Essays in Environmental Economics and Human Capital

by

Landry Kuate Fotue

A thesis submitted in partial fulfillment of the requirements for the Doctorate in Philosophy degree in Economics

Department of Economics
Faculty of Social Sciences
University of Ottawa

Abstract

Chapter 1 —This paper offers new causal evidence on how the timing of prenatal temperature shocks affects fetal health, sex ratio at birth, and early-age human capital. Analyzing data on nearly 2 million live births from sub-Saharan African countries and exploiting exogenous spatial and temporal variation in monthly temperature, we uncover three findings. First, we find that a cold temperature shock decreases the likelihood of a male birth. This effect is non-linear, being larger in the first and third trimesters of pregnancy. It is also highly heterogeneous, being larger for older women, higher parity births, and rural areas. Second, combining our empirical estimates with a climate model, we find that the number of fetal deaths caused by climate change will rise from 200 to 400 per 100,000 live births by 2050 throughout sub-Saharan Africa. Third, in contrast to their differential effect on fetal mortality, prenatal temperature shocks increase infant mortality more for females than for males, suggesting that only healthier male fetuses survive to adverse in utero conditions. Our analysis implies that the design of policies to avert the negative impacts of climate change on children should account for stages of fetal development.

Chapter 2 —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.

Chapter 3 —A large literature seeking to understand the labor market impacts associated with the clean energy transitions broadly finds opposite effects. On the one hand, a net positive impact on the workforce i.e. the new green jobs created in renewable energy sectors will compensate for the jobs lost in fossil-fuel sectors, while on the other hand, the so-called regulated dirty energy sector will reduce the fraction of workers hired. However, empirical and simulation models typically ignore transitional impacts associated with environmental regulations on labour. These relate to how workers adjust over time to environmental regulations, not just the steady state impact that is the focus of prior studies. We evaluate an environmental regulation (Ontario coal-fired electricity generating plants phase-out) regarding its transitional and long-term impacts on employee's outcomes including *(i)* wages; *(ii)* unemployment insurance; *(iii)* sector mobility; and *(iv)* geographic location. Using the Longitudinal Worker File (LWF) and Postal Codes Conversion File (PCCF) maintained by Statistics Canada, we estimate the labor market impacts of clean energy policy by comparing employees from affected coal plants to a comparable group of employees from non-affected plants. We find that, workers exposed to Ontario phase-out coal policy have earned on average 7000 $ CAD yearly less compared to those who weren't exposed. Our findings are consistent across a set of alternative specifications and robustness checks. Moreover, results from the event study approach suggest that the regulation leads to labor costs with the decline of wages just in transition. We provide supportive evidence on large labor costs due to environmental regulation policy and shed lights on the importance of reforms and training programs to support workers during the transition.

Declaration of Authorship

I, Landry Kuate Fotue, declare that this thesis titled, "Essays in Environmental Economics and Human Capital" and the work presented in it are my own.

Chapter 1 of this thesis was done jointly with Roland Pongou, and Nicholas Rivers. My contribution is equal to theirs.

Chapter 2 of this thesis was done jointly with Roland Pongou. My contribution is equal to his.

Chapter 3 of this thesis was done jointly with Nicholas Rivers. My contribution is equal to his.

I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ______________________________

Date: January 20, 2023

General Introduction

This dissertation organized around three distinct chapters, examines the short and long term consequences of climatic shocks and environmental regulations on human health and activities in both developing and developed countries. The first chapter answers the question of how the timing of prenatal temperature shocks affects fetal health, sex ratio at birth, and early-age human capital in the context of sub-Sahara Africa. The second chapter looks at the long-term consequences of early-life adverse climatic conditions on cognitive performance during aging. Finally, the third chapter studies the transitional impacts of decarbonization policies on labor market outcomes in the context of Canada. I contribute to several distinct strands of the economic literature, and highlight the importance of designing policies that target early-life period of an individual to shape his lifetime resilience and mitigation to climate

In the first chapter, my coauthors and I investigate how the *timing* of prenatal temperature shocks affects fetal health, sex ratio at birth, and sex-specific early-age human capital. We achieve a threefold goal. First, we examine the impacts of temperature shocks during pregnancy on sex differences in fetal mortality in sub-Saharan African countries. The absence of vital statistics on fetal deaths in most societies means that the true estimate of this relationship is hard to measure. We advance by leveraging the insight that males and females are differently susceptible to shocks in utero (Orzack et al., 2015). This differential susceptibility determines male-female differences in fetal death and hence sex ratio at birth, an important outcome. Second, using the insight from the first analysis, we estimate a lower bound on the impact of temperature shocks on total fetal deaths, and apply a climate model to predict the long-term fetal mortality due to predicted ambient temperature changes throughout sub-Saharan Africa. Third, we extend our analysis by estimating the effect of prenatal temperature shocks on infant mortality. To the extent that in utero mortality selection due to temperature differs for male and female fetuses, the effect of prenatal temperature on infant mortality may differ across the sexes, and it is likely that the direction of this difference will be opposite to its differential effect on fetal mortality.

Our study therefore sheds new light on how the effects of prenatal temperature differ for prenatal and postnatal outcomes. Results suggest that temperature shocks have differential impacts on male and female fetuses. We find that cold temperatures decrease the likelihood of live male births. Moreover, the effect of a cold temperature is more pronounced during the first and third trimesters of pregnancy, suggesting that these periods are critical windows of fetal development, especially for male fetuses. The impact of hot temperatures on sex ratio at birth is more ambiguous. Our findings have important policy implications. Estimates of change in fetal death, sex ratio at birth, and infant mortality are relevant as these outcomes affect future social movements such as marriage, crime, and the labor market. Our analysis can also inform public policies designed to prevent pregnant women from the adverse effects of climate shocks. It implies that such policies should account for stages of fetal development.

In the second chapter, my coauthor and I explore the fundamental and long-run causes of cognitive aging. 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). We examine the relationship between ambient temperature during different stages of pregnancy and cognitive performance in the context of older South African adults. 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.

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. 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.

In the third chapter, my coauthor and I contribute to the debate regarding the trade-off between jobs and environmental regulations in the context of Canada. The clean energy transition presents both opportunities and challenges to Canadian workers, as some sectors are likely to contract, and some expand, when Greenhouse Gas (GHG) policies are applied. An obvious example is in the electricity generation sector, where reducing greenhouse gas emissions may involve closure of coal-fired generating plants, and expansion of renewable power generating facilities. The goal of this paper is to characterize the transitional and long-term implications of environmental regulation at both workers and community levels. We exploit the rapid changes in the electricity sector resulting from policies that aim to reduce emissions, to capture the effects of decarbonization policies, especially the phase-out coal-fired generating facilities on employees outcomes including, jobs displacement, earnings, social assistance

claims. We use Longitudinal Worker File (LWF) and Postal Codes Conversion Files (PCCF) maintained by Statistics Canada, to follow workers in affected facilities over time, in order to gain an understanding of worker-level impacts of environmental regulation.

Our findings suggest that workers exposed to Ontario phase-out coal policy have earned on average 7000 $ CAD yearly less compared to those who weren't exposed. Our findings are consistent across a set of alternative specifications and robustness checks. Moreover, results from the event study approach suggest that the regulation leads to labor costs with the decline of wages just in transition. We provide supportive evidence on large labor costs due to environmental regulation policy and shed lights on the importance of reforms and training programs to support workers during the transition.

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*To my Dad:**Kuate Christophe***
because I owe it all to you.

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Chapter 1

Timing Matters: Prenatal Climate Shocks, Sex Ratio, and Human Capital

By Landry Kuate, Roland Pongou and Nicholas Rivers

Abstract

This paper offers new causal evidence on how the timing of prenatal temperature shocks affects fetal health, sex ratio at birth, and early-age human capital. Analyzing data on nearly 2 million live births from sub-Saharan African countries and exploiting exogenous spatial and temporal variation in monthly temperature, we uncover three findings. First, we find that a cold temperature shock decreases the likelihood of a male birth. This effect is non-linear, being larger in the first and third trimesters of pregnancy. It is also highly heterogeneous, being larger for older women, higher parity births, and rural areas. Second, combining our empirical estimates with a climate model, we find that the number of fetal deaths caused by climate change will rise from 200 to 400 per 100,000 live births by 2050 throughout sub-Saharan Africa. Third, in contrast to their differential effect on fetal mortality, prenatal temperature shocks increase infant mortality more for females than for males, suggesting that only healthier male fetuses survive to adverse in utero conditions. Our analysis implies that the design of policies to avert the negative impacts of climate change on children should account for stages of fetal development.

1.1 Introduction

The ratio of men to women has been shown to affect important social and economic outcomes including marriage (Angrist, 2002; Abramitzky et al., 2011), entrepreneurship (Wei and Zhang, 2011), crime rates (Edlund et al., 2013; Cameron et al., 2019), female labor force participation (Amuedo-Dorantes and Grossbard, 2007), exchange rates (Du and Wei, 2011), and sexual infidelity and diseases (Kang and Pongou, 2019), among others. Imbalanced sex ratio is explained by male-female disparities in mortality. Studies investigating the causes of these disparities find that they vary significantly across life stages. However, it is also generally acknowledged that knowledge of these causes is still incomplete, especially in very early life stages when critical development takes place. In particular, the economic literature has paid little attention to the period of fetal formation and development, despite mounting empirical evidence showing that circumstances experienced in utero have significant impacts on later-life outcomes (Barker, 1997; Almond et al., 2018). The general lack of knowledge about the causes of sex imbalance in very early life constitutes an important constraint on policy actions likely to avert its negative socioeconomic impacts.

This paper offers new causal evidence on how the *timing* of prenatal temperature shocks affects fetal health, sex ratio at birth, and sex-specific early-age human capital. We achieve a threefold goal. First, we examine the impacts of temperature shocks during pregnancy on sex differences in fetal mortality in sub-Saharan African countries. The absence of vital statistics on fetal deaths in most societies means that the true estimate of this relationship is hard to measure. We advance by leveraging the insight that males and females are differently susceptible to shocks in utero (Orzack et al., 2015). This differential susceptibility determines male-female differences in fetal death and hence sex ratio at birth, an important outcome. Second, using the insight from the first analysis, we estimate a lower bound on the impact of temperature shocks on total fetal deaths, and apply a climate model to predict the long-term fetal mortality due to predicted ambient temperature changes throughout sub-Saharan Africa. Third, we extend our analysis by estimating the effect of prenatal temperature shocks on infant mortality. To the extent that in utero mortality selection due to temperature differs for male and female fetuses, the effect of prenatal temperature on infant mortality may differ across the sexes, and it is likely that the direction of this difference will be opposite to its differential effect on fetal mortality. Our study therefore sheds new light on how the effects of prenatal temperature differ for prenatal and postnatal outcomes. More importantly, by documenting how the timing of prenatal temperature shocks matters, our analysis offers novel findings with direct implications for how the design of policies aimed at averting the negative impacts of climate change on early-life human capital formation should account for stages of fetal development.

Our analysis is related to recent research showing that human demographic impacts are likely to be amongst the most severe costs of climate change, with impacts on both mortality (Carleton et al., 2018; Barreca et al., 2016) and fertility (Barreca et al., 2018; Dessy et al., 2019). Such mortality-related effects could be even more harmful for fetuses and infants who are especially sensitive to hot temperature due to the early development stage in thermoregulatory and nervous system (Young, 2002; Knobel and Holditch-Davis, 2007). However, while there is a growing literature seeking to understand the impacts of prenatal shocks on subsequent human capital formation throughout the individual lifetime (Isen et al., 2017; Wilde et al., 2017), little research has studied how environmental insults directly affect humans in utero or the viability of the embryo or fetus — whether or not it produces a live birth. Moreover, little attention has been paid to how the timing of prenatal shocks matters. Prior studies have discussed the biological fragility of the male fetus which is at great risk of death or damage from almost all the obstetric catastrophes and external maternal stress including climate shocks (Catalano et al., 2008; Kraemer, 2000). Therefore, prenatal shocks could impair offspring sex ratio at birth as a result of fetal death as well as sex differences in postnatal outcomes, thus impacting the long-term population gender composition of society, a key driver of social movements such as marriage markets, labour force participation, or crime rates. Examining the effects of climatic conditions experienced during in utero period is therefore crucial for long-term social and economic stability.

In investigating the question of how ambient temperature at different stages of fetal development (or at different periods during pregnancy) affects fetal outcomes, sex ratio at birth, and sex-specific infant mortality, we focus our attention on how environmental conditions affect the likelihood of fetal maturation only after conception.[1] Exposure to weather shocks among pregnant mothers can affect fetal death and offspring's sex ratio through three potential mechanisms that impact the fetus either directly or indirectly through mother's responses. These include: *(i)* biological effect induced by heat stress which might result in several health issues including risk of placenta abruption (He et al., 2018), preterm and still-

[1]We do not study the effect of temperature on sex determination at conception. Temperature may influence primary sex determination by the variable fertilization success of X- and Y- bearing sperm (McLachlan and Storey, 2003). Moreover, there is evidence supporting that ambient temperature and stressful environmental conditions affect the steroid concentrations of ovarian follicles (Wolfenson et al., 2000; De Rensis and Scaramuzzi, 2003), and may also impair sperm mobility and potentially promoting female biased birth sex ratio (Fukuda et al., 1996). In some specifications of our model, we account for these two channels by analyzing the effect of temperature after conception has already occurred.

birth (Carolan-Olah and Frankowska, 2014; Strand et al., 2011b) and pregnancy loss (Beltran et al., 2014); *(ii)* behavioral mechanism involving a change in consumption habits (food selection, appetite loss); and *(iii)* income, owing to negative impacts of extreme temperature on agricultural yields and thus household resources.

Sub-Saharan Africa is an ideal setting for our analysis. It is a rapidly developing region with wide ecological, climatic and cultural diversity. By 2050, its population is projected to approach 2 billion people (DESA (2015)), a dynamic which comes with both opportunities and challenges to policy makers. At the same time, the region is undergoing permanent changes in climatic conditions. However, little is known about how these changes will affect different population groups. There is little investment aimed at protecting against climate shocks, and individuals in the region are in majority involved in out-door activities (agriculture, outside trading activities, etc.) and therefore are exposed to weather variations including extreme temperature. In addition, economic activities are dominated by agriculture, which is highly dependent on climatic conditions. As a consequence, a weather shock that leads to a change in agricultural yields may reduce household resources (Brown and Funk, 2008; Hertel, 2016) and affect fertility and reproductive health (Dessy et al., 2019; Grace, 2017). However, the distributional effect of climate shocks across different population subgroups in this region has been little studied. Our examination of the effects of temperature shocks at different stages of pregnancy on sex difference in fetal death and infant mortality contributes to filling this gap.

We use data from 85 rounds of Demographic and Health Surveys (DHS) with geo-coded information collected in 34 Sub-Saharan African countries between 1980 and 2010. The DHS collects information on complete fertility history from mothers aged 15-49 years old and their children. We link these surveys to historical gridded monthly air temperature and precipitation data from the University of Delaware's air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). We identify weather conditions experienced during the prenatal period for all children born to women surveyed in the DHS. To estimate the impact of in-utero mean-temperature on the sex ratio at birth and sex-specific infant mortality, we use a non-linear specification with region and month of birth fixed effects.

Our results show that temperature shocks have differential impacts on male and female fetuses. We find that cold temperatures decrease the likelihood of live male births. Moreover, the effect of a cold temperature is more pronounced during the first and third trimesters of pregnancy, suggesting that these periods are critical windows of fetal development, especially for male fetuses. The impact of hot temperatures on sex ratio at birth is more ambiguous. Our findings are robust to different specifications including alternative functional forms, different controls, and inclusion of different fixed effects. We show that our main findings survive several robustness checks especially when we control for the interaction term month of birth and region fixed effects.

We document possible mechanisms driving our findings by examining heterogeneity in the effect of ambient temperature on fetal outcomes. These mechanisms may be biological, behavioral, or/and operating through income. In our analysis, they are captured using mother's age at delivery, child birth order, and place of residence (either urban or rural). Our findings show that the adverse impact of a cold prenatal temperature shock is offset in younger mothers with fewer children. We also find that cold prenatal temperature is more harmful for mothers who live in rural areas compared to their counterparts living in urban areas. These results are consistent with the notion that the adverse effects of poor environmental conditions are partly mediated through mother's health and reduced income for households whose livelihoods depend on weather conditions.

Quantifying the causal impact of temperature during pregnancy on sex ratio at birth raises several econometric challenges. First, while it is generally assumed that the gestational length is a random variable, it also acknowledged that it could be endogenous to environmental insults in-utero (Schifano et al., 2016). The randomness of gestational length implies that the time of conception is difficult to determine.[2] Therefore, this raises a classical measurement errors concern as we imperfectly measure the temperature at the time of conception. With such measurement error in our data, the bias would be towards zero. We show that this is a minor concern given that our main findings change little when we vary the assumed length of pregnancy period from 9 months to 8 or 10 months. Second, we assume place of birth to be the same as the place of residence, which might not be the case as a mother might have moved after conception or before birth. Place of residence refers to mother's place of residence at the time of the interview, and place of birth is the location during birth. To deal with this issue, we examine if the effect of temperature shocks varies according to how long a mother has been living in her place of residence, and we do not find that it varies. Lastly, although human sex ratio at birth allows to capture both natural sex selection and culling effects, it is difficult to test these effects separately. However, we provide some evidence that the impacts of temperature shocks on sex ratio at birth occur primarily through culling (or fetal deaths), but we cannot exclude the possibility that a portion of the impact occurs via sex selection.

As our second goal, we use our estimated marginal effects of temperature on sex ratio at

[2]Changes would be, generally, on the range of days and thus their effect would be minimal in the context of full-term pregnancies, (Jukic et al., 2013).

birth to quantify a lower bound on climate-related fetal mortality. Our results suggest that at least 200 fetuses per 100,000 live births are lost due to adverse temperature throughout sub-Saharan Africa. In addition, we use the climate models from the Coupled Model Intercomparison Project 5 (CMIP5) under the Representative Concentration Pathways (RCP) 8.5 scenario, to predict that fetal deaths will increase to around 400 per 100,000 live births by 2050 due to changes in temperature. The estimation of fetal mortality is considered as a lower bound since our setting captures only the unbalanced effect of average temperature on a given sex; that is, if the change in temperature affects identically male and female fetuses, we do not measure it.

As our third and final goal, we generalize the hypothesis that temperature shocks experienced at different stages of pregnancy operate by mostly affecting fetuses with low biological endowment by exploring their effect on sex differences in infant mortality. We find that the effect of a temperature shock occurring during pregnancy sex-specific infant mortality is opposite to its effect on sex ratio at birth. Now, a cold temperature shock decreases the probability of infant mortality, and this effect is more pronounced among males compared to females. Moreover, while hot prenatal temperature increases infant mortality, its effect is greater for female children. These findings are expected under the assumption that only healthy male fetuses survive to adverse conditions during pregnancy (Trivers and Willard, 1973; Kraemer, 2000). This is consistent with our main hypothesis that in-utero temperature shocks affect sex ratio at birth by mostly killing male fetuses.

The remainder of the paper proceeds as follows. Section 1.2 presents our contribution to the closely related literature while section 1.3 describes the conceptual framework which underlines the mechanism behind the impacts of temperature shocks on sex ratio at birth. Sections 1.4 and 1.5 present and discuss our data and methods respectively. The findings and robustness checks are presented in section 1.6. Sections 1.7 and 1.8 show lower bound estimation of fetal mortality and discuss mechanisms behind our main results. Section 1.9 presents an extension of the paper to sex differences infant mortality. We conclude in section 1.10.

