |
| | **Before conception (0-3 months)** | | |
| temp | 0.06909 | 0.11926 | 0.05798 |
| | (0.06210) | (0.06538) | (0.06123) |
| $temp^2$ | -0.00158 | -0.00274 | -0.00128 |
| | (0.00147) | (0.00156) | (0.00143) |
| | **First trimester** | | |
| temp | -0.20086*** | -0.20430*** | -0.12061* |
| | (0.06310) | (0.06903) | (0.06385) |
| $temp^2$ | 0.00450*** | 0.00460*** | 0.00275** |
| | (0.00138) | (0.00149) | (0.00139) |
| | **Second trimester** | | |
| temp | 0.00659 | -0.01512 | 0.03325 |
| | (0.03103) | (0.03073) | (0.03003) |
| $temp^2$ | 0.00030 | 0.00069 | -0.00039 |
| | (0.00069) | (0.00069) | (0.00068) |
| | **Third trimester** | | |
| temp | -0.20795*** | -0.15266*** | -0.09008** |
| | (0.02351) | (0.02700) | (0.04502) |
| $temp^2$ | 0.00621*** | 0.00561*** | 0.00432*** |
| | (0.00061) | (0.00068) | (0.00089) |
| | **After birth (0-3 months)** | | |
| temp | -0.23986*** | -0.27566*** | -0.23986*** |
| | (0.04888) | (0.04511) | (0.04805) |
| $temp^2$ | 0.00559*** | 0.00646*** | 0.00559*** |
| | (0.00124) | (0.00111) | (0.00122) |
| Municipality of Birth | Y | Y | Y |
| Month of Birth | Y | Y | Y |
| Year of Birth | Y | Y | Y |
| Individual Controls | Y | Y | Y |
| Month of Interview | | Y | |
| Contemporaneous Weather | | | Y |
| Observations | 3,103 | 3,103 | 3,103 |
| $R^2$ | 0.19001 | 0.12713 | 0.19178 |

**Notes**: *p<0.1; **p<0.05; ***p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature of a given trimester of pregnancy on later-life cognition score. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as age, gender, ethnicity, religion. We try a series of specifications from column (1) to (3) with different controls and fixed effects. Column (3) reports estimates from our preferred specification.

Table 4: Robustness Checks (1): Additional controls and parental occupation

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Cognition score** | | | |
| | (1) | (2) | (3) | (4) |
| Before conception (0-3 months) | 0.00001 | 0.00493 | 0.00002 | 0.00298 |
| | (0.00664) | (0.00359) | (0.00666) | (0.00627) |
| Before conception (0-3 months)$^2$ | -0.00265 | -0.00212 | -0.00269 | -0.00221 |
| | (0.00157) | (0.00142) | (0.00156) | (0.00125) |
| temp | -0.21209$^{***}$ | -0.23899$^{***}$ | -0.21198$^{***}$ | -0.21835$^{***}$ |
| | (0.04565) | (0.01496) | (0.04551) | (0.02410) |
| temp$^2$ | 0.00596$^{***}$ | 0.00661$^{***}$ | 0.00597$^{***}$ | 0.00615$^{***}$ |
| | (0.00100) | (0.00034) | (0.00100) | (0.00056) |
| After birth (0-3 months) | -0.22786$^{***}$ | -0.26090$^{***}$ | -0.22808$^{***}$ | -0.28469$^{***}$ |
| | (0.05103) | (0.06540) | (0.05111) | (0.04090) |
| After birth (0-3 months)$^2$ | 0.00524$^{***}$ | 0.00611$^{***}$ | 0.00525$^{***}$ | 0.00654$^{***}$ |
| | (0.00115) | (0.00149) | (0.00116) | (0.00099) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y |
| Month of Interview | Y | Y | Y | Y |
| Contemporaneous Weather | Y | Y | Y | Y |
| Municipality $\times Month\ of\ Birth$ | | Y | | |
| Precipitation | | | Y | |
| Father's occupation | | | | Y |
| Observations | 3,103 | 3,103 | 3,103 | 2,856 |
| R$^2$ | 0.20389 | 0.29385 | 0.20392 | 0.13715 |

**Notes**: $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature on later-life cognition score. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as age, gender, ethnicity, religion. We try a series of specifications from column (1) to (4) with different controls and fixed effects. We subsequently control for interaction term of municipalities and month of birth, level of precipitation during the nine-month pregnancy period, and father's occupation.

Table 5: Robustness Checks (2): Extension of window to one year around the pregnancy period

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Cognition score** | | | |
| | (1) | (2) | (3) | (4) |
| Before conception (0-12 months) | -0.22839 | -0.28807 | -0.22832 | -0.24422 |
| | (0.14326) | (0.18544) | (0.14291) | (0.17611) |
| Before conception (0-12 months)$^2$ | 0.00550 | 0.00691 | 0.00550 | 0.00587 |
| | (0.00374) | (0.00467) | (0.00373) | (0.00437) |
| temp | -0.19807*** | -0.27607*** | -0.19796*** | -0.22644*** |
| | (0.06656) | (0.04759) | (0.06637) | (0.03410) |
| temp$^2$ | 0.00451*** | 0.00634*** | 0.00452*** | 0.00637*** |
| | (0.00144) | (0.00106) | (0.00144) | (0.00075) |
| After birth (0-12 months) | -0.16752** | 0.04071 | -0.16550** | 0.00507 |
| | (0.07416) | (0.08750) | (0.07366) | (0.17159) |
| After birth (0-12 months)$^2$ | 0.00370** | -0.00104 | 0.00366** | -0.00024 |
| | (0.00183) | (0.00212) | (0.00182) | (0.00454) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y |
| Month of Interview | Y | Y | Y | Y |
| Contemporaneous Weather | Y | Y | Y | Y |
| Municipality $\times Month\ of\ Birth$ | | Y | | |
| Precipitation | | | Y | |
| Father's occupation | | | | Y |
| Observations | 2,989 | 2,640 | 2,989 | 2,445 |
| $R^2$ | 0.32278 | 0.32883 | 0.32279 | 0.20964 |

**Notes**: *p<0.1; **p<0.05; ***p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature on later-life cognition score. In all regressions, standard errors are clustered at the municipalities of birth. In this table, we extend the window of the pregnancy period to one year before the conception and after birth(12 months). All regressions control for individual characteristics such as age, gender, ethnicity, religion. We try a series of specifications from column (1) to (4) with different controls and fixed effects. We subsequently control for interaction term of municipalities and month of birth, level of precipitation during the nine-month pregnancy period, and father's occupation.

Table 6: Temperature effects on cognition score using binned model

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Cognition score** | | | |
| | (1) | (2) | (3) | (4) |
| Temperature bins | | | | |
| 20-22 ° C | -0.09236*** | -0.09500*** | -0.09315*** | -0.15086*** |
| | (0.02535) | (0.02691) | (0.02468) | (0.03058) |
| 22-24 ° C | -0.04343** | -0.04918** | -0.04776** | -0.11616*** |
| | (0.01963) | (0.02158) | (0.02121) | (0.02770) |
| >24 ° C | 0.01023 | 0.00610 | 0.03405 | -0.04209 |
| | (0.01919) | (0.02486) | (0.02084) | (0.03052) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | | Y | Y | Y |
| Month of Interview | | | Y | |
| Contemporaneous Weather | | | | Y |
| Observations | 3,153 | 3,153 | 3,153 | 3,153 |
| $R^2$ | 0.32034 | 0.32326 | 0.34862 | 0.34945 |

**Notes**: *p<0.1; **p<0.05; ***p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature ranges in a given bin on later-life cognition score. These bins include < 20°C; 20-22°C; 22-24°C; >24° C with < 20°C considers as the reference category. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as age, gender, ethnicity, religion. We try a series of specifications from column (1) to (4) with different controls and fixed effects. Column (4) reports estimates from our preferred specification.

Table 7: Heterogeneity in the impacts of prenatal temperature on cognition z-score

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | **Cognition score** | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| temp | -0.32574*** | -0.31546*** | -0.20437*** | -0.26197*** | -0.19432*** |
| | (0.05477) | (0.06301) | (0.05181) | (0.01509) | (0.02385) |
| $\text{temp}^2$ | 0.00861*** | 0.00812*** | 0.00464*** | 0.00597*** | 0.00472*** |
| | (0.00129) | (0.00137) | (0.00117) | (0.00033) | (0.00050) |
| | **Gender** | | | | |
| male | -0.55130 | | | | |
| | (1.23207) | | | | |
| $\text{temp}\times male$ | 0.08138 | | | | |
| | (0.12281) | | | | |
| $\text{temp}^2 \times male$ | -0.00228 | | | | |
| | (0.00296) | | | | |
| | | **Season** | | | |
| $\text{temp}\times hot$ | | 0.46359*** | | | |
| | | (0.06285) | | | |
| $\text{temp}^2 \times hot$ | | -0.01168*** | | | |
| | | (0.00138) | | | |
| | | | **Age-group** | | |
| $\text{temp}\times(55-65)$ | | | -0.03749 | | |
| | | | (0.07576) | | |
| $\text{temp}^2 \times (55-65)$ | | | 0.00036 | | |
| | | | (0.00170) | | |
| $\text{temp}\times(65-75)$ | | | 0.01765 | | |
| | | | (0.08010) | | |
| $\text{temp}^2 \times (65-75)$ | | | -0.00047 | | |
| | | | (0.00198) | | |
| $\text{temp}\times(>75)$ | | | -0.16971** | | |
| | | | (0.08545) | | |
| $\text{temp}^2 \times (>75)$ | | | 0.00395** | | |
| | | | (0.00181) | | |
| | | | | **Family attributes** | |
| | | | | **siblings** | |
| $\text{temp}\times$ *no sibling* | | | | 0.17905* | |
| | | | | (0.10079) | |
| $\text{temp}^2 \times$ *no sibling* | | | | -0.00511** | |
| | | | | (0.00253) | |
| | | | | | **grandchildren** |
| $\text{temp}\times$ *no grandchildren* | | | | | -0.00575 |
| | | | | | (0.14465) |
| $\text{temp}^2 \times$ *no grandchildren* | | | | | -0.00041 |
| | | | | | (0.00351) |
| Municipality of Birth | Y | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y | Y |
| Month of Interview | Y | Y | Y | Y | Y |
| Contemporaneous Weather | Y | Y | Y | Y | Y |
| Current Location | Y | Y | Y | Y | Y |
| Observations | 3,103 | 3,103 | 3,083 | 3,100 | 2,902 |
| $R^2$ | 0.42120 | 0.42351 | 0.41279 | 0.42596 | 0.44938 |

**Notes**: $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature on later-life cognition score. In all regressions, standard errors are clustered at the municipalities of birth. In this table, we examine the heterogeneity in the impacts by considering four attributes: gender (male vs female); season (hot vs cold); age-group (40-55; 55-65; 65-75; >75) with 40-55 treated as the reference category and family attributes (having or not siblings or grandchildren). All regressions control for individual characteristics such as age, gender, ethnicity, religion.