1.2 Contributions to the Closely Related Literature

Numerous studies have documented short-term impacts of in utero environmental shocks on various birth outcomes, although the focus in this literature is different from ours. For instance, Strand et al. (2011a) show that extreme temperature might induce heat stress in the mother, possibly causing a mix of biological and behavioral responses such as an increase in

blood flow, dehydration, changes in food selection, and appetite loss, all of which are associated with the risk of pregnancy loss. Deschênes et al. (2009) find that exposure to extremely hot temperature during pregnancy leads to lower birth weight in the United States. Using the Islamic month of Ramadan as a natural experiment, Almond and Mazumder (2011) examine the impacts of maternal fasting on a set of birth outcomes. Among their results, the authors find that prenatal exposure to Ramadan in the first month of pregnancy reduces the number of male births. Catalano et al. (2008) document that cold ambient temperatures during gestation predict lower secondary sex ratios and longer life span of males in annual birth cohorts composed of Danes, Finns, Norwegians, and Swedes born between 1878 and 1914. Schifano et al. (2016) estimate the effect of exposure to air pollution and ambient temperature on the risk of birth by week of gestation on singleton live births in Rome and Barcelona. Their results suggest that both temperature and air pollutants have an effect on preterm birth. The period around the second half of the second trimester of pregnancy seem to be the most susceptible, although effects are detected in the whole preterm period and among early at term for temperature.
However, few studies have investigated the impacts of prenatal temperature shocks in the context of developing countries especially sub-Saharan Africa. Wilde et al. (2017) test whether temperature spikes at conception, in utero, 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. Our paper differs from theirs in that we are concerned about prenatal temperatures shocks short-term impacts rather than the long run human capital consequences.

Our paper differs from the aforementioned literature in four important respects. First, few studies have shown how the impacts of ambient prenatal temperature shocks vary by *stage of pregnancy*, especially in the context of *developing countries* as we do for sub-Saharan Africa. In addition, while outcomes such as sex ratio at birth have been examined, fetal death and male-female differences in infant mortality have been less studied. We find that a cold temperature occurring during the first or the third trimester of pregnancy decreases the likelihood of a male birth, but increases male survival in the infant period. This finding is consistent with the assumption that only healthier male fetuses survive to adverse climatic conditions during pregnancy whereas female fetuses survive these conditions regardless of their health. To our knowledge, these results are new. They add to the general literature showing that climate shocks have uneven distributional impacts in different population subgroups. Unlike our analysis, however, this literature has primarily focused on outcomes occurring after birth.

Second, the extant literature examining the consequences of prenatal temperature shocks has primarily documented "average" effects. We show that the effects of these shocks are highly heterogeneous, being larger for older women, higher parity births, and rural residents. Analyzing impact heterogeneity not only shows that prenatal temperature shocks have uneven distributional impacts, but it is also useful to understand some of the important mechanisms through which these shocks affect outcomes.

Third, our paper is one of the few studies that document male-female differences in responses to external shocks. Existing studies have analyzed the impact of ambient total suspended particulate matter (Sanders and Stoecker, 2015), earthquake intensity (Liu et al., 2015), and temperature shocks (Catalano et al., 2008). However, the focus in these studies is somewhat different from ours. Indeed, we provide the first evidence that the differential effects of temperature shocks on male and female fetuses vary by period of gestation. So our focus on the *timing* of these shocks and on how its effect varies for prenatal vs. postnatal outcomes (that is, sex ratio at birth vs. infant mortality) is new.

Finally, we show how it is possible to use our estimated effect of temperature on sex ratio at birth to recover a lower bound of fetal mortality due to change in ambient temperature. This finding highlights the health cost of climate change in the context of sub-Saharan African countries, and can also be viewed as a contribution to the literature on the determinants of child and maternal health in the developing world. This is relevant not just for health policy design, but also for the analysis of the future impact of climate change. Policies focusing on population subgroups with low biological endowments are likely to avert the negative impacts of climatic shocks. Our results imply that these policies should account for stages of fetal development.

1.3 Conceptual Framework: How Do Temperature Shocks Affect Sex Ratio at Birth?

This section documents the possible channels through which climatic conditions including ambient temperatures (T) influence human sex ratio at birth (SRB). Factors determining the SRB are of two kinds: factors determining the primary sex ratio at conception (PSR) and factors determining sex differentials in intrauterine mortality ($SSIM$) (Chahnazarian, 1988). While the former factors are likely to play an important role in the early pregnancy period (i.e. around the period of conception), the latter factors play a role only after the fetus has been and over the course of the pregnancy. Formally, we can write the following expression:

$$SRB = PSR \times SSIM \tag{1.1}$$

where SRB is the number of live male births divided by the total number of live births (i.e. the proportion of male births), PSR is the proportion of fetuses that are conceived as male, and SSIM is the survival rate of males from conception through delivery divided by the survival rate of all babies from conception through delivery. SRB is observable in our dataset, whereas PSR and SSIM are not.

The change in the offspring sex ratio due to a marginal change in ambient temperature (T) is obtained by differentiating equation (1.1) with respect to temperature as follows:[3]

$$\frac{\partial SRB}{\partial T} = \frac{\partial PSR}{\partial T} SSIM + \frac{\partial SSIM}{\partial T} PSR \tag{1.2}$$

Temperature may influence primary sex determination by the variable fertilization success of X- and Y- bearing sperm (McLachlan and Storey, 2003). Moreover, there is evidence supporting that ambient temperature and stressful environmental conditions affect the steroid concentrations of ovarian follicles (Wolfenson et al., 2000; De Rensis and Scaramuzzi, 2003), and may also impair sperm mobility and potentially promoting female biased primary sex ratio (Fukuda et al., 1996). To help understand which of these channels drive our results we study how sex ratio at birth is impacted by temperature changes both around and after conception.[4]

The exposure to weather shocks among pregnant mothers can affect their offspring's sex ratio through three potential mechanisms that impact fetus either directly or indirectly through mother's responses. These include: *(i)* biological effect induced by heat stress which might result in several health issues including risk of placenta abruption (He et al., 2018), preterm and stillbirth (Carolan-Olah and Frankowska, 2014; Strand et al., 2011b) or pregnancy loss (Beltran et al., 2014); *(ii)* behavioral mechanism with change in consumption habits (food selection, appetite loss); given the importance of nutrition on maternal health and birth outcomes (Figlio et al., 2009), change in consumption behavior as a result of variation in ambient temperature is therefore fundamental for fetal development; *(iii)* income channel which refers to negative impacts of extreme temperature on agricultural yields and thus household resources. For instance, in rural areas where a significant fraction of income is derived from agriculture, crop yields might change in response to adverse weather shocks. Recent literature documents the relationship between high temperatures and crop yield including Schlenker and Roberts (2009) and Burgess et al. (2011).[5]

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[3]For notational simplicity, we ignore the time variable.

[4]We report these point estimates in Table 1-A.2 in appendix.

[5]For instance, Schlenker and Roberts (2009) find that temperatures above about 85 $^\circ$ F cause damages to corn and soybeans yields.

1.4 Data

1.4.1 Data Sources

Sex ratio at birth and maternal characteristics. We extract data on sex ratio at birth and on maternal characteristics from the Demographic and Health Surveys (DHS). DHS are representative at the national and subnational level, and are comparable across countries and years for most variables. They use a two-stage sampling technique, selecting clusters at the first stage and households at the second stage. The focus in these surveys is primarily on women and their children. We construct a sample of all live births using these surveys. We analyze 85 surveys from 34 countries, obtaining a sample of 1,985,399 live births. All the surveys and the years in which they were conducted are listed in Appendix Table 1-A.1. Our primary outcome of interest is an indicator that equals 1 if the child is male, and 0 otherwise. We use the information on place of residence and date of birth for each of the children born to mothers surveyed by the DHS. For each birth, we define the pregnancy period as the nine-month period that precedes the month of birth. The whole pregnancy period is divided in three trimesters. Information on maternal demographic and socioeconomic characteristics include age at delivery, marital status, educational attainment, and a household wealth index.[6] For each child, we also use information on preceding birth interval in months and number of prior children (or child birth other).

Weather variables. Historical weather data are obtained from University of Delaware air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). UDEL data are gridded at the $0.5 \times 0.5\,^{\circ}$ spatial resolution with monthly average measure 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.[7] The weather dataset extracted from UDEL is then merged to DHS using the child year and month of birth, and mother's place of residence. The merging consists of assigning to each DHS cluster unit — census enumeration area — the weather conditions of the nearest grid cell at the time of pregnancy. In keeping with the literature (Deschênes et al., 2009), we investigate whether temperature effects are non-linear by looking at the impact of average monthly temperature falling into each of five temperature bins ($<$ 18 °C, 18-22 °C, 22-26 °C, 26-30 °C, $>$ 30 °C),

[6] This index is made available in the DHS data. It aggregates the assets owned by a household using factor analysis. A greater score on the index indicates ownership of more items such as radios or motorcycles. In specifications controlling for this variable, we lose sample size because information on this variable is missing for a large number of observations.

[7] Long-term and geographically representative weather records are not widely available at the daily level in SSA countries.

with 22-26 °C considered as a reference category.[8]

Climate change predictions. To project the future impact of climate change on fetal deaths in our SSA sample, we use the CIMP5 models to obtain the predictions for the future monthly average distribution of temperature and precipitation variables used in our empirical analysis. CIMP5 models provide the most straightforward and scientifically accepted way to project future climate conditions under different RCPs.[9] The CIMP5 suggests that temperature increases for Africa with the high emissions trajectory (i.e. RCP 8.5 scenario) is 1.7°C by the year 2030, 2.7°C by the year 2050, and 4.5°C by the year 2080 (Girvetz et al., 2019), relative to a historical period (1970-2000).

Figure 1-1 represents the average temperature during pregnancy experienced by individuals in our sample of SSA countries over 1980-2010. It shows that this region of the world has experienced climate change as temperatures tend to increase over time.

1.4.2 Summary Statistics

Table 1-1 summarizes the key variables used in our analysis. Our sample period 1980-2010 covers about 1,985,399 live births with 50.8 % of them being male. The average mothers' age at delivery is around 25 years old, with few of them single (12.9%), almost half with no education (43.8%) and 26.3% living in urban areas. Regarding weather conditions during the pregnancy period, individuals were exposed to 23.96 °C and 8.9 cm of average monthly temperature and precipitation, respectively.

Figure 1-2 depicts histograms of actual (f_a^b) and predicted mid-century (under the RCP8.5 scenario) (f_p^b) distribution of average temperature by bin (b) $\in \{ <18$ °C, 18-22 °C, 22-26 °C, 26-30 °C, > 30 °C$\}$, respectively. The difference in the height of the bars represents the change in frequency of individuals exposed to a given temperature bin. Figure 1-2 suggests that most births were exposed to average temperature range between 22 to 30 °C, with few observations for extreme temperatures (i.e. <18 °C and >30 °C). However, regarding the long term predictions, Figure 1-2 reveals that individuals will be more exposed to hot temperatures rather than to cold temperatures. As projected by most of the climate models, SSA countries considered in our sample are expected to warm in the future with more hot days.

[8]Later, we show that our estimates of fetal deaths do not vary as we change the reference category bin to 18-22 and 26-30.

[9]Four RCPs were selected and defined by their total radiative forcing (cumulative measure of human emissions of GHGs from all sources expressed in Watts per square meter) pathway and level by 2100. The RCPs were chosen to represent a broad range of climate outcomes, based on a literature review, and are neither forecasts nor policy recommendations.

Figure 1-3 depicts the cross-sectional association between SRB and average temperature during the whole pregnancy period at the macro level of SSA sample countries. We group together for the entire surveyed population and for a given country the average level of temperature observed during pregnancy and the corresponding sex ratio over the entire period 1980-2010. In other words, each dot represents for a given country, aggregate average SRB (ratio of male over total babies) level associated to average temperature experienced during pregnancy. The blue line shows the trend of the relationship between the percentage of births that are male and the monthly average temperature. The shaded area represents the 0.95 confidence interval associated to this correlation.

In the cross-section, extreme cold and hot temperatures during pregnancy are positively correlated with the percentage of male births, whereas moderate temperatures positively affect female births. While this is not evidence of a causal relationship given that there might be confounders at the country level that could contribute to explaining SRB, it is a suggestive evidence that temperature affects the human SRB. Whereas Figure 1-3 captures the cross-sectional relationship between temperature and SRB at the country level, in Figure 1-4, we show the same relationship at the individual level. In this chart, for each live birth in our data, we calculate the average temperature during the entire pregnancy. This temperature is then plotted against the probability that the baby is a male. Once again, there are not controls for other potential determinants of child or mother health, so this should be taken as suggestive evidence of a possible relationship between these two variables. Two insights are derived from this chart: First, the association between prenatal average temperature and SRB seems to be non-linear. Second, the graph below is consistent with the conclusion observed at the country level, i.e., extreme temperatures are positively associated with male births, and moderate temperatures are correlated with female births. Indeed, starting from the reference bin $22 - 26$ °C moving either to the hot temperature (right) or to the cold temperature (left) increases the likelihood of a male birth.

1.5 Methods

1.5.1 Identification Strategy

The identification strategy exploits the fact that realization of temperature is as good as random once we control for location and time. In order words, after adding month and region of birth fixed effects, the observed variation in monthly temperatures experienced by pregnant mothers is as good as random. These quasi-random temperature shocks reveal the causal impacts of monthly temperature variations on the outcome of interest — gender of birth. A particular feature of this approach is that although our interest is in sex differences in fetal mortality, we only observe live births – that is, we do not observe any of the fetuses that died as a result of adverse climatic conditions. Instead, we infer fetal mortality from differences in the sex ratio at birth for live births conditional on climatic conditions (see Appendix Notes 2-B.1).[10]

Our primary specification is non-linear and investigates how SRB varies across temperature bins. Formally, we decompose temperature into each of five bins b, corresponding to < 18 °C, 18-22 °C, 22-26 °C, 26-30 °C and > 30 °C, with 22-26 °C being considered as the reference category.[11] Our main regressor — average temperature experienced on a given period or window of pregnancy including the whole 9-months pregnancy — is a categorical temperature variable.[12] We therefore estimate the following non-linear specification:

$$Male_{ijrt} = \sum_{b} \alpha_b * TEMP^b_{ijrt} + X_j\beta + \mu_r + \delta_m + \epsilon_{ijrt}, \tag{1.3}$$

where $Male_{ijrt}$ is a binary variable that equals 1 if child i born to mother j in region r, at a given time of pregnancy stage t , is a male, and 0 otherwise. Note that t corresponds to a trimester of pregnancy (first, second and third) or the whole nine month pregnancy period depending on the specification. The region r reflects the DHS cluster unit in which the child was born. DHS cluster units are small geographic areas similar to census enumeration areas. $TEMP^b_{ijrt}$ is an indicator that equals 1 if the average temperature on the corresponding window of pregnancy (first, second or third trimester) is in bin b and 0 otherwise. For instance, if an individual experienced an average temperature of 20 °C during the whole pregnancy period, $TEMP^b_{ijrt}$ equals 1 if b$\in$ 18-22 °C and 0 otherwise. X_j is a set of control variables of mother characteristics such as age at delivery, marital status, birth interval in months, number of prior sons, number of prior children (or child birth other), household's wealth and educational attainment.[13] To account for regional and seasonal variation in activities (employment level, change in climatic conditions, etc.) specific to each region, we add region and month of birth fixed effects, μ_r and δ_m, respectively. Finally, the error term,

[10]Figure 1-B.2 describes the relative change in fetal death due to an extreme temperature shock for different values of the primary sex ratio.

[11]We choose 22-26 °C as the reference category because the average monthly temperature in our sample is about 23 °C. We are therefore interested in how temperature deviation from this reference category impacts our primary outcome, the SRB.

[12]Much of the recent literature studying the effects of temperature on socio-economic outcomes uses daily or even hourly measures of temperature. In contrast, our paper uses monthly average temperature, since daily temperature observations for SSA are sporadic, more scarce and unreliable than in any other region in the world (see Dell et al. (2014) for a more detailed discussion).

[13]This set of regressors follows Chahnazarian (1988) and controls for socio-economic determinants of human sex ratio at birth (SRB).

ϵ_{ijrt}, represents unobserved shocks and is assumed to be uncorrelated with the regressor of interest.

Later, as a robustness check, we model a polynomial specification of the relationship between SRB and a continuous measure of temperature experienced on a whole gestational period. Specifically, the functional form includes quadratic terms of temperature:

$$Male_{ijrt} = f(TEMP_{ijrt}) + X_j\beta + \mu_r + \delta_m + \epsilon_{ijrt} \tag{1.4}$$

In addition to the above specification in equation 1.4, we consider changes from our preferred specification (equation 1.3) as alternative specifications. One concern with our main specification is that there are unobserved mother characteristics that might be correlated with sex ratio, and that mothers are heterogeneous in their ability to time pregnancies. To address this potential source of confounding, we run a specification that includes mother fixed effects. Identification in this model is derived from variation in temperature exposure across siblings born to the same mother, and addresses potential concerns related to heterogeneous timing of births across mothers with different characteristics. Another threat to causal inference is that other weather indicators, especially rainfall variation, could interplay with our results. We run our main specification of the impact of temperature shocks on SRB controlling for average precipitation level, given that the latter is a key determinant of agricultural yields and susceptible to significantly affect the likelihood of infectious diseases with negative impacts on mother's health. We also interact region and month of birth, along with year of birth fixed effects to capture regional changes from year to year rather than monthly frequency, susceptible to impact birth outcomes such as investments in public health infrastructures and modern technologies in pregnancy follow-up.

Since we cover the entire SSA countries and because the temperature profile in the different months throughout the calendar year does not necessarily follow the same pattern, we interact month FE with country FE. Alternatively, we estimate our preferred specification for each country separately and show whether the effects vary by country.

Second, our setting assumes that place of birth is the same as the place of residence, which might not be the case as women might move after conception or before birth. As a result our estimates can be biased since we imperfectly measure the exposure to temperature shocks. To check the robustness of our results, we run our preferred specification on a sub-sample of women who reported they have been living in the same place for at least 10 years.

As an attempt to study possible mechanisms through which temperatures affect sex ratio, in section 1.8, we study heterogeneity in temperature effects. We include interaction terms between temperature variables and mother's characteristics such as age at birth, birth order, and education. We are uncertain whether or not the learning process by mother from birth to birth dominates over her health status which declines with age and with the number of prior children born. We test these two channels by estimating heterogeneous treatment effects.

In an extension, in section 1.9, we further explore the impacts of temperature shock on the infant mortality (mortality occurring within the first year after birth) for each sex category. Looking at the differential impact of temperature on infant mortality by sex serves to validate our argument of fetal mortality as a main driver of offspring sex ratio. Indeed, if we believe that male fetuses are more fragile than female fetuses (Kraemer, 2000), we expect to find a greater effect of temperature shocks on females after birth as sex-biased in utero mortality selection implies that among fetuses that survive to birth, males are healthier than females.

1.6 Main Results

1.6.1 Impact of Extreme Temperature on Sex Ratio at Birth

We find that cold temperature at the time of pregnancy is negatively correlated with a male birth. Table 1-2 reports our main estimates of equation 1.3. Each column refers to the estimation of equation 1.3 for a given trimester of pregnancy as well as the whole gestational period. All regressions include region and month of birth fixed effects, and control for mother's characteristics. The latter includes mother's age at delivery, marital status, birth interval in month, number of prior children (or child birth order), and educational attainment.[14] The coefficient estimates are interpreted relative to the reference temperature bin 22-26 °C. It follows that, irrespective of the trimester of pregnancy, cold temperatures decrease the likelihood of a male birth. For instance, relative to ambient temperature in 22-26 °C, an average temperature below 18 °C experienced during pregnancy decreases by 0.712 percentage points the probability of a male birth, which is a substantial effect.