Table 8: Temperature effects on related human capital outcomes

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Cognition score** | | | |
| | Childhood health | Literacy | Hours of sleep | Quality of sleep |
| | (1) | (2) | (3) | (4) |
| Before conception (0-3 months) | -0.00718 | -0.02637 | -0.01759 | -0.00084 |
| | (0.00793) | (0.03129) | (0.09945) | (0.02939) |
| Before conception (0-3 months)$^2$ | 0.00009 | 0.00076 | -0.00007 | 0.00019 |
| | (0.00018) | (0.00076) | (0.00236) | (0.00070) |
| temp | -0.00627 | -0.12449$^{***}$ | 0.33672$^{***}$ | -0.02760$^{**}$ |
| | (0.00780) | (0.00765) | (0.05363) | (0.01234) |
| temp$^2$ | 0.00024 | 0.00281$^{***}$ | -0.00733$^{***}$ | 0.00055$^{**}$ |
| | (0.00016) | (0.00015) | (0.00118) | (0.00026) |
| After birth (0-3 months) | -0.00722 | -0.05603 | 0.14014$^{*}$ | -0.20834$^{***}$ |
| | (0.00984) | (0.03872) | (0.08039) | (0.04032) |
| After birth (0-3 months)$^2$ | 0.00012 | 0.00142 | -0.00265 | 0.00491$^{***}$ |
| | (0.00023) | (0.00093) | (0.00195) | (0.00090) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y |
| Month of Interview | Y | Y | Y | Y |
| Contemporaneous Weather | Y | Y | Y | Y |
| Observations | 3,147 | 3,148 | 3,006 | 3,145 |
| $R^2$ | 0.28718 | 0.36236 | 0.23679 | 0.26592 |

**Notes**: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature on later-life related human capital outcomes. We consider self-rate childhood health, literacy rate, number and quality of sleep. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as age, gender, ethnicity, religion.

Table 9: Temperature effects on cognition score conditional on drought (hot vs cold) exposure in first trimester

| | *Dependent variable:* | |
|---|---|---|
| | **Cognition score** | |
| **First trimester is:** | Hot | Cold |
| | (1) | (2) |
| Before conception (0-3 months) | 0.00002 | 0.00370 |
| | (0.00664) | (0.00884) |
| Before conception (0-3 months)$^2$ | 0.00001 | 0.00320 |
| | (0.00464) | (0.00184) |
| temp | -0.27012*** | -0.23849*** |
| | (0.07079) | (0.06300) |
| temp$^2$ | 0.00617*** | 0.00536*** |
| | (0.00154) | (0.00137) |
| After birth (0-3 months) | -0.01172*** | -0.01132*** |
| | (0.00231) | (0.00266) |
| After birth (0-3 months)$^2$ | -0.01192*** | -0.01232*** |
| | (0.00231) | (0.00266) |
| Municipality of Birth | Y | Y |
| Month of Birth | Y | Y |
| Year of Birth | Y | Y |
| Individual Controls | Y | Y |
| Month of Interview | Y | Y |
| Contemporaneous Weather | Y | Y |
| Current Location | Y | Y |
| Observations | 1,403 | 1,654 |
| $R^2$ | 0.34993 | 0.32209 |

**Notes**: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The table reports non-linear estimates of the impact of average prenatal temperature on later-life related human capital outcomes. We consider literacy rate, number and quality of sleep, depression score. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as age, gender, ethnicity, religion.