The effects of hot temperatures on male birth depend on the trimester of pregnancy. Our estimates show that, relative to an average temperature in 22-26 °C, a mean temperature above 30 °C experienced in the first and third trimester of pregnancy decreases the probability of a female birth by 0.438 and 0.484 percentage points, respectively. The magnitudes of the effects are statistically significant and consistent across trimesters. Figure 1-A.1 represents graphically these point estimates of the effects of mean temperature on a male birth by trimester of pregnancy. The shaded areas represent the 95 percent confidence interval

[14]Our results do not vary as we remove those mother's controls. In other words, they are not likely to be driven by selection on unobservables.

associated to these point estimates.

These point estimates are obtained with a dummy indicator for whether the entire pregnancy had an average temperature in a certain bin. One concern with this way of measuring average temperature during pregnancy is that differences in distribution of temperatures across the 9-month gestational period may influence mothers differently. For instance, an average temperature of 20 °C during pregnancy that results from a 20 °C temperature in each month of the 9-month of pregnancy period has a different effect than an average temperature of 20 °C obtained from a distribution in which temperature varies from one month to another during the pregnancy period. To account for this possibility, we use a count variable of the number of months where temperature belongs to a specific bin. Table 1-A.4 reports results of this specification where we estimate equation 1.3 in which we replace our main regressor by a count variable of the number of months on a given window of pregnancy, where temperature falls in a specific bin. Our findings are consistent with the main results of this paper solely when we consider the effects during the first trimester of pregnancy as shown in column (2). We have two plausible explanations to that: First, this result implies that first trimester appears to be the most critical window of gestational period, consistent with the biology literature. Second, this finding could be due to the fact that most individuals from our sample were less exposed to average temperature in extreme cold and hot bins in the rest of trimesters of gestation.

Our estimates are consistent with those from prior studies, which indicate that cold temperatures during pregnancy negatively affect the probability of a male birth (Catalano et al., 2008). According to Trivers and Willard (1973), these prenatal adverse conditions induced by cold temperatures should be more crucial for male fetuses compared to female fetuses. Our findings are supportive to the latter hypothesis. Moreover, the effect we find persists over the different stages of pregnancy. Since primary sex formation occurs during the first trimester, this evidence suggests that the effect of temperature operates primarily through sex selective intrauterine mortality, rather than primary sex selection.

What could explain mortality in females when it is hot? Or said differently, why does the occurrence of male births increase with higher temperature in SSA? Although we do not have direct answer to this question, our explanation is based on the fact that people in tropical countries are familiar to average hot temperature. It follows that, cold temperatures, more unusual, are perceived as a negative shock to individual health. Therefore under the assumption that negative environmental conditions are associated with cold temperatures, our results are in line with Trivers and Willard (1973) and provide evidence that with warmer expected temperatures in the future, the sex ratio at birth will be biased towards males.

1.6.2 Robustness Checks

Non-linearity in the Effect of Temperature

Our main specification uses a non-parametric binning approach to allow for non-linearity in the effect of temperature on the probability of being born male in equation 1.3. In this section, we estimate equation 1.4, which allows temperature to non-linearly affect SRB using a polynomial specification. For ease of presentation, we present these estimates graphically. Figure 1-4 in section 2.5 suggests a quadratic functional form of the relationship between temperature and the probability of a male birth. We therefore regress a binary indicator for male birth on the level and the quadratic term of the average temperature experienced during pregnancy minus 22 °C . The coefficients of interest are therefore interpreted as marginal effects of relative average temperature (compared to 22 °C) on the probability of having a male birth. This effect is graphically represented by Figure 1-5.

Results are consistent with those obtained with the temperature bins model. Although the point estimates are percentage point higher than those obtained with the binned model, the shape of the relationship stays constant with hot temperatures tending to favour male birth.

Alternative Specifications

We replicate our preferred specification, this time using the average temperature of the whole period of pregnancy as the main predictor, and adding controls such as rainfall together with different fixed effects as in Table 1-2. Table 1-3 summarizes our results. For ease of analysis, we estimate our main specification in column (1). We then consider different alternative specifications presented in columns (2)-(6) where each of them differ from our preferred specification in column (1) by a given set of controls and/or fixed effects.

Column (2) adds to our preferred specification mother's fixed effect. This variable controls for the possibility that there might be unobserved mother's characteristics correlated to sex ratio and pregnancy timing, given that mothers are heterogeneous in their ability to time pregnancies. Estimates in column (2) show that cold temperature negatively affects the likelihood of male birth. Specifically, an average temperature below 18 °C experienced during pregnancy, decreases the probability of male birth by 0.512 percentage points.

Column (3) accounts for the possibility that regional changes are more likely to happen from year to year rather than on a monthly basis. It therefore controls for year of birth fixed effects. Our findings are consistent with those obtained from the main specification.

Column (4) controls for average precipitation during pregnancy. Findings are consistent with those from the main specification and suggest that despite variation in rainfall, cold temperatures still have an economically and statistically significant impact on the likelihood of male birth. Finally, column (5) and (6) report our estimated coefficients in which we interact month of birth and country, and month of birth and region fixed effect, respectively. The latter specification aims to capture the difference in seasons across countries and regions within country. Therefore, our coefficients of interest are interpreted as the net effect of change in temperature on the likelihood of a male birth. Results from this specification in column (5) and (6) are consistent with the main result of the paper, i.e., extreme cold temperature are associated with fewer male births while hot ones are negatively associated to female births.

Addressing Migration Concerns

One potential source of bias in our estimates is migration that occurs after conception but before birth. Since we only observe the place of residence and not the place of birth nor the place of conception, so far, we have assumed that they are all the same.[15] If this is not the case, one cannot be sure that the individuals in our sample were exposed to the realized temperatures in their region of birth. In order to support the robustness of our results, we interact our main regressor — average temperature during pregnancy — with a dummy variable equal to 1 if the mother has lived at least 10 years at the place of residence, and 0 otherwise. Figure 1-6 reveals that results are consistent with those obtained in Table 1-2. Indeed, irrespective of the number of years a typical mother has spent at the place of residence, a cold weather shock decreases the probability of a male birth whereas a hot weather reduces the probability of a female birth.

1.7 Long-term Effect of Climate Change on Fetal Mortality

This section shows how to recover, from our reduced-form model, a lower bound of fetal mortality (for males and females pooled together) due to change in average temperature. We consider fetal mortality estimation as a lower bound given that our empirical setting only captures the unbalanced effect of temperature shock on a given sex; that is, if the shock affects identically male and female fetuses, we do not measure it. In others words, deviation of point estimates from 0 indicates mortality in one sex relative to the other due to ambient

[15] See Wilde et al. (2017) for similar assumptions.

temperature. Therefore, our setting measures a lower bound of the true impact. In order to estimate fetal mortality, we assume that temperatures between 22 and 26 degree Celsius are optimal, such that deviations in the sex ratio that correlate with temperatures above or below this range reflect fetal deaths. We later test the sensitivity of our results to this assumption.

In keeping with the literature (Zhang et al., 2018), we derive a lower bound of fetal mortality due to variation in current temperature as a weighted summation of all marginal effects observed during the whole pregnancy period. Following column (1) of Table 1-2, estimates are associated to each of our five temperature bins. To derive the lower bound of fetal deaths, we weighted each estimates to the corresponding actual temperatures bins distribution f_a^b experienced during the entire pregnancy period. Given that each point estimate corresponds to the marginal effect of a typical temperature bin on the likelihood of a male birth, adding these point estimates weighted by the distribution of temperature bins allows to derive an estimation of a lower bound of fetal mortality. Formally, the lower bound is obtained from equation 1.5 as follows:

$$LowerBound = \sum_b f_a^b \mid \hat{\alpha}_b \mid, \tag{1.5}$$

where f_a^b indicates the actual distribution of average monthly temperature by bin. Solving equation 1.5 leads to 200 fetal deaths per 100,000 live births in our SSA sample due to actual distribution of temperature.

To predict the effect of climate change on fetal mortality and sex ratio at birth (SRB) by mid-century (2050) in our SSA sample, we use the regression coefficient estimates for each temperature bin variable from equation 1.3. We then calculate the predicted difference in each temperature bin as $(f_p^b - f_a^b)$ as projected by CIMP5 models under RCP 8.5 scenario by 2050. These predicted differences are then multiplied by the relevant estimated regression coefficient to infer the impacts of climate change on fetal mortality and SRB for individuals from our SSA sample. Standard errors are calculated using the delta method.[16] It is important to explain some of the assumptions behind these climate predictions. While we allow climate change to affect the distribution of weather variables such as temperature and precipitation, we hold all other determinants of SRB constant. This includes, among others, change in socio-demographic characteristics, technology improvement related to maternal health, fertility rate dynamics. Finally, our calculations suggest that fetal mortality is projected to be around 400 deaths per 100,000 live births by mid-century in our SSA sample.

[16]The delta method is a simple and widely used tool to derive the asymptotic distribution of nonlinear functional of an estimator. The essence of the delta method is a first order Taylor expansion of the functional.

We summarize our estimations of lower bound of fetal mortality due to temperature shocks as well as the corresponding SRB in Table 1-4. This prediction might seem counter-intuitive as our paper main finding highlights the detrimental effects of cold shocks on the likelihood of male birth. Therefore, understand how long term warming will lead to increase in fetal deaths is somehow confusing. To help clarified the long-term prediction, we put together two results derive from our analysis. The first is drawn from figure 1-2 which shows that under the RCP 8.5 scenario predicts an increase in hot days, that is days with average temperature greater than 26-30 degrees Celsius. The second result presents in table 1-2 shows that there is a fraction of mortality in female babies that comes with higher temperatures. Together, these two evidence support our long term predictions and suggest that mortality will be higher among female babies as we expected to have more frequent hot days.

As we acknowledge, one concern is that our estimates might depend on the chosen reference temperature bin. To address this treat to our results, we repeat this exercise and report the actual and predicted estimations of fetal mortality by temperature bin. As shown in Table 1-A.3 in appendix, our results do not vary with reference temperature bin.

1.8 Mechanisms: Heterogeneous Effects of Temperature Shocks

In this section we explore the potential channels through which prenatal ambient temperatures affect fetal outcomes. While it is beyond the scope of this study, and beyond the limitations of the available data, to disentangle all possible mechanisms, we can use heterogeneous treatment impacts to help reduce the set of plausible explanations and to understand some possible policy implications regarding the mitigation of climate shocks.

Our heterogeneity in the impacts of average temperature during pregnancy underlines two possible channels which both affect mother's behavior and health. The direct effects that capture the parental experience analyzes how impacts vary with mother's education, age at delivery and child birth order. Through these heterogeneity effects we aim to test whether or not, mother's learning process and adaptation to climate shocks dominate over the health status, as the later is supposed to change over time.

Temperature can also affect mother indirectly via the effects of agricultural yields in rural areas and through the quality of health infrastructures and technology specific to maternal follow-up. These two ideas (change in income agriculture and quality of health infrastructure) are examined using DHS variable individual place of residence, either rural or urban zone.

To test these heterogeneous treatments, we estimate the non-linear version of equation 1.3, considering four intrinsic characteristics of the mother — education, age at delivery, birth order, and place of residence (urban vs rural). Formally, we run the following model:

$$Male_{ijrt} = \sum_{b} \alpha_b * TEMP^{b}_{ijrt} \times H + X_j\beta + \mu_{rm} + \epsilon_{ijrt} \tag{1.6}$$

where H $\in \Big\{$ education; age at delivery; birth order; place of residence. $\Big\}$

Results are reported in Table 1-5. The dependent variable is an indicator equal to 1 if the sex at birth is male and 0 otherwise. This table shows temperature heterogeneous effects for the whole pregnancy period — estimated coefficients with standard errors in the brackets. Heterogeneous characteristics consider mother's education, age at delivery, child's birth order, and place of residence (urban vs. rural). The omitted categories considered are mother having education, and living in rural area for variables education and place of residence (urban or rural), respectively. We run our preferred specification with region and month of birth fixed effects and controls for mother's characteristics.

Overall, our heterogeneous results indicate that age at delivery, child birth order, and place of residence are important determinants of the sensitivity of fetus to high and low temperatures. While the estimates show that the effect of temperature of the probability of a male birth does not vary significantly by education, we find that it is larger for rural women compared to their urban counterparts. More precisely, unlike in rural areas, a cold shock in urban areas observed during pregnancy is more likely to increase a male birth. The previous result on the effect of temperature shock on the probability of a male birth in urban areas is intuitive. Indeed, in most SSA countries, urban areas have a level of development that offers better health infrastructures and a better quality of life compared to poorer rural areas. This difference in the level of development therefore affects the quality of health care and prenatal supervision enjoyed by women living in urban areas relative to those living in rural ones. The main result in this paper indicates that cold (respectively, hot) average temperatures experienced during pregnancy reduce the likelihood of a male (respectively, female) birth. This heterogeneous result thus indicates that the negative effect of cold (respectively, hot) average temperatures shock on a male (respectively, female) birth is mitigated in urban areas endowed with better infrastructures compared to rural areas.

Relative to parental experience to adapt and learn from climate shocks, our results are not conclusive. Indeed, younger mother with few births are less affected by temperature shocks compared to their counterparts. This result is consistent with the biological literature which states that age and multiple births are both risk factors susceptible to reduce the probability to carry fetus through delivery.

1.9 An Extension: Sex-specific Effect of Temperature on Infant Mortality

So far, we have shown that in utero average temperature affects the offspring sex ratio and that this effect differs across stages of pregnancy. We have also examined how these effects vary with mother's characteristics and how estimates can be used to recover a lower bound of climate related fetal death rate. In this section, we extend the analysis to infant death, which lends additional credence to our argument that temperature shocks affect sex ratio at birth through fetal death. The infant period —the period between birth and the age of one year —is a natural extension of the period during which critical child development continues. In addition, before the age of five, death rates are the highest during the infant period (Pongou et al. (2019)).

In analyzing the effect of in utero temperature shocks on infant mortality, we distinguish between male and female children. In regions where females are not discriminated against in the allocation of foods and other health resources, death rates are higher for boys compared to girls due to sex differences in prenatal and biological factors (Pongou (2013), Pongou (2015), Pongou et al. (2017), Pongou (2020)). If prenatal temperature shocks have a greater effect on weaker male fetuses than on weaker female fetuses, then fetuses that survive to adverse prenatal conditions will produce stronger boys than girls. If so, male-female differences in the effects of prenatal temperature shocks on infant mortality will be in the opposite direction to their effects on sex ratio at birth.

The findings are reported in Table 1-6. All regressions are clustered at the mother level and control for child birth order. We consider the average temperature in each temperature bin experienced during the whole 9-month pregnancy period. The coefficient estimates are interpreted relative to a reference temperature bin, 22-26 °C, with standard errors in brackets. We find that a cold temperature shock experienced during pregnancy decreases the probability of infant mortality. This effect is larger for boys than for girls, and is opposite to what happens in utero, as a cold temperature shock reduces sex ratio at birth, meaning that its effect on fetal mortality is greater for male fetuses than for female fetuses. Our results therefore indicate that poor conditions in utero are more harmful for males relatives to females (Kraemer, 2000).

While Table 1-6 reports non-linear estimates of the effects of temperature in each bin averaged over the whole 9-month pregnancy period, Table 1-2 breaks the analysis by trimester of pregnancy. Our findings show that cold temperatures in the first trimester only reduce infant mortality (Panel A). In the first trimester, an average temperature below 18 °C decreases mortality more in girls than in boys, and an average temperature in the range 18-22 °C decreases mortality more in boys than in girls (Panels B and C). A cold temperature shock occurring in the second trimester of pregnancy increases infant mortality. The effect larger for boys than for girls for average temperature below 18 °C, and larger for girls for average temperature in the range 18-22 °C (Panels B and C). Temperature shocks occurring in the third trimester have no significant effect in general (Panel A), except in girls in which they increase mortality (Panels B and C). Our results are somewhat consistent with the notion that only healthy males are likely to survive to fetal insults, whereas the survival of female fetuses depends less on their health.

1.10 Conclusion

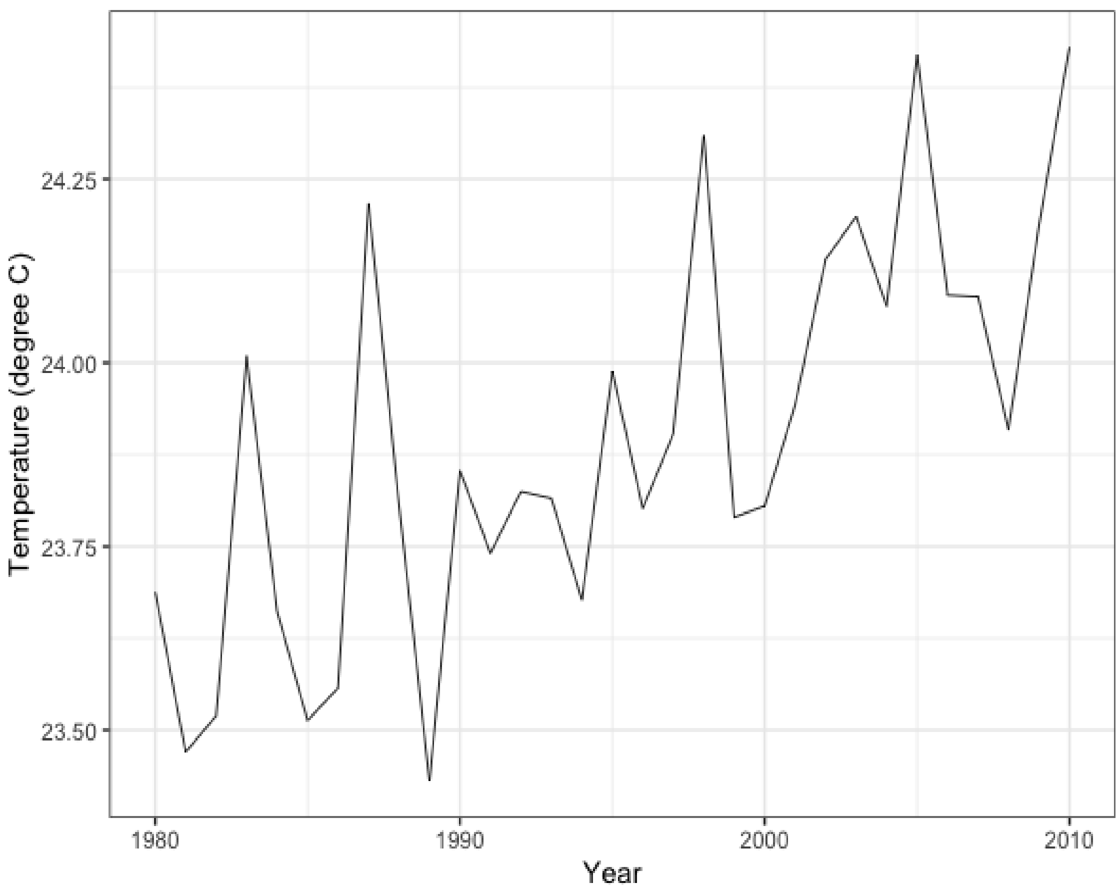
This study provides new causal evidence on how the timing of prenatal climate shocks affects early-life human capital formation. We achieve a threefold goal. First, we estimate the direct impact of average temperature during pregnancy on sex ratio at birth, and document for the first time how this effect varies over the course of pregnancy. Adjustment in the sex ratio at birth in response to adverse climatic shocks is used as an alternative measure of fetal mortality. Second, using our estimated effects in combination with a climate model, we are able to uncover a lower bound of the actual and long-term impacts of climate change on fetal mortality (for male and female fetuses pooled together). Third, as an extension of our analysis, we analyze the sex-specific impact of prenatal temperature on infant mortality. In addition to these analyses, we provide evidence for the heterogeneous effects of temperature shocks, therefore documenting some key mechanisms through which these shocks operate.

Our analyses use Demographic and Health Surveys (DHS) from sub-Saharan African countries and historical gridded monthly data on temperature and precipitation from University of Delaware precipitation dataset (UDEL). Our main findings show that male and female fetuses are affected differently by adverse environmental conditions, and that these effects vary with gestation period. Irrespective of the trimester of pregnancy, a cold temperature shock decreases the likelihood of a male birth. For instance, relative to ambient temperature in 22-26 °C, an average temperature below 18 °C experienced during pregnancy decreases by 0.712 percentage points the probability of a male birth. These findings are consistent with those obtained in developed countries, where adverse climatic conditions such as ambient colder temperature during pregnancy is more harmful for males relative to females (Catalano et al., 2008). In our analysis, we find that the effects of prenatal temperature shocks are non-linear, being more pronounced in the first and third trimesters of pregnancy. They are also highly heterogeneous, being larger for older women, higher parity births, and rural residents. We further provide a lower bound estimate of fetal mortality of around 200 fetal deaths per 100,000 live births in response to actual cold and hot temperature experienced during the pregnancy period. Moreover, using a well-known climate model, we derive the future predictions of fetal deaths of around 400 per 100,000 live births by 2050 throughout sub-Saharan Africa. Finally, we extend our analysis to infant mortality, finding that, in contrast to their differential effects on fetal mortality, prenatal temperature shocks increase infant mortality more for girls than for boys, which suggests that only healthier male fetuses survive to fetal insults.

Our findings have important policy implications. Estimates of change in fetal death, sex ratio at birth, and infant mortality are relevant as these outcomes affect future social movements such as marriage, crime, and the labor market. Our analysis can also inform public policies designed to prevent pregnant women from the adverse effects of climate shocks. It implies that such policies should account for stages of fetal development.

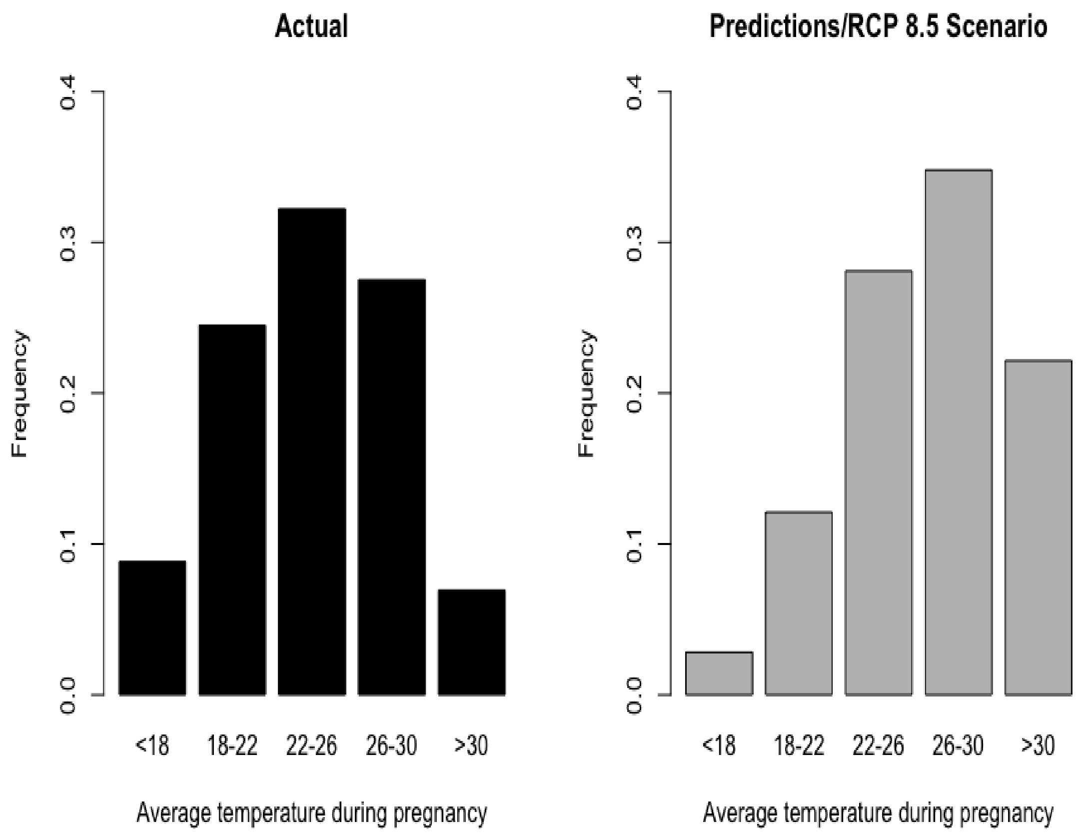
Figures and Tables

Figure 1-1: Average temperature during pregnancy in our sample of SSA countries over 1980-2010



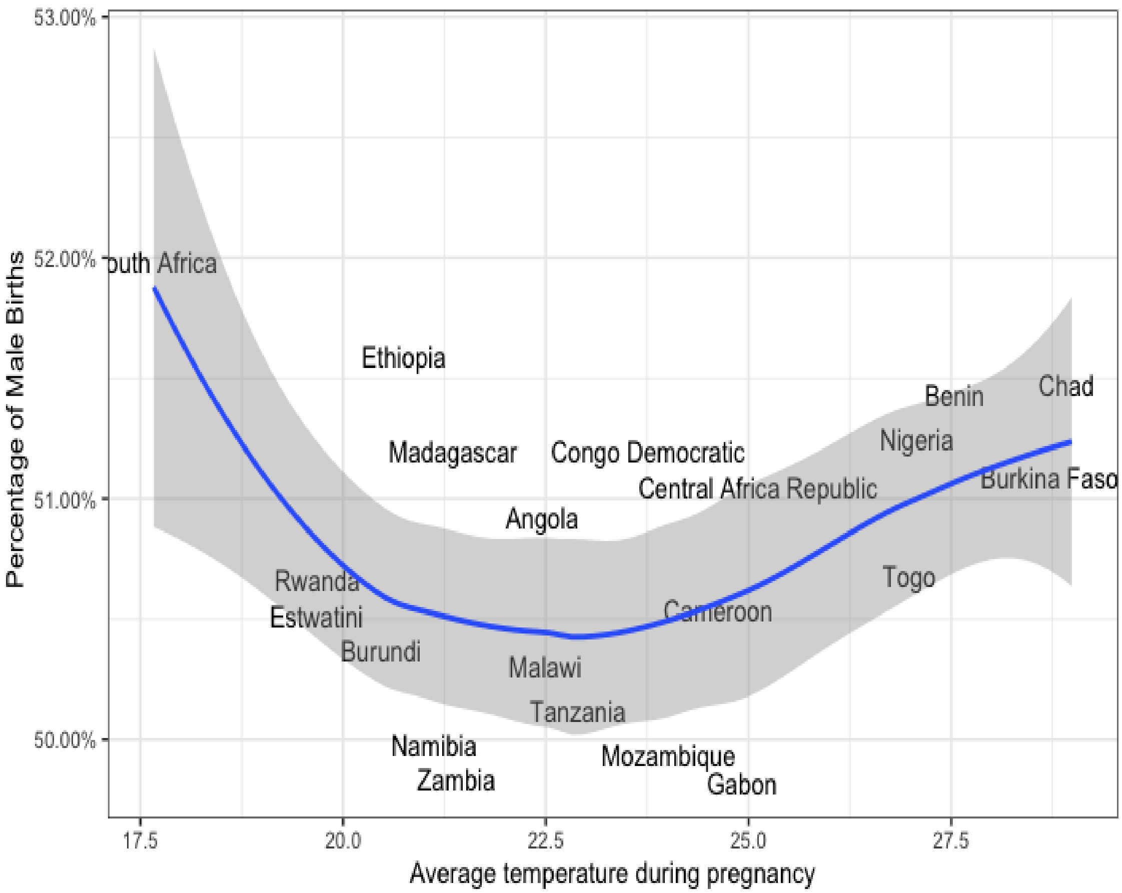
Notes: The figure above plots the change in average temperature experienced by individuals during their 9-month pregnancy period over 1980-2010.

Figure 1-2: Distribution of actual and predicted monthly average temperature bins



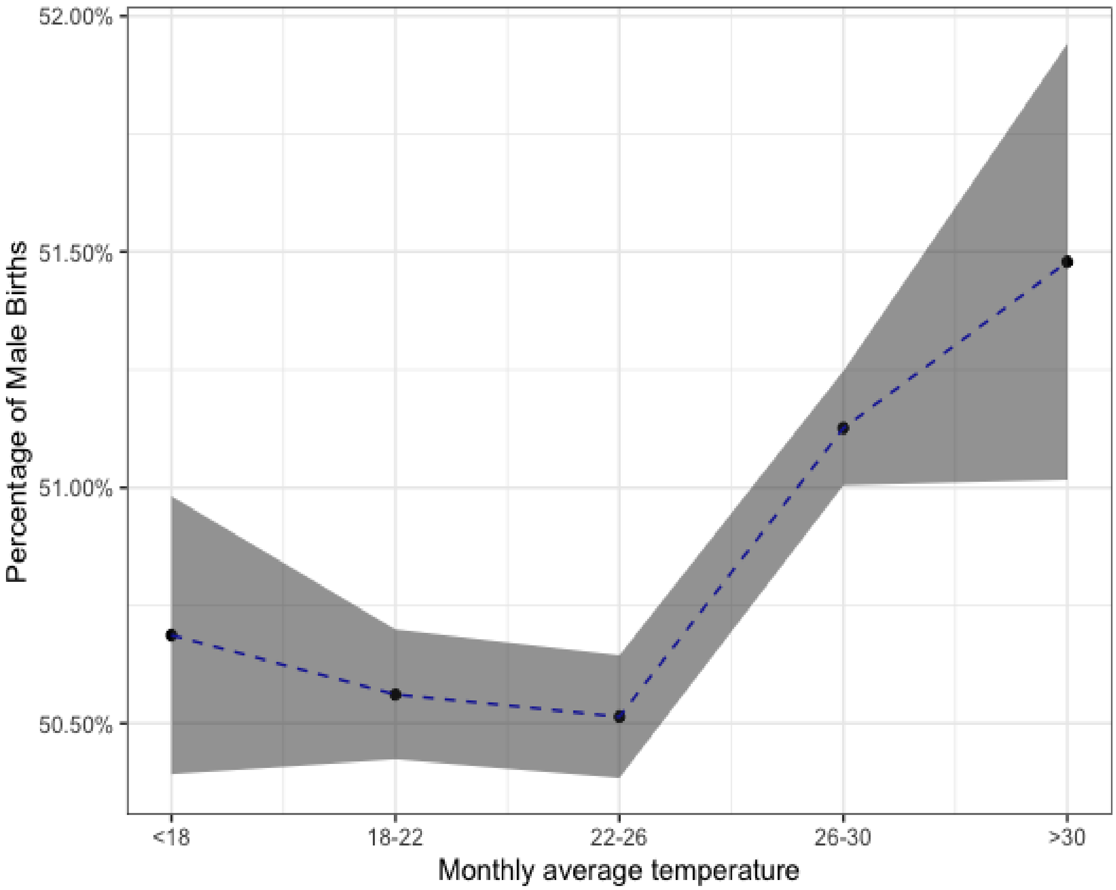
Notes: The figure above plots the actual and long-term predictions of monthly average temperatures. The projections of future temperature are obtained from CIMP5 models under the RCP 8.5 scenario. This model projects a change of 2.7°C in temperature by 2050, relative to a historical period (1970-2000).

Figure 1-3: Country-level percentage of male births and temperature over the period 1980-2010



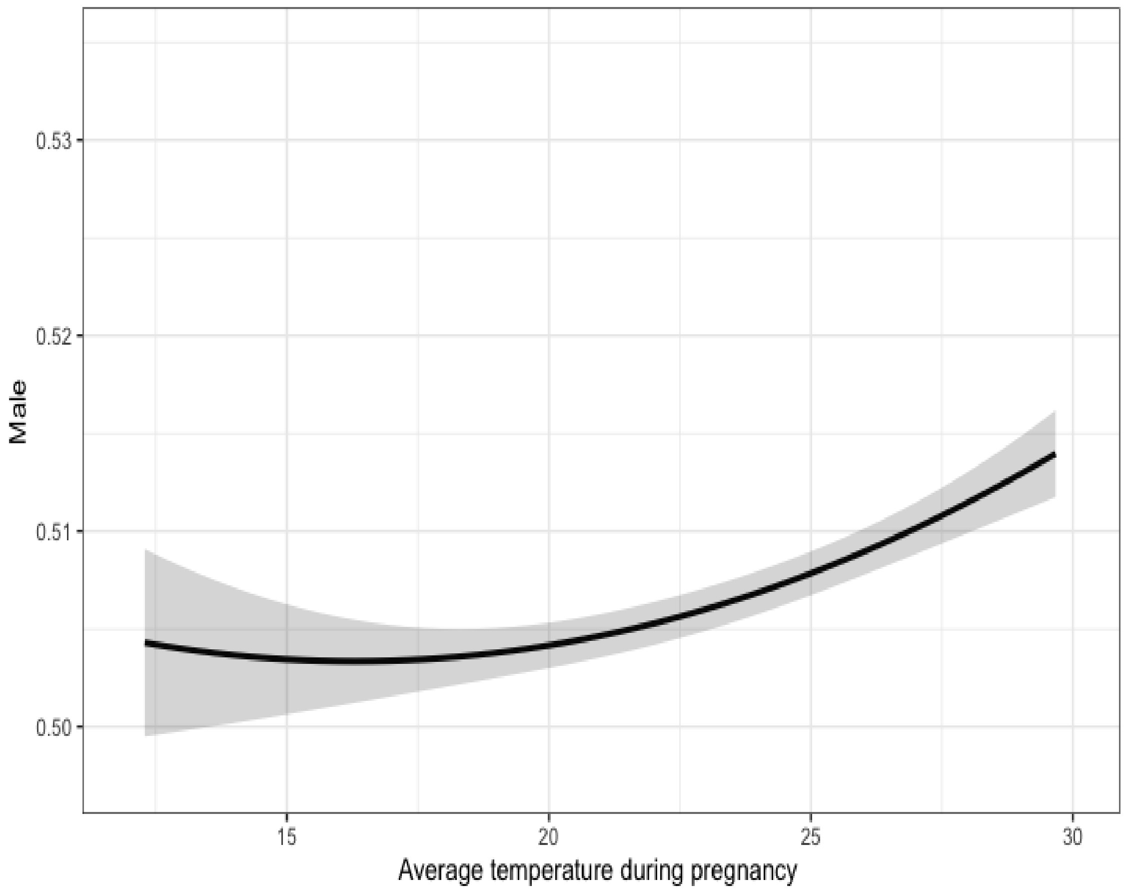
Notes: The figure above is obtained from DHS data on live births. We group these observations by country for a sample period 1980-2010. We represent for a given country aggregate average SRB (ratio of male over total live births) level associated to average temperature experienced during pregnancy. The blue line shows the trend of the relationship between the percentage of births that are male and the monthly average temperature. The shaded area represents the 0.95 confidence interval associated to this correlation.

Figure 1-4: Percentage of male births by temperature bins during gestational period



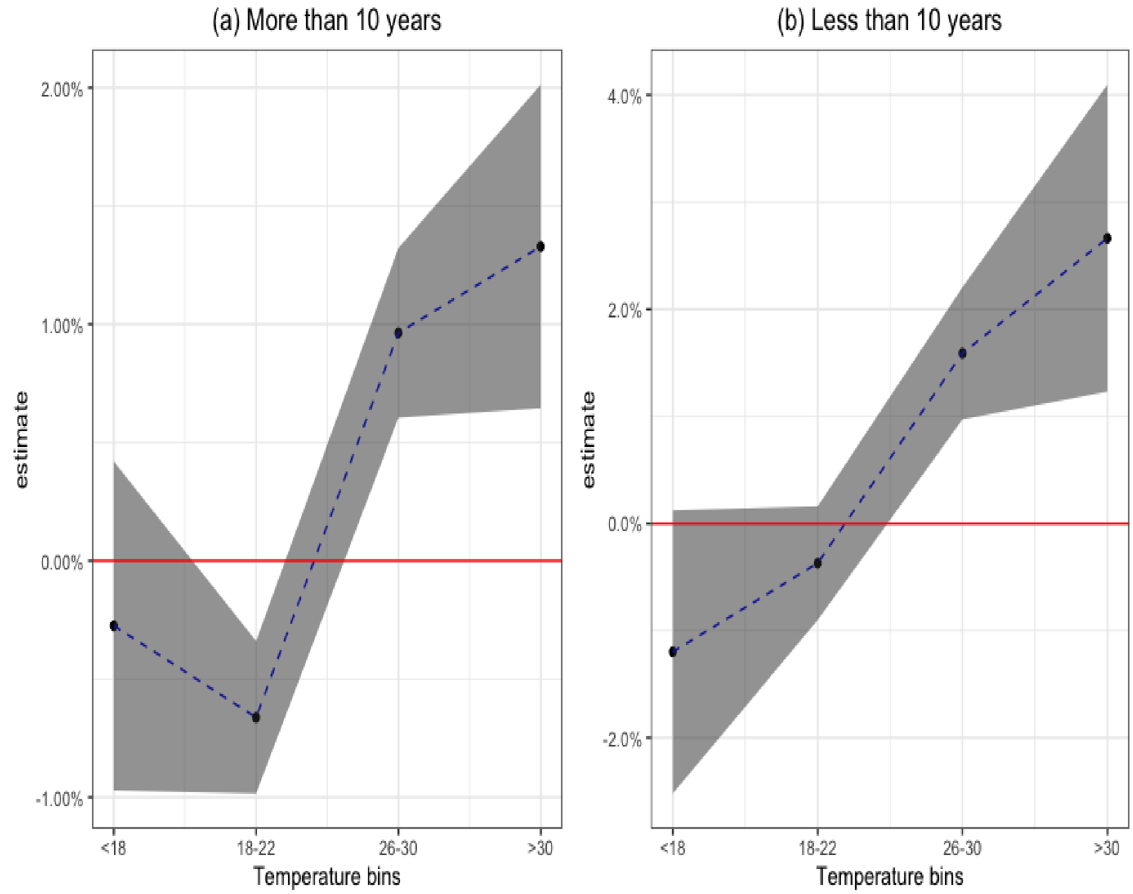
Notes: The figure above is obtained from DHS data on a sample of live births. We aggregate temperature bins during the gestational period for the whole sample period 1980-2010. This chart shows the association between male births and temperature bins with 22-26 °C as reference category. Shaded area represents 0.95 confidence interval. Roughly, it appears a non-linear relationship between temperature and male births.

Figure 1-5: Temperature effect on male birth using a quadratic model



Notes: The figure above represents a quadratic polynomial functional form of the relationship between average temperature during the pregnancy period and probability of male birth. The coefficient estimates represent the marginal effects of average temperature on male birth. The shaded area represents the 0.95 confidence interval.