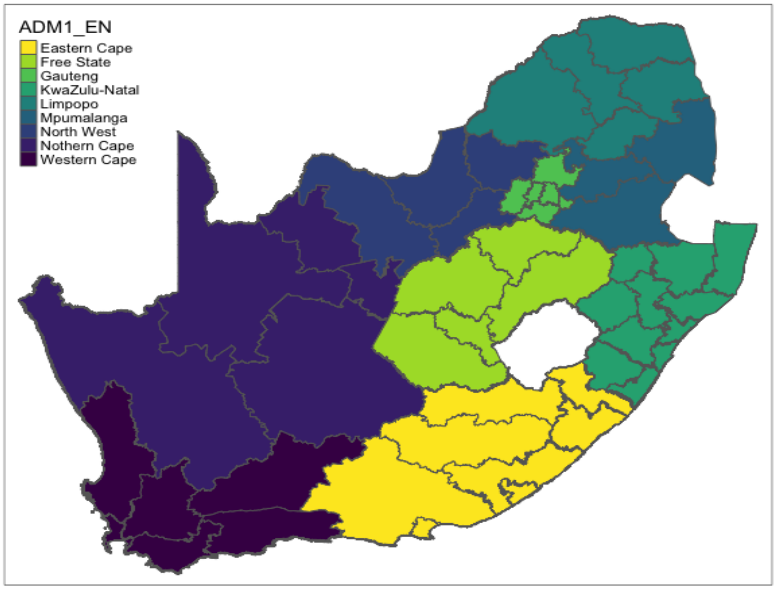
# Appendix

Table A1: Review of related literature

| Papers | Research Questions | Time Horizon | Age group |
|---|---|---|---|
| Adhvaryu et al. (2015) | How do temperature shocks in utero affect self-reported symptoms of mental illness | Long-term | 18 to 65 years |
| Almond and Mazumder (2011) | How does prenatal exposure to ramadan impact birth outcomes | Short-term | 20 to 80 years |
| Barreca (2010) | Economic impact of in utero and postnatal exposure to malaria | Long-term | 24 to 60 years |
| Carrillo (2020) | In utero exposure to abnormal rainfall events and human health consequences | Long-term | 25 to 65 years |
| Charil et al. (2010) | Prenatal stress and abnormal cognitive, behavioral, psychosocial outcomes | Long-term | – |
| Cook and Heyes (2020) | How does outdoor cold temperature affect indoor cognitive performance | Short-term | 18 to 35 years |
| Currie and Vogl (2013) | Early-life health and adult circumstance in developing countries | Long-term | – |
| De Rooij et al. (2010) | How does prenatal undernutrition affect cognitive function in late adulthood | Long-term | 50 to 59 years |
| Deschênes et al. (2009) | Ho does exposure to prenatal climate shocks affect birth outcomes | Short-term | 16 to 45 years |
| Dinkelman (2017) | Effects of early childhood exposure to drought on later-life physical and mental disabilities | Long-term | 10 to 48 years |

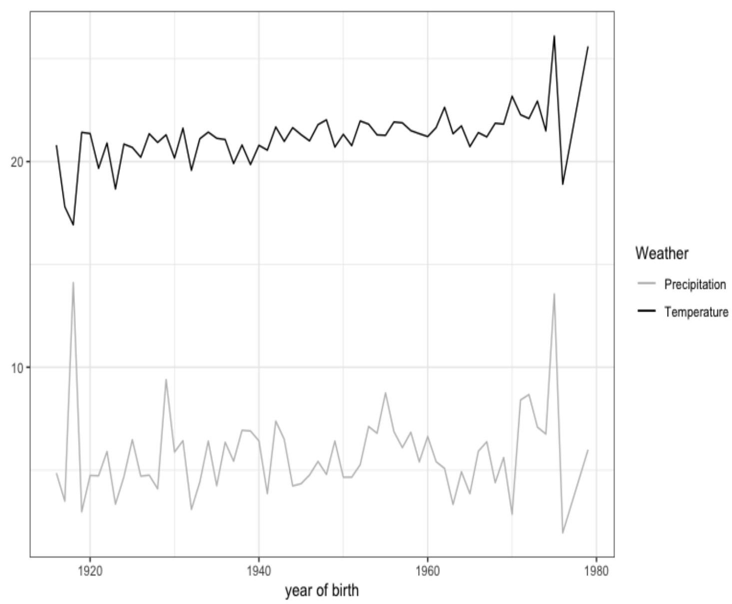
**Notes:** This review covers recent papers on both short and long run consequences of fetal insults on human capital accumulation. Overall, prior studies investigated the impacts of early life exposure to various shocks including malaria, drought, pollution, among others on key determinants of human capital accumulation such as birth height, weight, education, mental disorders, etc. In terms of age-group of individuals, studies covered mostly children and young adults. Indeed, there are only few studies related to old people as well as focusing on cognitive performance as we do here.