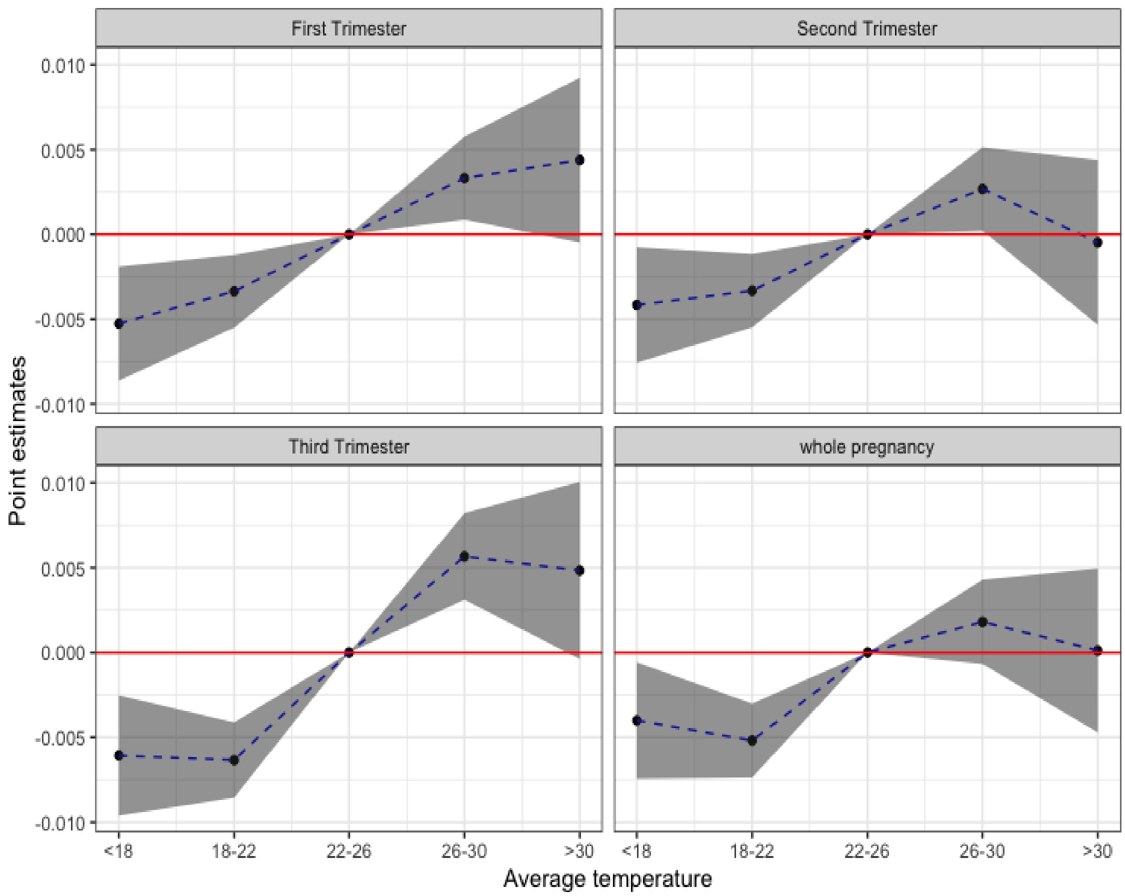
Figure 1-6: Temperature effect on male birth by number of years lived at place of residence



Notes: The figure above represents the point estimates of the relationship between average temperature during pregnancy and probability of a male birth. This relationship is shown for mothers who have spent more than 10 years in their place of residence at the survey (Panel (a)), and for mothers who have spent less than 10 years (Panel (b)). The coefficient estimates represent the marginal effects of average temperature on male birth. The blue line shows the trend of the relationship between these variables and the shaded area represents the 0.95 confidence interval associated to these points estimates.

1-A Appendix

Figure 1-A.1: Non-linear effects of temperature shocks on male birth (%)



Notes: The figure above is obtained from DHS data on live births. It represents the point estimates of change in probability of male birth due to temperature bins by trimester of pregnancy. Shaded area represents 0.95 confidence interval.

1-B Notes

1-B.1 How do we recover the fetal death?

In this section, we explain how we recover the magnitude of fetal death. The sex ratio at birth is a product of the primary sex ratio and sex selective intrauterine mortality:

$$SRB = PSR \times SSIM$$

Neither the primary sex ratio nor the sex selective intrauterine mortality are observed directly. We postulate that intrauterine mortality is dependent on temperature during pregnancy and gender of the fetus, such that the probability of fetal mortality (FM) is:

$$FM = \beta \times 1[male] \times 1[extreme]$$

Where *extreme* is a binary variable that is indicative of a temperature extreme experienced by the fetus during pregnancy (i.e., extreme cold or extreme heat), and β is the probability of male fetal mortality as a result of extreme temperature during pregnancy. This simple specification allows for gender-specific differences in fetal response to adverse climatic conditions. With these definitions, we can define the expectation that the gender of a baby is male:

$$\begin{aligned} E[male] &= PSR \times SSIM \\ &= PSR \times \frac{(1 - \beta \times 1[extreme])}{(PSR(1 - \beta \times 1[extreme]) + (1 - PSR))} \\ &= \frac{(1 - \beta \times 1[extreme])}{(1/PSR - \beta \times 1[extreme])} \end{aligned}$$

A regression of male on *extreme* will then recover an intercept of PSR and a coefficient on *extreme* of $\frac{\beta(PSR-1)}{1/PSR-\beta}$. For a PSR of 0.5, for example, this reduces to: $\frac{-0.5\beta}{2-\beta}$. For example, if the probability of male fetal mortality during extreme temperature is $\beta = 0.5$, the regression will recover a coefficient of -0.17. In general, as shown in the figure below (Figure 1-B.2), the relationship between β and the coefficient recovered in the regression of a male dummy on an extreme temperature dummy is non-linear. Our regression recovers a coefficient of -0.007 from a regression of a male dummy on a cold weather dummy, with controls. Assuming a PSR of 0.5, this suggests that cold weather kills 2.8% of male fetuses (relative to female). Figure 1-B.2 below shows how the coefficient depends on β for different values of the primary sex ratio.

Figure 1-B.2: Fetal mortality due to extreme temperature

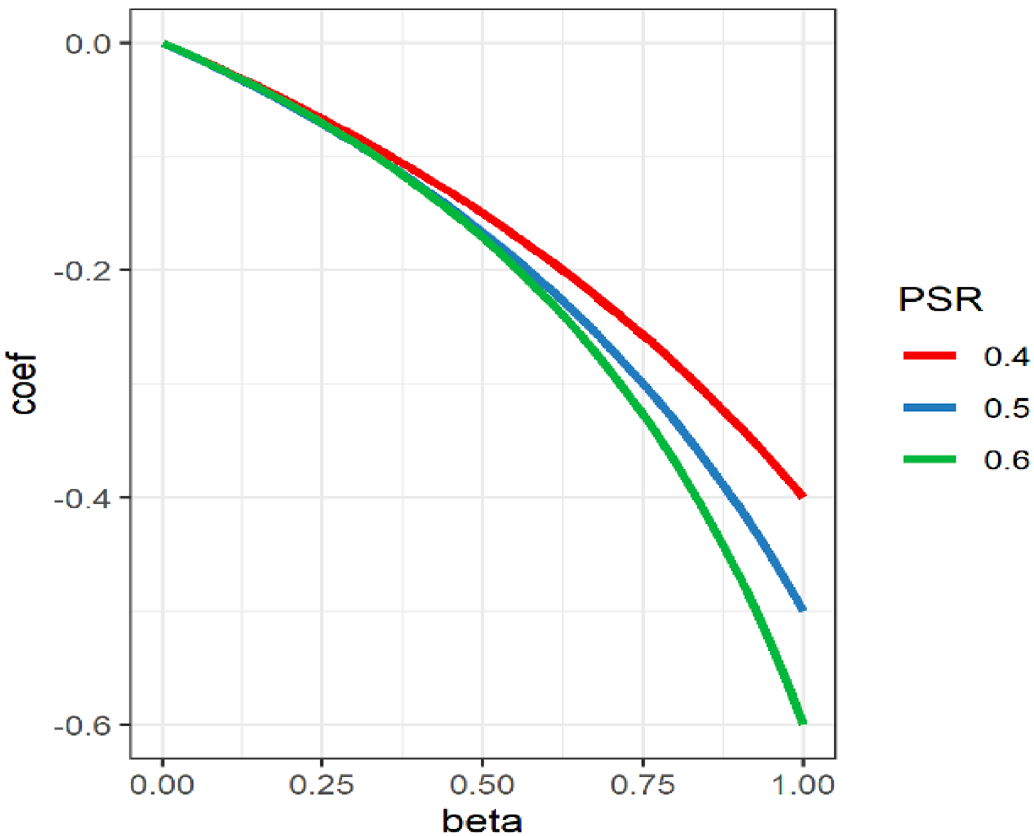


Table 1-1: Descriptive statistics

Variables	N	Mean	St. Dev.
Births			
male	1,985,399	0.508	0.500
alive	1,985,399	0.859	0.348
birth order	1,985,399	3.370	2.276
Average Weather during 9-months pregnancy			
temperature (°C)	1,885,953	23.964	4.360
precipitation (cm)	1,885,953	8.975	9.465
Mother's characteristics			
age at delivery	1,704,866	25.506	6.358
no education	1,917,912	0.438	0.496
single	1,878,060	0.129	0.335
urban	1,985,399	0.263	0.440

Notes: Authors'calculations. The sample period is 1980-2010.

Table 1-2: Non-linear effects of temperature on male birth

	Dependent variable:			
	male			
	Whole Pregnancy	First Trimester	Second Trimester	Third Trimester
	(1)	(2)	(3)	(4)
Average Temperature Bins (°C)				
< 18	-0.00712^{**}	-0.00526^{***}	-0.00416^{**}	-0.00607^{***}
	(0.00326)	(0.00171)	(0.00174)	(0.00181)
18-22	-0.00380^{*}	-0.00336^{***}	-0.00332^{***}	-0.00634^{***}
	(0.00224)	(0.00109)	(0.00110)	(0.00113)
26-30	0.00407^{*}	0.00331^{***}	0.00267^{**}	0.00566^{***}
	(0.00234)	(0.00125)	(0.00126)	(0.00130)
> 30	0.00369	0.00438^{*}	−0.00048	0.00484^{*}
	(0.00394)	(0.00248)	(0.00248)	(0.00267)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y
Observations	1,562,678	1,567,293	1,567,253	1,567,145
R^2	0.09708	0.09717	0.09715	0.09710

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports non-linear estimates of the impact of each temperature bin on male birth by trimester of pregnancy. In all regressions, standard errors are clustered at the DHS cluster level. All regressions control for mother's characteristics comprising age at delivery, marital status, birth interval in month, number of prior children (or child birth order), household wealth index, and educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Table 1-3: Alternative specifications

	Dependent variable:					
	male					
	(1)	(2)	(3)	(4)	(5)	(6)
Average Temperature Bins (°C)						
< 18	-0.00712^{**}	-0.00512^{**}	-0.00390^{**}	-0.00401^{**}	-0.00583^{*}	-0.00682^{**}
	(0.00326)	(0.00245)	(0.00175)	(0.00175)	(0.00343)	(0.00328)
18-22	-0.00380^{*}	-0.00014	-0.00592^{***}	-0.00518^{***}	-0.00041	-0.00345
	(0.00224)	(0.00258)	(0.00111)	(0.00111)	(0.00483)	(0.00227)
26-30	0.00407^{*}	-0.00126	0.00083	0.00192	0.00172	0.00420^{*}
	(0.00234)	(0.00249)	(0.00127)	(0.00127)	(0.00396)	(0.00235)
> 30	0.00369	-0.00274	-0.00277	0.00020	0.00524	0.00382
	(0.00394)	(0.00408)	(0.00247)	(0.00247)	(0.00628)	(0.00394)
Region FE	Y	Y	Y	Y	Y	
Month of Birth FE	Y	Y	Y	Y	Y	Y
Controls for Mother's Characteristics	Y		Y	Y	Y	Y
Mother FE		Y				
Year of Birth FE			Y			
Controls for precipitation				Y		
Month of Birth ×*Country FE*					Y	
Month of Birth ×*Region FE*						Y
Observations	1,562,678	1,560,472	1,560,472	1,560,472	1,560,472	1,560,472
R^2	0.09708	0.26650	0.09905	0.09709	0.10573	0.09690

Notes: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is an indicator equals 1 if the sex at birth is male and 0 otherwise. The table shows temperature effects for the whole pregnancy period — estimated coefficients with standard errors are in brackets. Our standard errors are clustered at region of birth level.

Table 1-4: Predictions of lower bound of fetal mortality and SRB due to average temperatures

Estimation	Fetal mortality (per 1000 births)	SRB (boys per 100 girls)
Actual	2.1318	102.78
	(0.0023)	(0.1108)
Predicted	3.5195	103.68
	(0.0021)	(0.1566)

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports estimations of fetal mortality and SRB obtained with actual and 2050 predicted distribution of monthly average temperature in our SSA sample. Here, fetal mortality is for males and females pooled together.

Table 1-5: Heterogeneity in temperature impacts on male birth.

	Dependent variable:			
	male			
	(1)	(2)	(3)	(4)
< 18	-0.00425^{*}	0.01547^{**}	-0.00233	-0.00834^{***}
	(0.00221)	(0.00670)	(0.00296)	(0.00196)
> 30	-0.00737	0.01804	0.00676	0.00433
	(0.00700)	(0.01097)	(0.00496)	(0.00331)
$< 18 \times$ *no education*	-0.00346			
	(0.00314)			
$> 30 \times$ *no education*	0.00698			
	(0.00727)			
$< 18 \times$ *age*		-0.00060^{***}		
		(0.00019)		
$> 30 \times$ *age*		-0.00058^{*}		
		(0.00032)		
$< 18 \times$ *birth order*			-0.00164^{**}	
			(0.00068)	
$> 30 \times$ *birth order*			-0.00133	
			(0.00101)	
$< 18 \times$ *urban*				0.01234^{***}
				(0.00364)
$> 30 \times$ *urban*				-0.02650^{***}
				(0.00591)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y
Observations	1,823,073	1,823,073	1,823,073	1,823,073
R^2	0.07144	0.07147	0.07060	0.07152

Notes: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is an indicator equal to 1 if the sex at birth is male, and 0 otherwise. The table shows temperature heterogeneous effects for the whole pregnancy period — estimated coefficients with standard errors in the brackets. Heterogeneous characteristics consider mother's education, age at delivery, child's birth order, and place of residence (urban vs. rural). The omitted categories considered are mother having education, and living in rural for variables education, and place of residence (urban or rural), respectively. We run our preferred specification with region and month of birth fixed effects and controls for mother's characteristics. The latter include mother's marital status, ethnicity, and religion.

Table 1-6: Temperature effects on infant mortality

	Dependent variable:		
	infant mortality		
	All	Males	Females
	(1)	(2)	(3)
Average Temperature Bins (°C)			
<18	−0.01399**	−0.01577**	−0.01193**
	(0.00571)	(0.00612)	(0.00567)
18-22	−0.00770**	−0.00747*	−0.00793**
	(0.00390)	(0.00416)	(0.00381)
26-30	0.00642*	0.00604	0.00678
	(0.00387)	(0.00392)	(0.00415)
> 30	0.00937*	0.00431	0.01442**
	(0.00555)	(0.00642)	(0.00561)
Region FE	Y	Y	Y
Month of Birth FE	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y
Observations	1,878,989	953,998	924,991
R^2	0.02404	0.02560	0.02736

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports the non-linear estimate of impact of each temperature bins on infant mortality, that is up to one year after birth. All regressions are clustered at mother level and controls for child birth order. We consider the temperature bins distribution experienced during the whole 9-months pregnancy period. The coefficients estimates are interpreted relative to a reference temperature bin 22-26 °C, with standard errors in brackets.

Table 1-A.1: Demographic and Health Surveys (DHS) used in the analysis

Country	DHS Survey Year	Total Births	Sex Ratio
Angola	2016, 2011	35583	1.0292
Benin	2017, 2011, 2001, 1996	77349	1.0542
Burkina Faso	2010, 2003, 1998	88735	1.0381
Burundi	2016, 2010	40167	1.0198
Cameroon	2011, 2004	51330	1.0171
Central Africa Republic	1994	9624	1.0441
Chad	2014	42236	1.0465
Congo Democratic	2007	22007	1.0344
Comores	2012	7516	1.0513
Estwatini	2006	7646	1.0335
Ethiopia	2016, 2011, 2005, 2000	110649	1.0587
Gabon	2012	15336	0.9767
Ghana	2014, 2008, 2003	32053	1.0460
Guinea	2012, 2005, 1999	54386	1.0463
Ivory-Coast	2011, 1998, 1994	38368	1.0283
Kenya	2014, 2008, 2003	79930	1.0356
Lesotho	2014, 2004	15129	1.0250
Liberia	2013, 2007	36250	1.0474
Madagascar	2008, 1997	48807	1.0427
Malawi	2015, 2010, 2004, 2000	142912	1.0137
Mali	2012, 2006, 2001, 1995	121136	1.0398
Mozambique	2015, 2011	26059	1.0003
Namibia	2013, 2006, 2000	31559	1.0018
Niger	1998, 1992	33154	1.0415
Nigeria	2013, 2008, 2003, 1990	189838	1.0382
Rwanda	2014, 2010, 2007, 2005	76816	1.0275
Senegal	2005, 1997, 1992	59009	1.0371
Sierra Leone	2013, 2008	45045	1.0321
South Africa	2016	5421	1.0762
Tanzania	2015, 2010, 1999	49736	1.0010
Togo	2013, 1998	33253	1.0240
Uganda	2016, 2011, 2006, 2000	90954	1.0117
Zambia	2013, 2007	46180	0.9976
Zimbabwe	2015, 2010, 2005, 1999	43177	1.0211
34	85	1807350	1.0305

Notes: This table lists all the sub-Saharan African countries and Demographic and Health Surveys (DHS) used for our analysis. There are 34 countries and 85 surveys in total.

Table 1-A.2: Temperature effects on male birth (%) and length of gestational period

	Dependent variable:		
	male		
	Whole Pregnancy (9-months)	8-months	10-months
	(1)	(2)	(3)
Average Temperature Bins (°C)			
< 18	−0.00712**	−0.00649**	−0.00606*
	(0.00326)	(0.00291)	(0.00327)
18-22	−0.00380*	−0.00426**	−0.00412*
	(0.00224)	(0.00204)	(0.00231)
26-30	0.00407*	0.00384*	0.00520**
	(0.00234)	(0.00225)	(0.00226)
> 30	0.00369	0.00268	0.00735*
	(0.00394)	(0.00421)	(0.00393)
Region FE	Y	Y	Y
Month of Birth FE	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y
Observations	1,562,678	1,563,425	1,561,949
R^2	0.09708	0.09708	0.09708

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports the non-linear estimate of impact of each temperature bins on male birth by length of pregnancy. All regressions are clustered at mother level and contain mother's characteristics such as age, marital status, birth interval in months, number of prior children (or child birth other), educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Table 1-A.3: Temperature effects on male birth (%) and PSR channel

	Dependent variable:		
	male		
	(1)	(2)	(3)
Before conception (0-3 months)	0.00049	0.00030	0.00023
	(0.00086)	(0.00087)	(0.00082)
First Trimester	−0.00137**	−0.00133**	−0.00063
	(0.00059)	(0.00059)	(0.00050)
Second Trimester	0.00122**	0.00131**	0.00097**
	(0.00059)	(0.00059)	(0.00049)
Third Trimester	−0.00117*	−0.00090	−0.00074
	(0.00067)	(0.00067)	(0.00058)
After Birth (0-3 months)	0.00127	0.00149*	0.00100
	(0.00081)	(0.00082)	(0.00076)
Region FE	Y	Y	N
Month of birth FE	Y	Y	N
Year of birth FE	N	Y	Y
Controls for Mother's Characteristics	Y	Y	Y
Observations	1,409,952	1,409,952	1,409,952
R^2	0.00473	0.01246	0.00112

Notes: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is an indicator equals 1 if the sex at birth is male and 0 otherwise. The regressors of interest involved the monthly temperature at different windows of pregnancy, that is from few months before conception up to 3 months after birth. All regressions are clustered at mother level and contain mother's characteristics such as age at delivery, marital status, birth interval in months, number of prior children (or child birth other), educational attainment, household wealth asset. Our standard errors are clustered at region level.