Figure A1: Administrative regions of South Africa



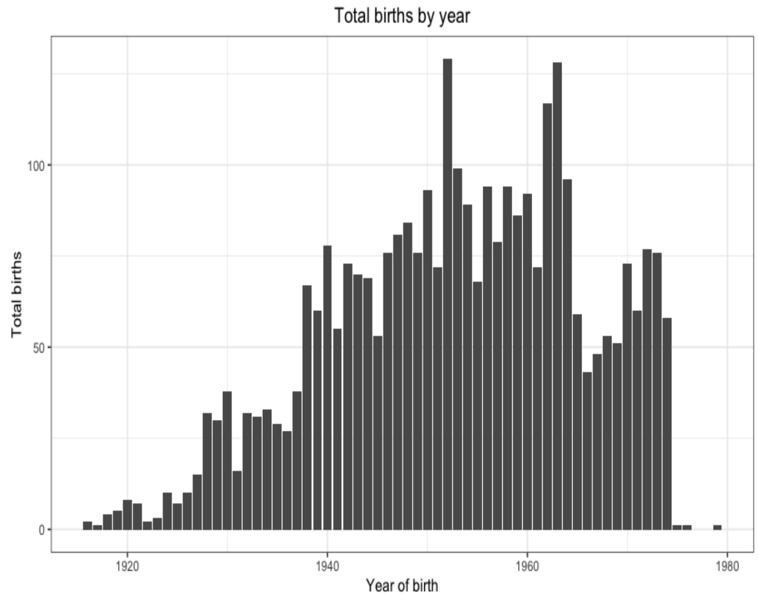

**Notes**: The figure above shows different administrative regions (ADM1_EN) of South Africa.

Figure A2: Change in temperature and precipitation by year of birth



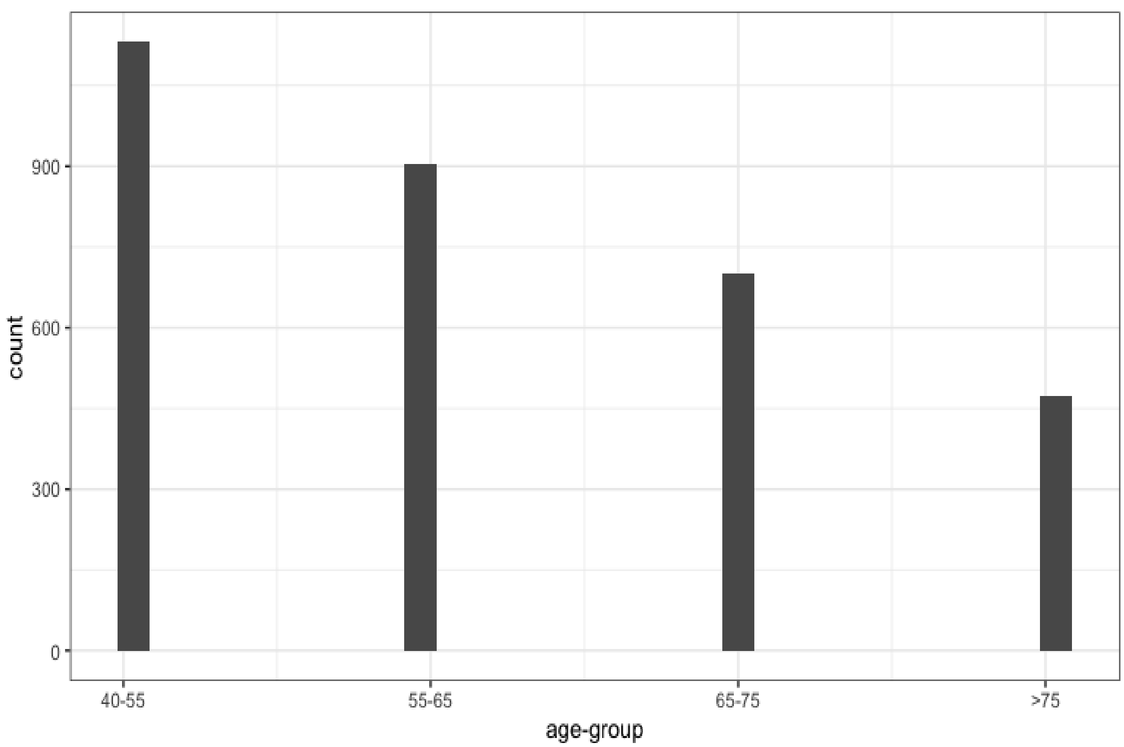

**Notes**: The figure above describes the change in weather indicators —average temperature and precipitation —over years. The period considers here covers the years of birth of individuals in the sample. While precipitation trend seems to be stable overtime, average monthly temperature shows an increase trend starting around 1940.

Figure A3: Total births by year of birth



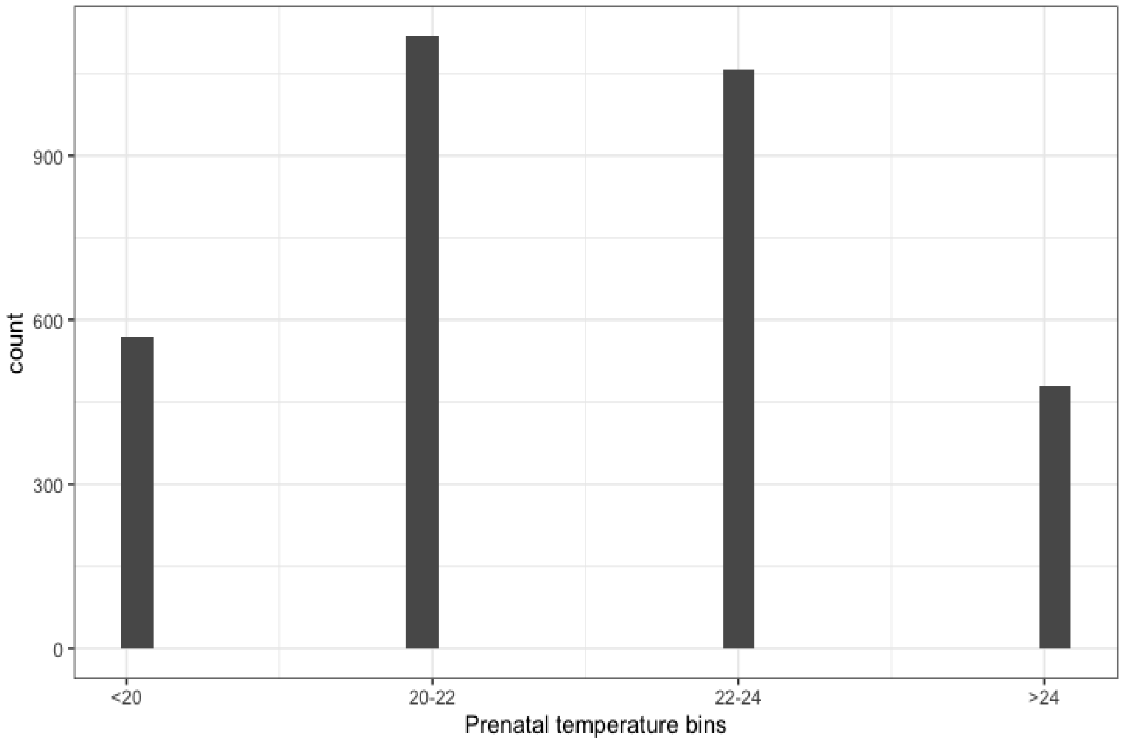

**Notes**: The figure above represents the distribution of total births by year of birth in our sample. It reveals that most of respondents were born between 1940 and 1970 post apartheid period.

Figure A4: Distribution of age group in the sample



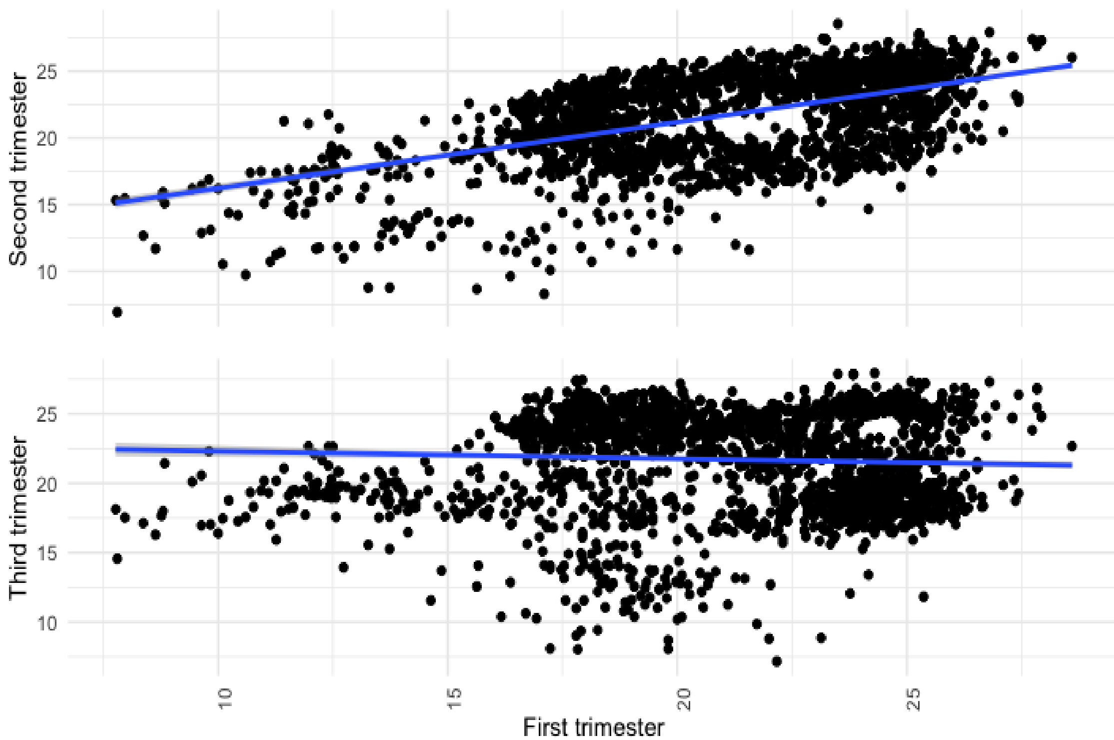

**Notes**: The figure above represents the distribution of age-group in our sample. We consider four groups: 40-55; 55-65; 65-75; and >75. In our analysis, we compare temperature impacts on cognition score by age-group relative to 40-55.

Figure A5: Distribution of average prenatal temperature bins in the sample




**Notes**: The figure above is the distribution of exposure to average prenatal temperature by bins. We consider four range of temperature bins $< 20$°C; 20-22°C; 22-24°C; $>$24° C with $< 20$°C considers as the reference category.

Figure A6: Correlations between average temperature of the first trimester and the second and third trimesters




**Notes**: The graph above plots average temperature during second and third trimesters against the first trimester one. While there is a positive relationship between first and second trimester average temperatures, suggesting that these windows of pregnancy share the same season, we notice that there is no correlation between first and third trimesters.

Table A2: Temperature effects on cognition z-score during aging using linear model

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Cognition score** | | | |
| | (1) | (2) | (3) | (4) |
| Before conception (0-3 months) | 0.00607 | 0.00524 | 0.00470 | 0.00001 |
| | (0.00693) | (0.00800) | (0.00784) | (0.00664) |
| temp | -0.10630*** | -0.11216*** | -0.23849*** | -0.27012*** |
| | (0.02935) | (0.02995) | (0.06300) | (0.07079) |
| After birth (0-3 months) | -0.01132*** | -0.01146*** | -0.01232*** | -0.01292*** |
| | (0.00280) | (0.00277) | (0.00266) | (0.00241) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y |
| Month of Interview | | Y | Y | Y |
| Contemporaneous Weather | | | Y | Y |
| Current Location | | | | Y |
| Observations | 3,106 | 3,106 | 3,106 | 3,106 |
| $R^2$ | 0.31919 | 0.32233 | 0.32107 | 0.32269 |

**Notes**: *p<0.1; **p<0.05; ***p<0.01. The table reports linear estimates of the impact of average prenatal temperature on later-life cognition score. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as gender, ethnicity, religion. We try a series of specifications from column (1) to (4) with different controls and fixed effects. Column (4) reports estimates from our preferred specification.