Table 1-A.4: Non-linear effects of average temperature on male birth using number of months in a specific bin as a main regressor

	Dependent variable:			
	male			
	Whole Pregnancy	First Trimester	Second Trimester	Third Trimester
	(1)	(2)	(3)	(4)
Number of months				
< 18	-0.00072	-0.00235^{**}	-0.00161	-0.00078
	(0.00044)	(0.00101)	(0.00106)	(0.00117)
18-22	-0.00079^{*}	-0.00197^{**}	-0.00112	-0.00197^{**}
	(0.00041)	(0.00093)	(0.00081)	(0.00096)
26-30	0.00045	0.00083	0.00089	0.00134^{*}
	(0.00036)	(0.00075)	(0.00073)	(0.00070)
> 30	0.00005	0.00143	0.00011	0.00012
	(0.00053)	(0.00108)	(0.00122)	(0.00097)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y
Observations	1,548,073	1,552,578	1,552,556	1,552,477
R^2	0.09694	0.09700	0.09698	0.09695

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports the non-linear estimate of impact of each temperature bins on male birth by each trimester of pregnancy. These point estimates are obtained with specification 2.1 in which we replace average temperature by a count variables that is the number of months in a given window of pregnancy where an average temperature fall in a specific bin. All regressions are clustered at DHS cluster level and contain mother's characteristics such as age at delivery, marital status, birth interval in months, number of prior children (or child birth other), wealth asset, educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Table 1-A.5: Predictions of lower bound of fetal mortality due to extreme temperatures using different reference bins.

	Fetal mortality (per 1000 births)	
Reference bin	Actual	Predicted
22-26 (Baseline)	2.1318	3.5195
	(0.0023)	(0.0021)
18-22	2.1972	3.7201
	(0.0034)	(0.2106)
26-30	2.4603	3.8103
	(0.0042)	(0.3207)

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports estimations of fetal mortality using different reference temperature bins, from actual and 2050 predicted distribution of monthly average temperature in our SSA sample. Here, fetal mortality is for males and females pooled together.

Table 1-A.6: Non-linear effects of temperature on infant mortality

	Dependent variable: infant mortality			
	Whole Pregnancy	First Trimester	Second Trimester	Third Trimester
	(1)	(2)	(3)	(4)
Average Temperature Bins (°C)				
	Panel A. All			
< 18	-0.01399^{**}	-0.01154^{***}	0.00770^{***}	0.00528
	(0.00571)	(0.00438)	(0.00273)	(0.00328)
18-22	-0.00770^{**}	-0.00523^{*}	0.01219^{***}	0.00801
	(0.00390)	(0.00292)	(0.00437)	(0.00538)
26-30	0.00642^{*}	0.00118	0.01293^{**}	0.00337
	(0.00387)	(0.00234)	(0.00525)	(0.00619)
> 30	0.00937^{*}	0.00134	0.01369^{**}	0.00141
	(0.00555)	(0.00366)	(0.00612)	(0.00703)
	Panel B. Males			
< 18	-0.01577^{**}	-0.00983^{**}	0.00771^{***}	0.00331
	(0.00612)	(0.00418)	(0.00245)	(0.00313)
18-22	-0.00747^{*}	-0.00565^{*}	0.01114^{**}	0.00634
	(0.00416)	(0.00301)	(0.00442)	(0.00549)
26-30	0.00604	0.00256	0.01383^{**}	0.00363
	(0.00392)	(0.00262)	(0.00559)	(0.00644)
> 30	0.00431	0.00514	0.01386^{**}	0.00224
	(0.00642)	(0.00388)	(0.00628)	(0.00777)
	Panel C. Females			
< 18	-0.01193^{**}	-0.01300^{***}	0.00759^{**}	0.00723^{*}
	(0.00567)	(0.00496)	(0.00347)	(0.00377)
18-22	-0.00793^{**}	-0.00488	0.01306^{***}	0.00958^{*}
	(0.00381)	(0.00303)	(0.00477)	(0.00557)
26-30	0.00678	-0.00019	0.01184^{**}	0.00295
	(0.00415)	(0.00246)	(0.00549)	(0.00629)
> 30	0.01442^{**}	-0.00269	0.01309^{*}	0.00038
	(0.00561)	(0.00414)	(0.00684)	(0.00709)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports non-linear estimates of the impact of each temperature bin on infant mortality by trimester of pregnancy. We present our results in three panels: the whole sample (panel A); males (panel B); and females (panel C). In all regressions, standard errors are clustered at the DHS cluster level. All regressions control for mother's characteristics comprising age at delivery, marital status, birth interval in month, number of prior children (or child birth order), household wealth index, and educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Chapter 2

The Fetal Origins of Cognitive Aging

By Landry Kuate and Roland Pongou

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.

2.1 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 to, gender, age, religion, ethnicity, education level, and children and grandchildren. Because HAALSI does not provide geographic information (latitude and longitude) on place

[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

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 negatively 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,

[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.

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 2-1. 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, 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

[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.

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 2.2 discusses the related literature and outlines the paper's main contributions to this literature. Section 2.3 presents biological pathways linking ambient prenatal temperature to the brain's efficiency. Section 2.4 describes the data and variables pertaining to this study. Section 2.5 outlines the empirical strategy. Our findings are presented in section 2.6, while sections 2.7 presents robustness checks. Section 2.8 and 2.9 test and discuss possible mechanisms. We conclude in section 2.10.

2.2 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 2-A.1. 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, 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

[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.

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 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

[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).

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.

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

In Figure 2-1, 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) document 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

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

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.

2.4 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.

2.4.1 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 2-2, 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 2-A.1.

Demographic and Health Surveys collect information on demographic, health, and socioeconomic 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

[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.

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 × 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 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.

2.4.2 Summary statistics

Our main sample consists of 3,212 individuals (all born in South Africa). Figure 2-A.2 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 2-A.3).

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 2-3 plots the total distribution of births by month (see upper graph of Figure

[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.

2-3), combined with change of average temperature by trimester of pregnancy by month of birth (see lower graph of Figure 2-3). Figure 2-3 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 2-3 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 2-4 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 2-4 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 2-5. Each dot in figure 2-5 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 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 2-1 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.

[12]The quadratic shape can be seen in the temperature range corresponding to most observations, that is temperature between 16 and 24 degrees.

2.5 Methodology

2.5.1 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.

$$Cognition_{ijmt} = \alpha Temp_{ijmt} + \rho * (Temp_{ijmt})^2 + CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \quad (2.1)$$

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. α and ρ are the coefficients of interest associated with $Temp_{ijmt}$ and $(Temp_{ijmt})^2$, respectively. μ_j and λ_m correspond to municipality of birth and month of birth fixed effects, respectively. η_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, ϵ_{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:

$$Cognition_{ijmt} = \sum_{k=0}^{4} \left[\alpha_k * Temp^k_{ijmt} + \rho_k * (Temp^k_{ijmt})^2\right] + CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \quad (2.2)$$

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

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 (2.1) 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 (2.1)., 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).

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:

$$Cognition_{ijmt} = \sum_b \alpha_b * Temp^b_{ijmt} + CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \tag{2.3}$$

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

[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).

20 °C.

2.5.2 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 2-A.3. 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 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

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

[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."

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 2-A.5 and the analysis examining the impact on early life heath outcomes is shown in 2-A.6.

2.6 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.

2.6.1 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 (2.1). The dependent variable used for this set of regressions is the adult cognitive function z-score. Equation (2.1) also includes a quadratic term of average temperature to capture potential non-linearity in the effects. The results are presented in Table 2-2 with standard errors presented in the brackets. In column (1) we present estimates of equation 2.1 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 (2.1) 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 2-A.3 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 2-6 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 2-7 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 (2.2). Table 2-3 reports the coefficient estimates of equation (2.2). 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 2-8. 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.

2.6.2 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 (2.2). For expositional purposes, we show the results graphically.

Figure 2-9 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 2-3 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 2-3, 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.

2.7 Robustness Checks

2.7.1 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 2-4 reports results for the first set of robustness checks. Column (1) shows the results of our primary specification obtained using equation (2.1). 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 2-5. 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.

2.7.2 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 2-6. For ease in the exposition, we present these point estimates, along with their 95% confidence intervals, graphically in figure 2-10. 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.

2.8 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:

$$\begin{aligned} Cognition_{ijmt} = {} & \alpha Temp_{ijmt} + \rho(Temp_{ijmt})^2 + \beta Temp_{ijmt} * H + \gamma(Temp_{ijmt})^2 * H \\ & + CW_i + X_i\beta + \mu_j + \lambda_m + \eta_t + \epsilon_{ijmt} \end{aligned} \tag{2.4}$$

where H denotes each of the aforementioned individual specific characteristics. Table 2-7 reports the results for this regression specification. Each column of Table 2-7 reports the coefficient for the interaction term between temperature and the relevant characteristic. We also summarize these point estimates in figure 2-11.

Gender. Column (1) of table 2-7 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 2-7 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 2-7 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 2-7 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 2-7 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.

2.9 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 2-1 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.

2.9.1 Temperature effects on related human capital outcomes

Figure 2-1 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 2-8 as well as figure 2-12 report our coefficient estimates.

Childhood health. Column (1) of Table 2-8 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 2-8 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 2-8 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.

2.9.2 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., 2011b), 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 2-9 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 2-10. Column (1) reports the estimates of cognitive score given the self-report childhood health of the participants. We find that Cognitive score of people with good health during childhood period is higher compare to those with poor health when exposed to an increase in temperature shock. In the same line, individuals which parents main occupation was in farm or agriculture sector, tend to experienced better cognitive health conditional of being exposed on prenatal temperature shock, as shown in column (2). Finally, column (3) looks at the effects by family income. Findings reveals that, high-income family tends to suffer less from cognitive impairment. Overall, our findings are supportive of sample selection given that, individuals en-downed with good health during childhood and from high-income family are less likely to have a lower cognitive score. Through this analysis, we sort of capture the mitigation and adaptation channel coming from parents investments in their children human capital accumulation.

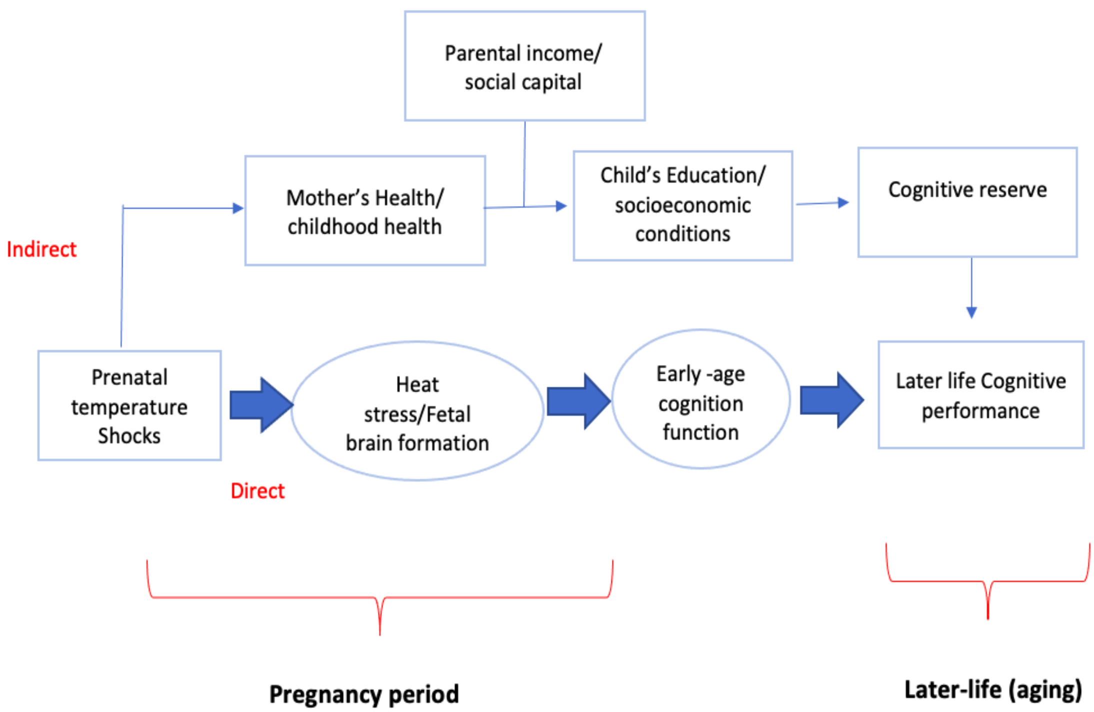
2.10 Conclusion

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.

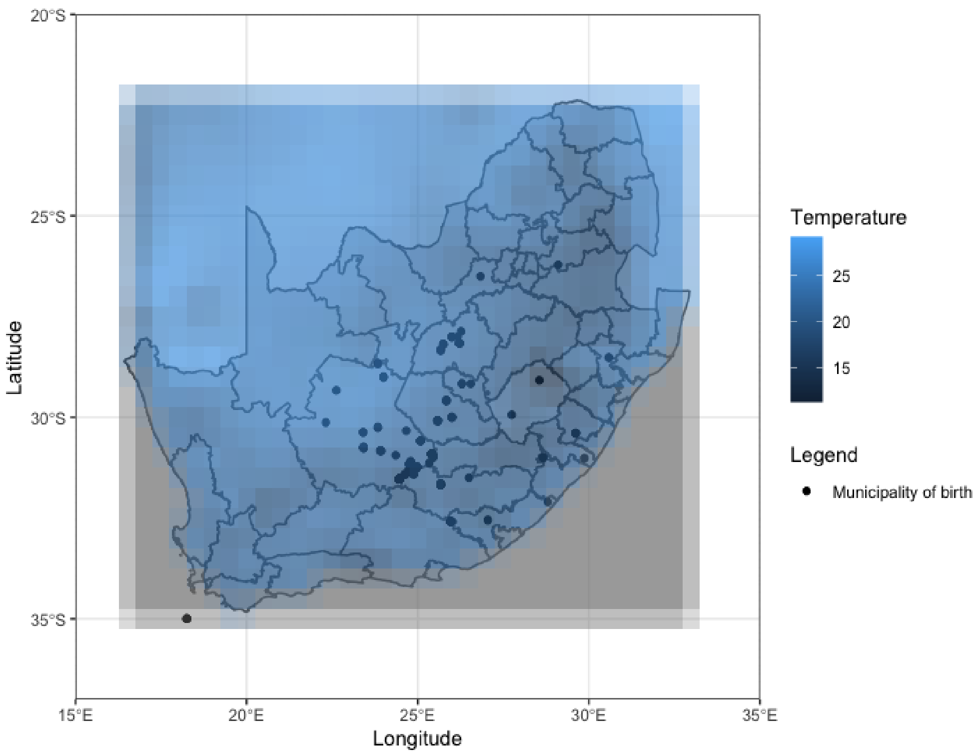
Figures and Tables

Figure 2-1: Conceptual framework: how does prenatal temperature shocks affect cognitive performance during aging?



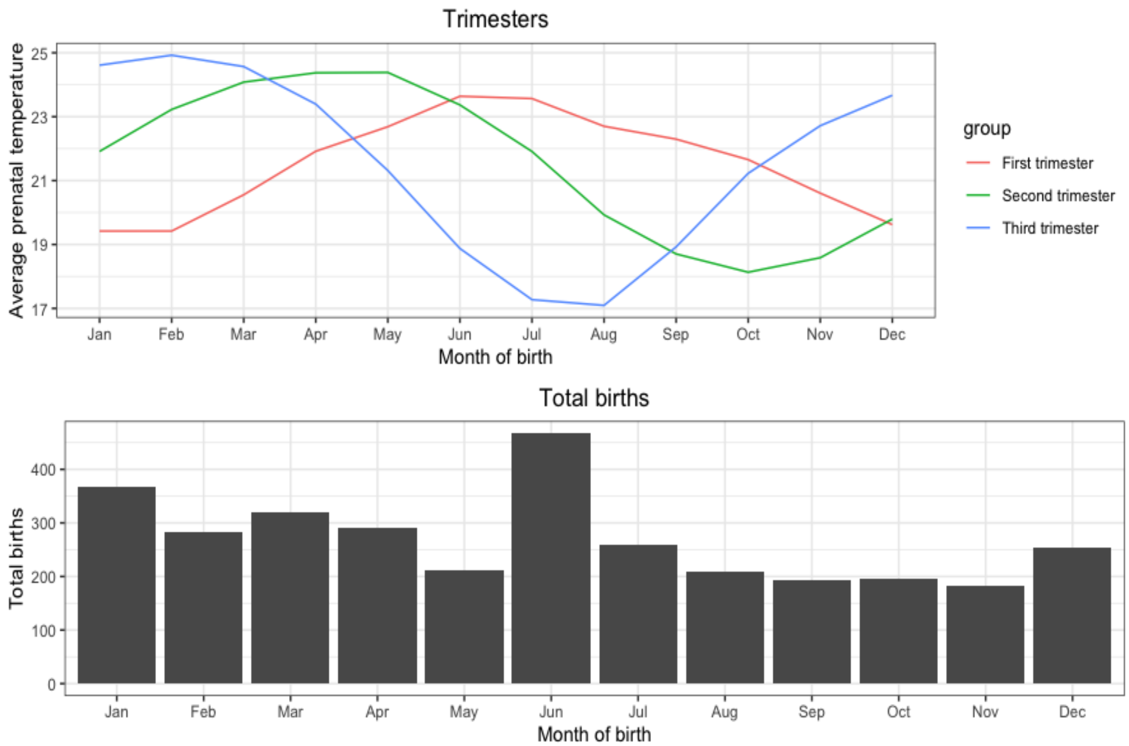
Notes: The figure above depicts the mechanisms through which prenatal temperature shocks affect later life cognitive performance. Broadly speaking, biology is the main channel through which prenatal temperature affects cognition during aging. A negative temperature has a direct effect on fetal development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

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



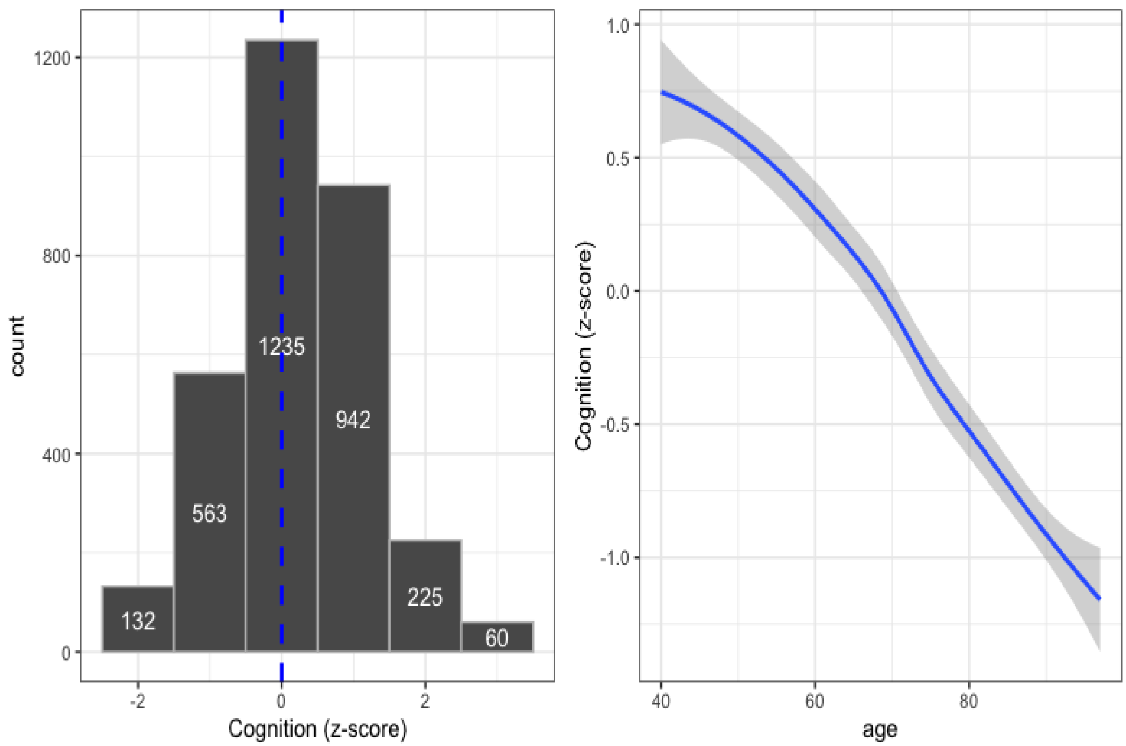
Notes: This chart shows the distribution of municipalities of birth in South Africa along with spatial variation of temperature on a given month. In this plot, we consider January, 1940 as an example. Each dot represents a given municipality of birth as reported by surveyed individuals.