Table A3: Temperature effects on cognition z-score by month of pregnancy using linear model

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Cognition score** | | | |
| | (1) | (2) | (3) | (4) |
| $\text{temp}_{t-9}$ | 0.02480*** | 0.02194*** | 0.01958** | 0.02126** |
| | (0.00835) | (0.00816) | (0.00822) | (0.00921) |
| $\text{temp}_{t-8}$ | -0.02975** | -0.02248* | -0.02126* | -0.02465* |
| | (0.01187) | (0.01186) | (0.01187) | (0.01303) |
| $\text{temp}_{t-7}$ | -0.00435 | -0.00843 | -0.01070 | -0.00616 |
| | (0.01065) | (0.01087) | (0.01115) | (0.01073) |
| $\text{temp}_{t-6}$ | 0.00583 | 0.00695 | 0.00984 | 0.00740 |
| | (0.01204) | (0.01154) | (0.01145) | (0.01166) |
| $\text{temp}_{t-5}$ | -0.00704 | -0.00588 | -0.00657 | -0.00362 |
| | (0.01333) | (0.01384) | (0.01369) | (0.01351) |
| $\text{temp}_{t-4}$ | 0.01360 | 0.01825* | 0.01482 | 0.01724* |
| | (0.00890) | (0.01088) | (0.01071) | (0.00929) |
| $\text{temp}_{t-3}$ | 0.01168 | 0.00729 | 0.00708 | 0.00122 |
| | (0.00758) | (0.00656) | (0.00653) | (0.00654) |
| $\text{temp}_{t-2}$ | 0.00635 | 0.00853 | 0.00566 | 0.01060 |
| | (0.01179) | (0.01176) | (0.01173) | (0.01059) |
| $\text{temp}_{t-1}$ | 0.00495 | 0.00741 | 0.00082 | -0.00044 |
| | (0.01042) | (0.01209) | (0.01214) | (0.01174) |
| $\text{temp}_{t}$ | -0.02244** | -0.02929*** | -0.03930*** | -0.03730*** |
| | (0.01045) | (0.00976) | (0.01072) | (0.01053) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y |
| Month of Interview | | Y | Y | Y |
| Contemporaneous Weather | | | Y | Y |
| Current Location | | | | Y |
| Observations | 3,153 | 3,153 | 3,153 | 3,153 |
| $R^2$ | 0.28582 | 0.32274 | 0.32328 | 0.34978 |

**Notes**: *p<0.1; **p<0.05; ***p<0.01. The table reports linear estimates of the impact of average temperature by each month of pregnancy on later-life cognition score. In all regressions, standard errors are clustered at the municipalities of birth. All regressions control for individual characteristics such as age, gender, ethnicity, religion. We try a series of specifications from column (1) to (4) with different controls and fixed effects. Column (4) reports estimates from our preferred specification.

Table A4: Temperature effects on various measures of cognition z-score

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **List words** | **Count** | **Concentration** | **Orientation** |
| | (1) | (2) | (3) | (4) |
| | **Before conception (0-3 months)** | | | |
| temp | -0.01974*** | 0.00760 | 0.05528* | -0.06120 |
| | (0.00447) | (0.02501) | (0.03231) | (0.07177) |
| $temp^2$ | 0.00041*** | -0.00032 | -0.00133* | 0.00126 |
| | (0.00011) | (0.00054) | (0.00071) | (0.00161) |
| | **First trimester** | | | |
| temp | -0.00574 | 0.00760 | 0.04528 | -0.06120 |
| | (0.00447) | (0.02501) | (0.03231) | (0.07177) |
| $temp^2$ | 0.00021 | -0.00032 | -0.00130 | 0.00126 |
| | (0.00015) | (0.00054) | (0.00081) | (0.00161) |
| | **Second trimester** | | | |
| temp | -0.02458*** | -0.01372 | -0.03581** | 0.00246 |
| | (0.00464) | (0.02305) | (0.01553) | (0.06477) |
| $temp^2$ | 0.00065*** | 0.00057 | 0.00100*** | 0.00070 |
| | (0.00011) | (0.00052) | (0.00036) | (0.00149) |
| | **Third trimester** | | | |
| temp | -0.02066*** | 0.06723** | 0.08082*** | -0.05921 |
| | (0.00587) | (0.02974) | (0.02331) | (0.06428) |
| $temp^2$ | 0.00047*** | -0.00162** | -0.00205*** | 0.00107 |
| | (0.00014) | (0.00072) | (0.00063) | (0.00143) |
| | **After birth (0-3 months)** | | | |
| temp | -0.02561*** | -0.02601*** | -0.02528*** | -0.02120*** |
| | (0.00447) | (0.00250) | (0.00323) | (0.00717) |
| $temp^2$ | 0.00561*** | 0.00301*** | 0.00416*** | -0.00410*** |
| | (0.00037) | (0.00050) | (0.00021) | (0.00069) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y |
| Month of Interview | Y | Y | Y | Y |
| Contemporaneous Weather | Y | Y | Y | Y |
| Current Location | Y | Y | Y | Y |
| Observations | 3,091 | 2,720 | 3,112 | 3,068 |
| $R^2$ | 0.12227 | 0.23727 | 0.16715 | 0.26788 |

**Notes:** *p<0.1; **p<0.05; ***p<0.01. The table reports the point estimates of the effect of average temperature of a given trimester of pregnancy on cognition z-score along with various measure of cognitive performance. These measures include individual ability to list words, count, concentrate, and orientation. Our findings suggest that, while moderate temperatures are worst off for cognitive abilities, the higher ones are associated with better cognitive functions.

Table A5: Temperature effects on measures of biological markers

| | *Dependent variable:* | | |
|---|---|---|---|
| | weight | height | male |
| | (1) | (2) | (3) |
| Before conception (0-3 months) | 0.00060 | -0.00297 | 0.00214 |
| | (0.00288) | (0.00780) | (0.00348) |
| Before conception (0-3 months)$^2$ | 0.00010 | -0.00182 | 0.00205 |
| | (0.00157) | (0.00570) | (0.00207) |
| temp | -0.03520* | -0.03570 | -0.02299 |
| | (0.01886) | (0.03917) | (0.01769) |
| temp$^2$ | 0.00079 | 0.00122 | 0.00063 |
| | (0.00067) | (0.00134) | (0.00045) |
| After Birth (0-3 months) | 0.00270 | -0.00387 | 0.00558 |
| | (0.00286) | (0.00643) | (0.00424) |
| After Birth (0-3 months)$^2$ | 0.00033 | -0.00082 | 0.00051 |
| | (0.00081) | (0.00073) | (0.00034) |
| Municipality of Birth | Y | Y | Y |
| Month of Birth | Y | Y | Y |
| Year of Birth | Y | Y | Y |
| Individual Controls | Y | Y | Y |
| Month of Interview | Y | Y | Y |
| Contemporaneous Weather | Y | Y | Y |
| Current Location | Y | Y | Y |
| Observations | 3,084 | 3,084 | 3,084 |
| $R^2$ | 0.01499 | 0.00811 | 0.00868 |

**Notes:** *p<0.1; **p<0.05; ***p<0.01. The table reports the point estimates of the effect of average temperature on biological markers weight, height, and sex at birth. Standard errors are reported in brackets.

Table A6: Temperature effects on early life investments

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | bcg | measles | vitamin | months of breastfeeding |
| | (1) | (2) | (3) | (4) |
| Before conception (0-3 months) | -0.00011 | -0.00044 | 0.00040 | 0.03226 |
| | (0.00123) | (0.00249) | (0.00164) | (0.20828) |
| Before conception (0-3 months)$^2$ | -0.00021 | -0.00044 | 0.00040 | 0.00226 |
| | (0.00023) | (0.00039) | (0.00063) | (0.00807) |
| temp | -0.00038 | -0.04924$^*$ | -0.01533 | 0.36804 |
| | (0.00606) | (0.02520) | (0.02718) | (1.41280) |
| temp$^2$ | 0.00011 | 0.00233$^{**}$ | 0.00092 | -0.03887 |
| | (0.00018) | (0.00088) | (0.00095) | (0.04899) |
| After birth (0-3 months) | -0.00030 | -0.00918$^{***}$ | -0.00547$^{**}$ | 0.35002$^*$ |
| | (0.00084) | (0.00165) | (0.00218) | (0.18787) |
| After birth (0-3 months)$^2$ | 0.00020 | -0.00018 | -0.00041 | 0.0002 |
| | (0.00054) | (0.00065) | (0.00208) | (0.0007) |
| Municipality of Birth | Y | Y | Y | Y |
| Month of Birth | Y | Y | Y | Y |
| Year of Birth | Y | Y | Y | Y |
| Individual Controls | Y | Y | Y | Y |
| Month of Interview | Y | Y | Y | Y |
| Contemporaneous Weather | Y | Y | Y | Y |
| Current Location | Y | Y | Y | Y |
| Observations | 3,084 | 3,084 | 3,084 | 2,723 |
| $R^2$ | 0.00934 | 0.05590 | 0.02639 | 0.02460 |

**Notes:** $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The table reports the point estimates of the effect of average temperature on individual early life health investments. These include received or not vaccine of bcg, measles, vitamin and the number of months of breastfeeding.

# Notes

## N1 Data Collection

In this section, we explain how we built our database, especially how we collect the spatial information. Roughly, we proceeded in three steps. First, using HAALSI survey data, we collected information on respondent's places of birth either at the municipality, district, or town geographic unit. We noticed that respondents often provided different names or spelling for the same place of birth. For instance, for Agincourt was sometimes pronounced or spelled as Agincort, Agincurt, Aincourt, Angnicourt, etc. We assigned a unique ID number to a location even if it was spelled in several ways in the data, as partly shown in the table below:

Table N1: List of municipalities of birth with geographical coordinates

| ID | Municipalities | Latitude | Longitude |
|---|---|---|---|
| 1 | Acornhoek 1 | -24.58 | 31.1 |
| 1 | Acohork | -24.58 | 31.1 |
| 1 | Acornhoeck | -24.58 | 31.1 |
| 1 | Acornhoeek | -24.58 | 31.1 |
| 1 | Acornhoek | -24.58 | 31.1 |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| 205 | Jobela | -34.01 | 18.62 |
| 205 | Jobera | -34.01 | 18.62 |
| 206 | Xere | -25.72 | 28.42 |
| 207 | Xihahlana | -28.25 | 29.11 |
| 208 | Xitenze | -26.17 | 28 |
| 209 | Zikinowa | -25.74 | 28.19 |
| 210 | Masana | -29.29 | 30.36 |
| 211 | Score | -25.74 | 28.19 |
| 212 | Botshabelo | -25.7 | 29.41 |
| 213 | Mativiti | -26.27 | 27.87 |

**Notes:** We list a total of 213 municipalities of birth in our sample for which we were able to collect geographical coordinates.

The second step of data collection consisted of gathering information on geographic coordinates of places of birth, and assigning each respondent in the HAALSI dataset geographic coordinates of their place of birth. The third and final step consisted of merging the HAALSI data with climate data from —UDEL —based on municipalities of birth, month of birth, and year of birth. By doing so we were able to obtain weather conditions during pregnancy period for 3212 respondents born in South Africa.