Figure 2-3: Total births and temperature distribution by month of birth



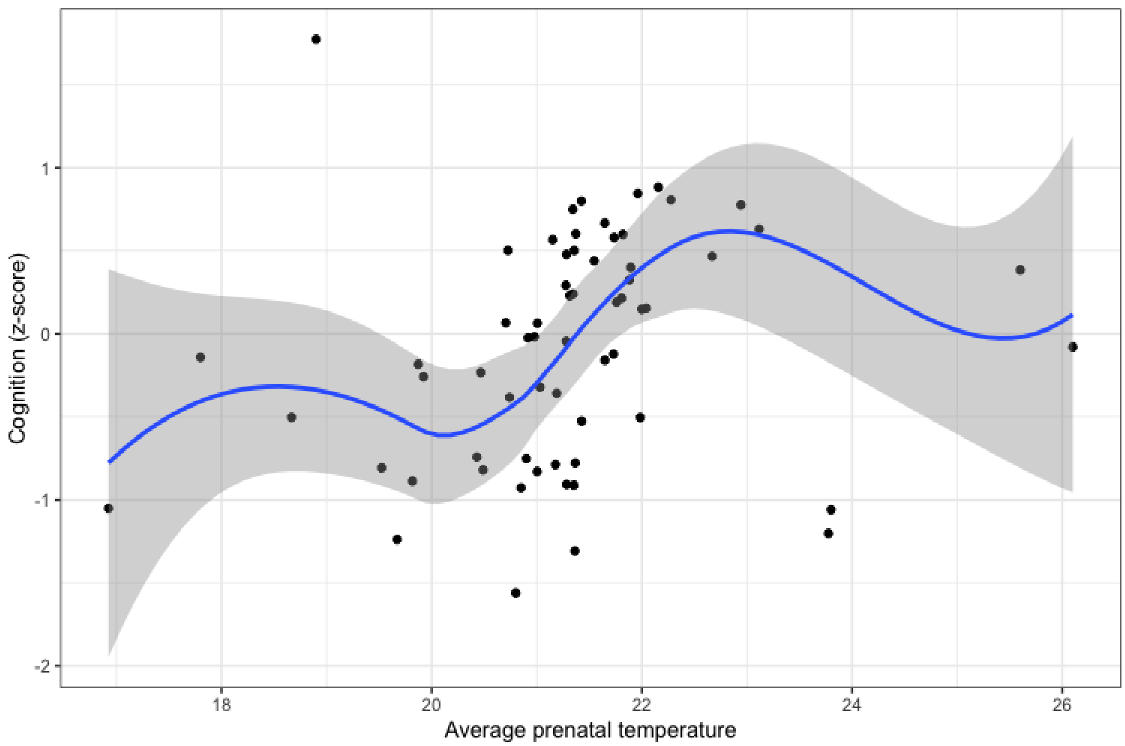
Notes: This chart plots together total births distribution combined with the change of average temperature by trimester of pregnancy by month of birth. It reveals that apart for June where we notice a peak in total births, they are equally distributed over the months. It suggests that individuals do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

Figure 2-4: Distribution of cognition z-score by age



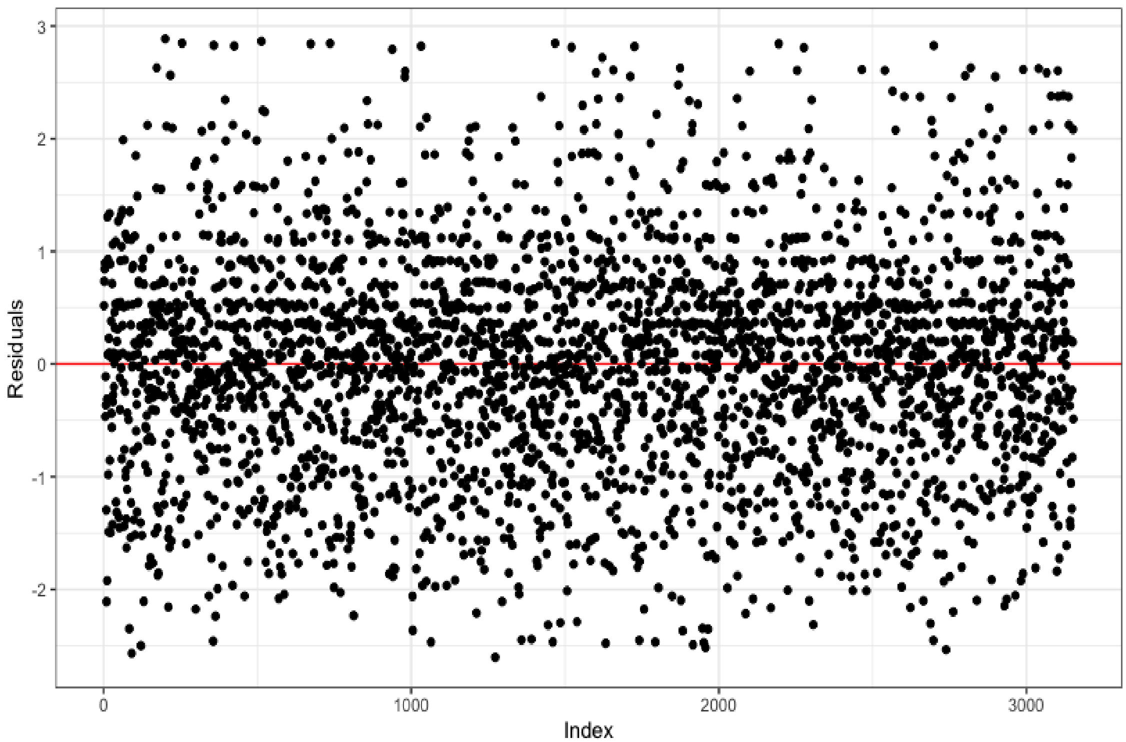
Notes: This figure shows the distribution of cognition z-score by age. The left panel is a histogram with a count of individuals by cognition score. On the right panel, we plot cognition z-score against individual's age. It appears that cognitive skills decline with age as expected.

Figure 2-5: Cognition z-score and average prenatal temperature



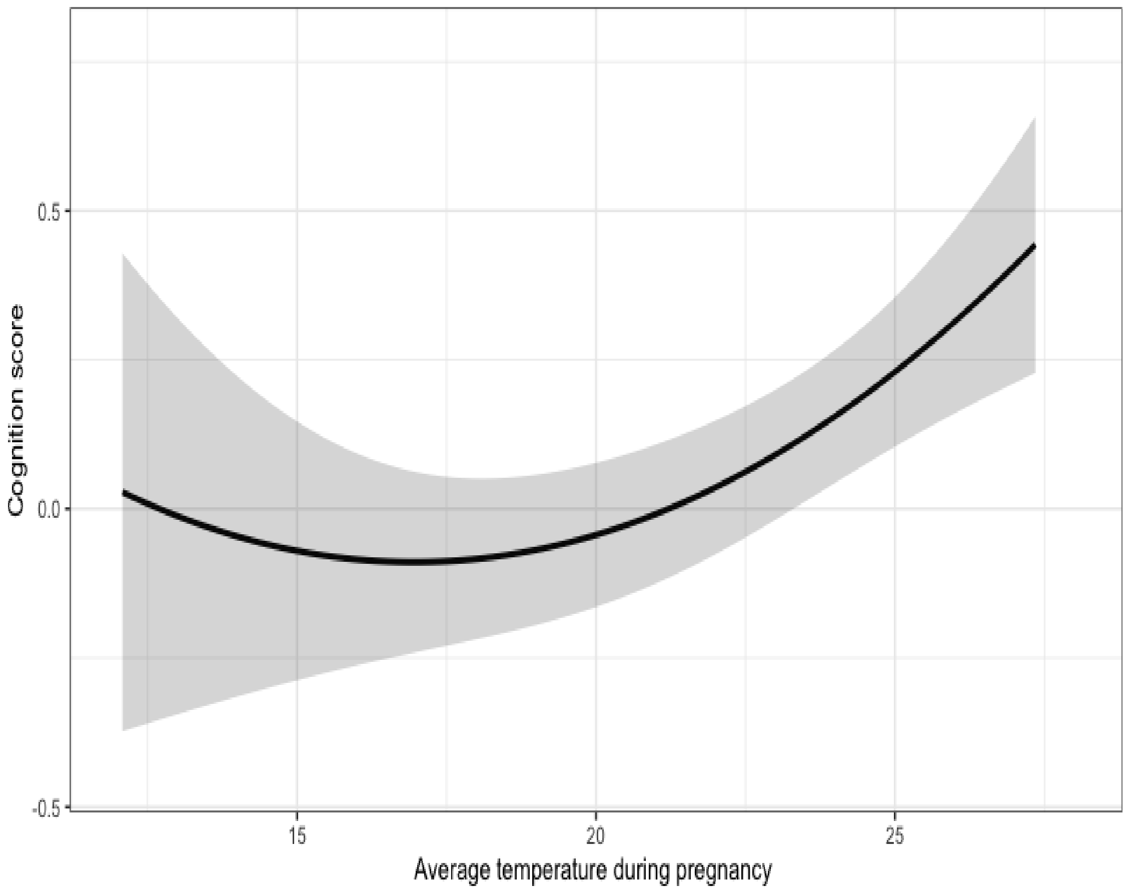
Notes: This figure shows the association between cognition z-score and average prenatal temperature. Each dot gives the cognition z-score at year of birth level associated to a given average temperature experienced during the nine months of pregnancy. This graph depicts a non-linear shape between these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

Figure 2-6: Residuals from the preferred specification



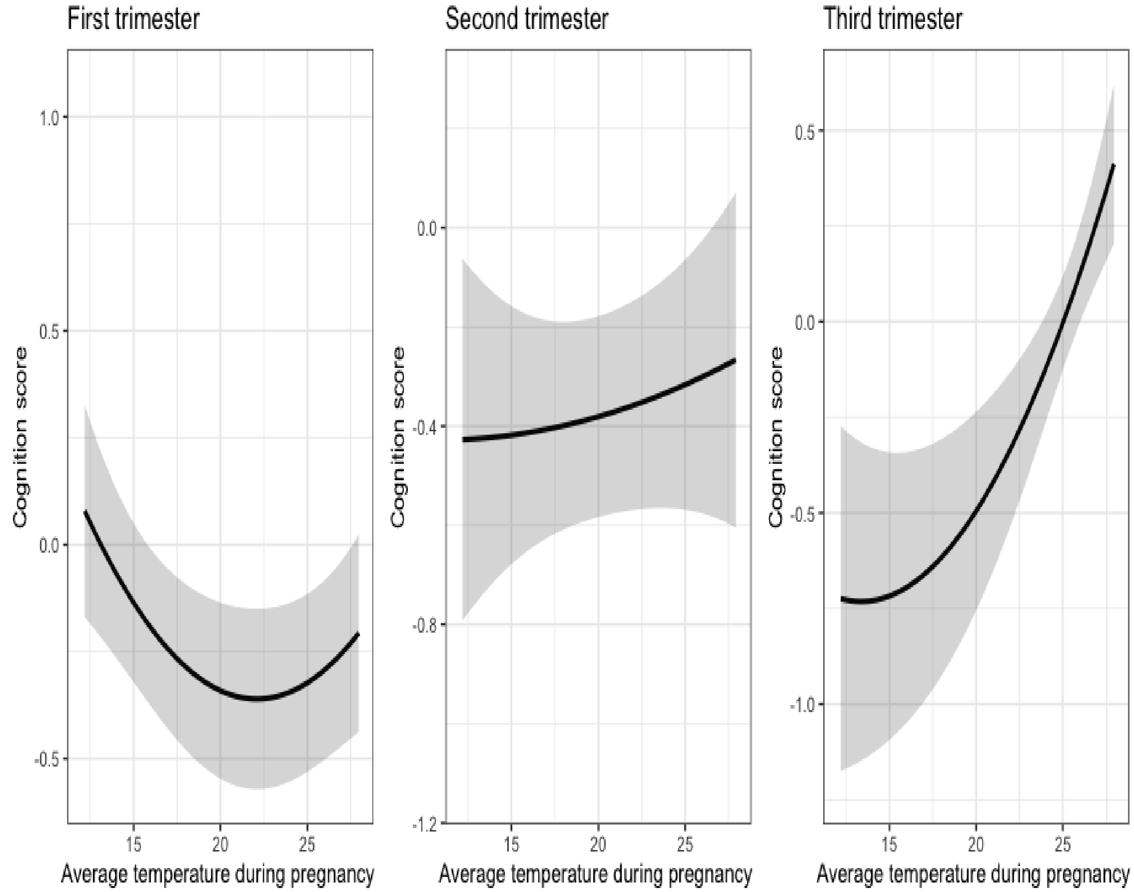
Notes: The figure above represents the distribution of the residuals obtained from our preferred specification in which we remove any controls and fixed effects.

Figure 2-7: Cognition score and change in average temperature of pregnancy



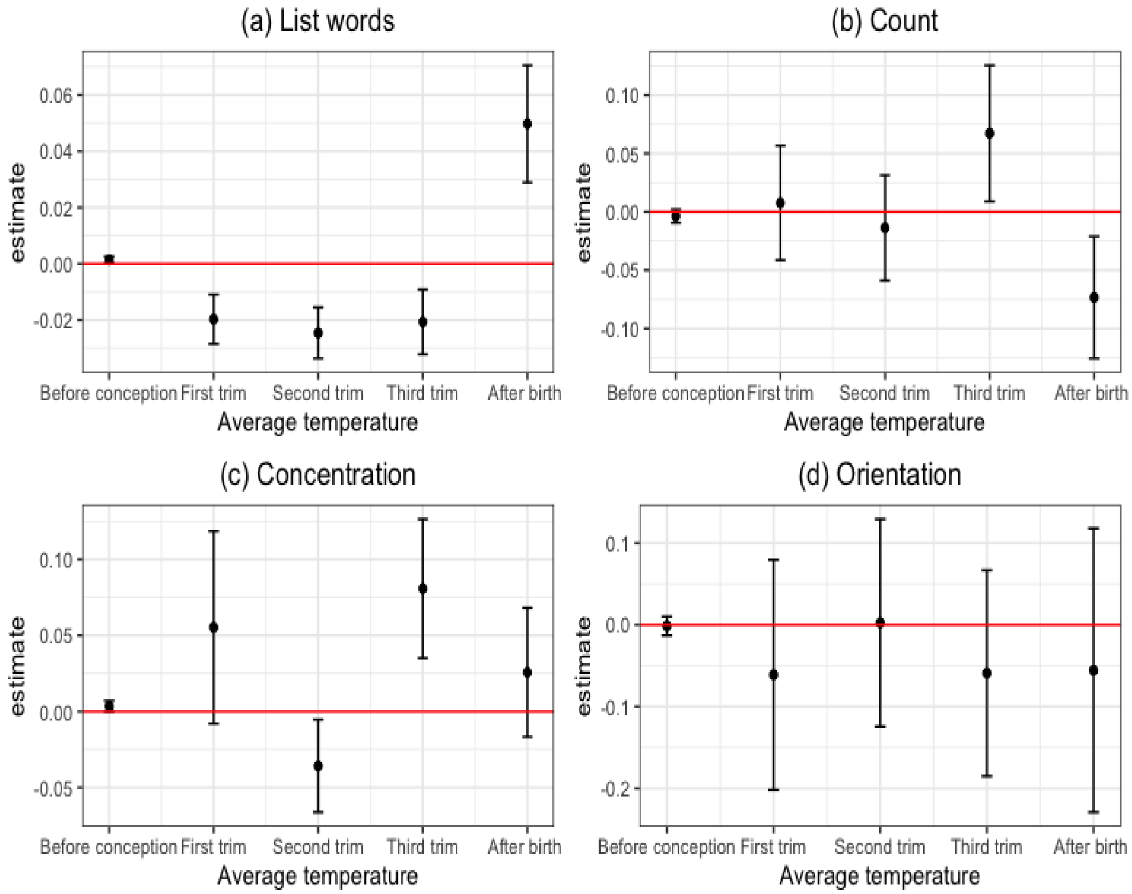
Notes: The figure above represents the prediction of cognition score with change of average prenatal temperature. This figure is derived form our preferred specification in which we control for individual characteristics, municipalities and month of birth fixed effects, along with a quadratic term of 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 2-8: Cognition score and change in average temperature by trimester of pregnancy



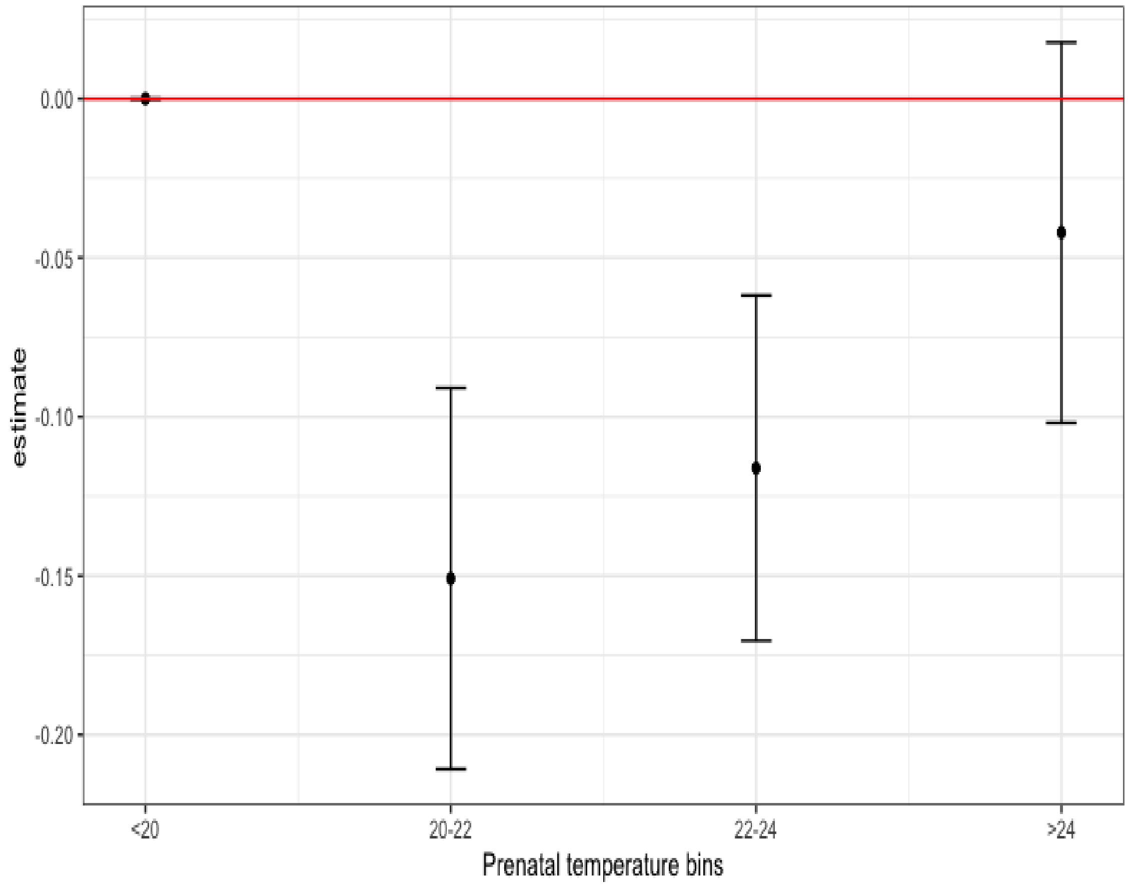
Notes: The figure above represents the prediction of cognition score with change of average prenatal temperature by trimester of pregnancy. This figure is derived from our preferred specification in which we control for individual characteristics, municipalities and month of birth fixed effects, along 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 2-9: Decomposition of the effect by various measures of cognition function



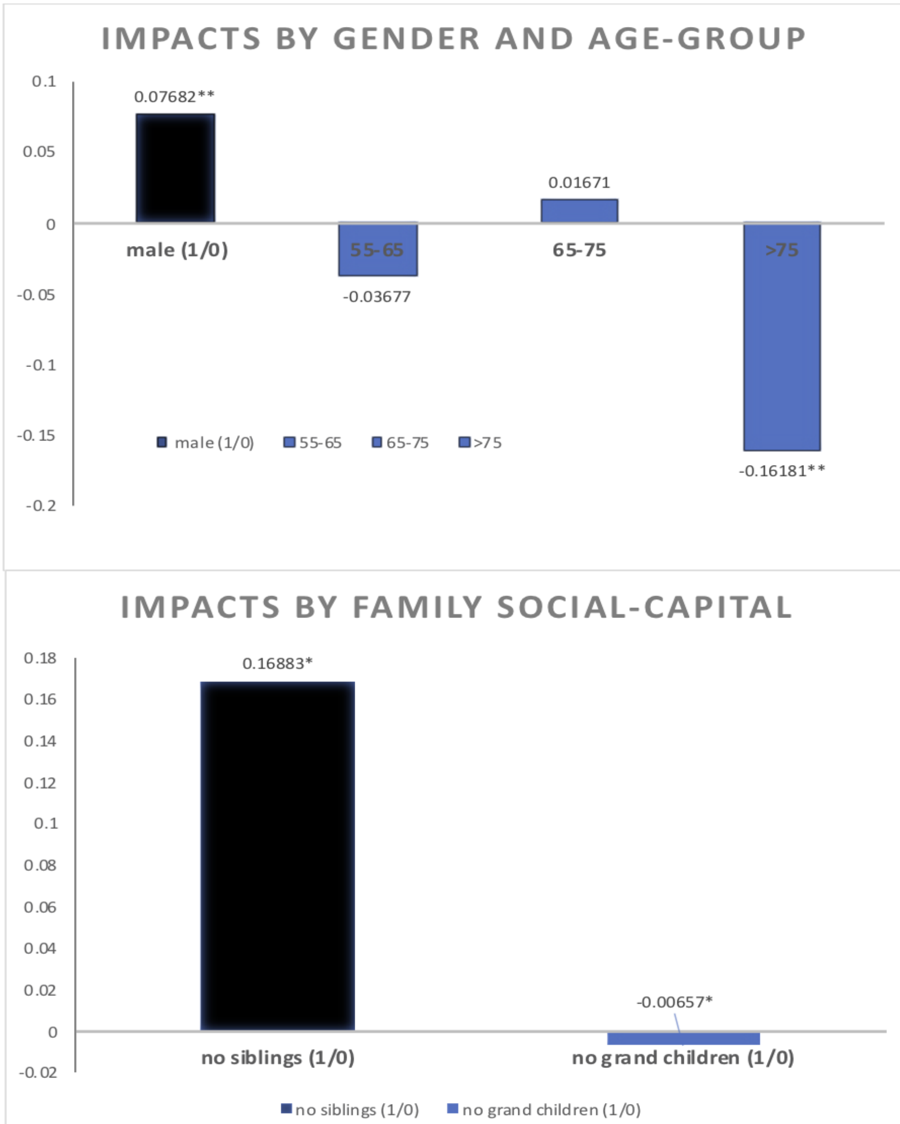
Notes: The figure above represents the point estimates of the effect of average temperature of a given trimester of pregnancy on cognition z-score along with various measure of cognitive performance. These measures include individual ability to list words, count, concentrate, and orientation. This figure 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 2-10: Non-linear effects on cognition score using prenatal temperature bins



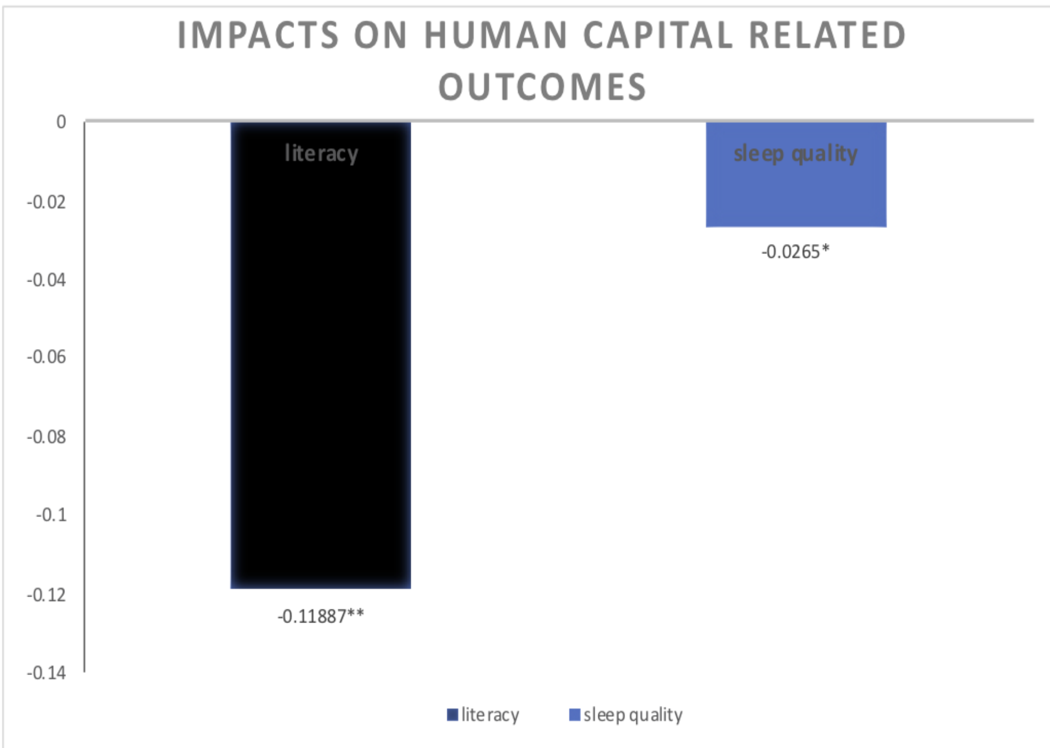
Notes: The figure above represents the point estimates of the effect of average prenatal temperature bins on cognition z-score along with various measure of cognitive performance. We consider four range of temperature bins < 20°C; 20-22°C; 22-24°C; ¿24° C with < 20°C considers as the reference category. 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 2-11: 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 2-12: 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 2-1: 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 2-2: 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 2-3: 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 2-4: 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 2-5: 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 2-6: 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 2-7: 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)
$temp^2$	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)				
temp×*male*	0.08138				
	(0.12281)				
$temp^2 \times male$	-0.00228				
	(0.00296)				
		Season			
temp×*hot*		0.46359***			
		(0.06285)			
$temp^2 \times hot$		-0.01168***			
		(0.00138)			
			Age-group		
temp×(55 − 65)			-0.03749		
			(0.07576)		
$temp^2 \times (55-65)$			0.00036		
			(0.00170)		
temp×(65 − 75)			0.01765		
			(0.08010)		
$temp^2 \times (65-75)$			-0.00047		
			(0.00198)		
temp×(> 75)			-0.16971**		
			(0.08545)		
$temp^2 \times (>75)$			0.00395**		
			(0.00181)		
				Family attributes	
				siblings	
temp× *no sibling*				0.17905*	
				(0.10079)	
$temp^2 \times$ *no sibling*				-0.00511**	
				(0.00253)	
					grandchildren
temp× *no grandchildren*					-0.00575
					(0.14465)
$temp^2 \times$ *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 2-8: 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 2-9: 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.

Table 2-10: Testing for selection

	Dependent variable:		
	Cognition score		
	(1)	(2)	(3)
temp	0.03580	-0.06287***	-0.51670***
	(0.04018)	(0.01906)	(0.06308)
temp^2	-0.00018	0.00178***	0.01380***
	(0.00098)	(0.00043)	(0.00159)
	Self-report childhood health		
good_health	4.02029***		
	(0.45504)		
temp×*good_health*	-0.36950***		
	(0.04655)		
$\text{temp}^2 \times good\_health$	0.00883***		
	(0.00114)		
		Parent occupation	
$\text{temp} \times farmer$		-0.27505***	
		(0.03111)	
$\text{temp}^2 \times farmer$		0.00681***	
		(0.00075)	
			High-income family
$\text{temp} \times high-income$			0.09532***
			(0.02094)
$\text{temp}^2 \times high-income$			-0.00250***
			(0.00051)
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	3,081	2,525	3,082
R^2	0.30422	0.33689	0.30578

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 test for the selection issue by examining the temperature impacts on cognitive performance conditional on (i) self-report health during childhood; (ii) whether or not they belong to high-income family, and (iii) by parent occupation. All regressions control for individual characteristics such as age, gender, ethnicity, religion.

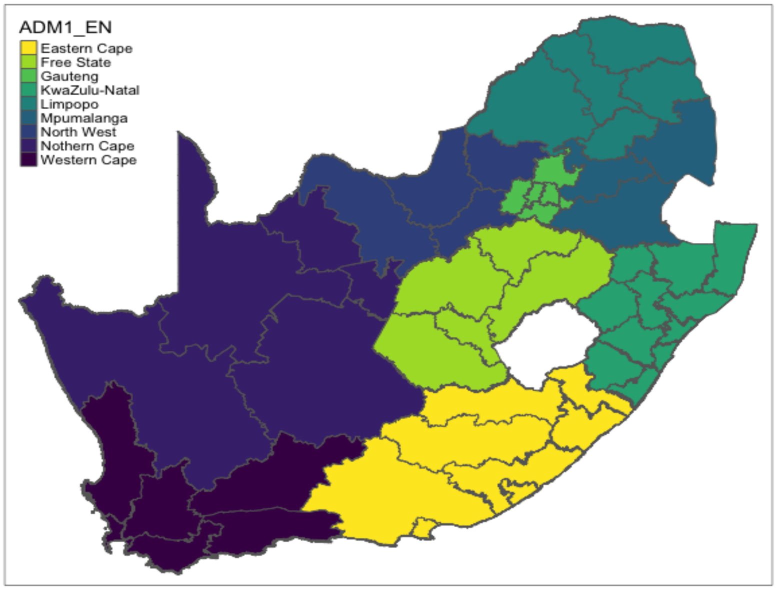
2-A Appendix

Table 2-A.1: 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

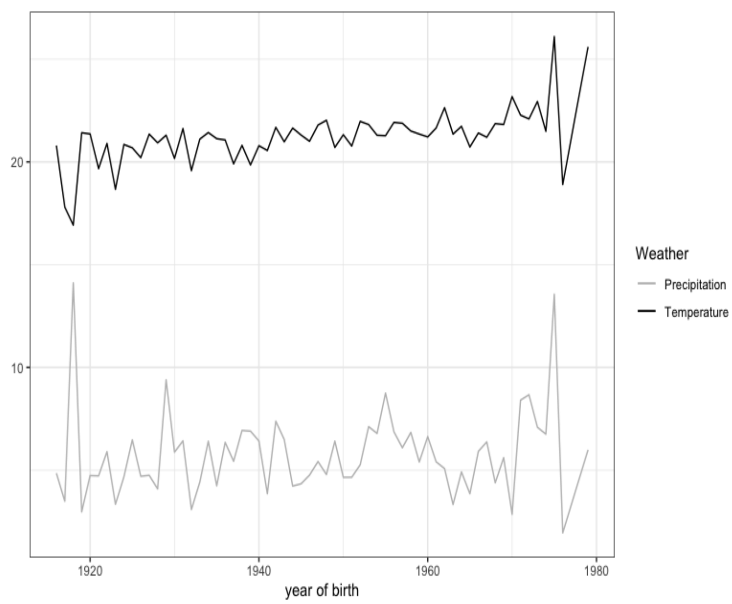
Notes: This review covers recent papers on both short and long run consequences of fetal insults on human capital accumulation. Overall, prior studies investigated the impacts of early life exposure to various shocks including malaria, drought, pollution, among others on key determinants of human capital 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 2-A.1: Administrative regions of South Africa



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

Figure 2-A.2: 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.

Table 2-A.2: 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 2-A.3: Temperature effects on cognition z-score by month of pregnancy using linear model

	Dependent variable:			
	Cognition score			
	(1)	(2)	(3)	(4)
$temp_{t-9}$	0.02480***	0.02194***	0.01958**	0.02126**
	(0.00835)	(0.00816)	(0.00822)	(0.00921)
$temp_{t-8}$	-0.02975**	-0.02248*	-0.02126*	-0.02465*
	(0.01187)	(0.01186)	(0.01187)	(0.01303)
$temp_{t-7}$	-0.00435	-0.00843	-0.01070	-0.00616
	(0.01065)	(0.01087)	(0.01115)	(0.01073)
$temp_{t-6}$	0.00583	0.00695	0.00984	0.00740
	(0.01204)	(0.01154)	(0.01145)	(0.01166)
$temp_{t-5}$	-0.00704	-0.00588	-0.00657	-0.00362
	(0.01333)	(0.01384)	(0.01369)	(0.01351)
$temp_{t-4}$	0.01360	0.01825*	0.01482	0.01724*
	(0.00890)	(0.01088)	(0.01071)	(0.00929)
$temp_{t-3}$	0.01168	0.00729	0.00708	0.00122
	(0.00758)	(0.00656)	(0.00653)	(0.00654)
$temp_{t-2}$	0.00635	0.00853	0.00566	0.01060
	(0.01179)	(0.01176)	(0.01173)	(0.01059)
$temp_{t-1}$	0.00495	0.00741	0.00082	-0.00044
	(0.01042)	(0.01209)	(0.01214)	(0.01174)
$temp_t$	-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 2-A.4: 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 2-A.5: 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 2-A.6: 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.

2-B Notes

2-B.1 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:

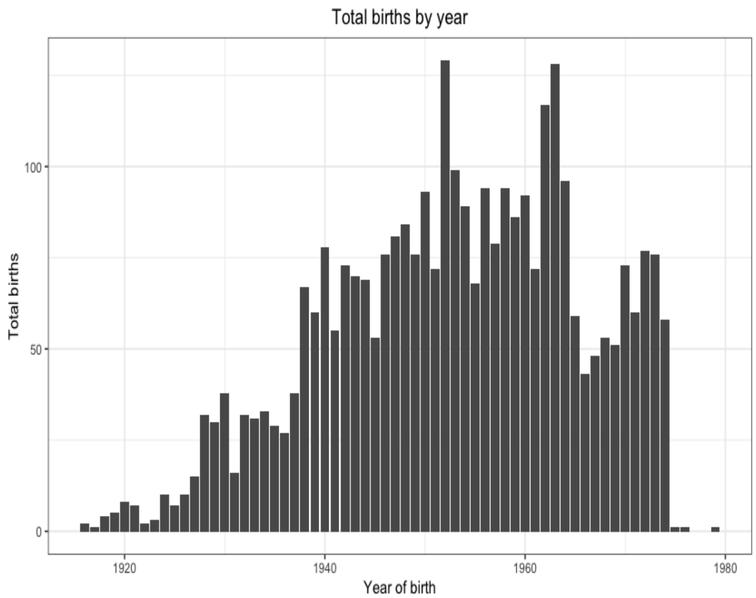
The second step of data collection consisted of gathering information on geographic coordinates of places of birth, and assigning each respondent in the HAALSI dataset geographic coordinates of their place of birth. The third and final step consisted of merging the HAALSI data with climate data from —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.

Table 2-B.7: 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
.	.	.	.
.	.	.	.
.	.	.	.
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

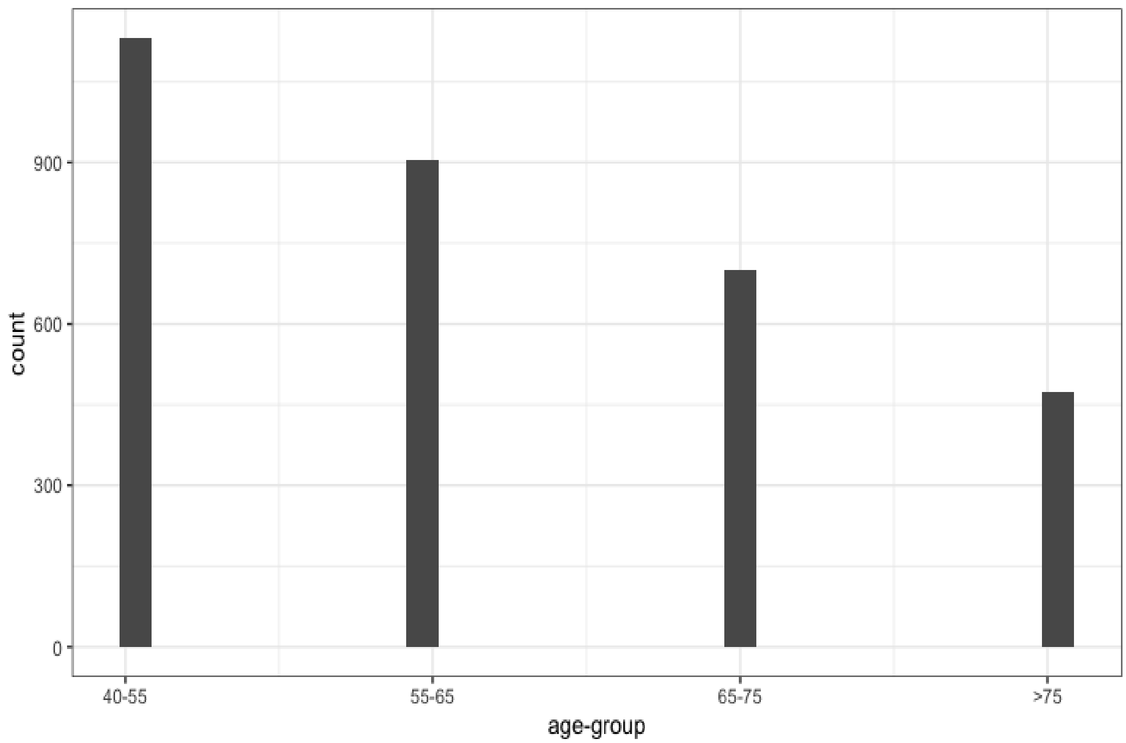
Notes: We list a total of 213 municipalities of birth in our sample for which we were able to collect geographical coordinates.

Figure 2-A.3: Total births by year of birth



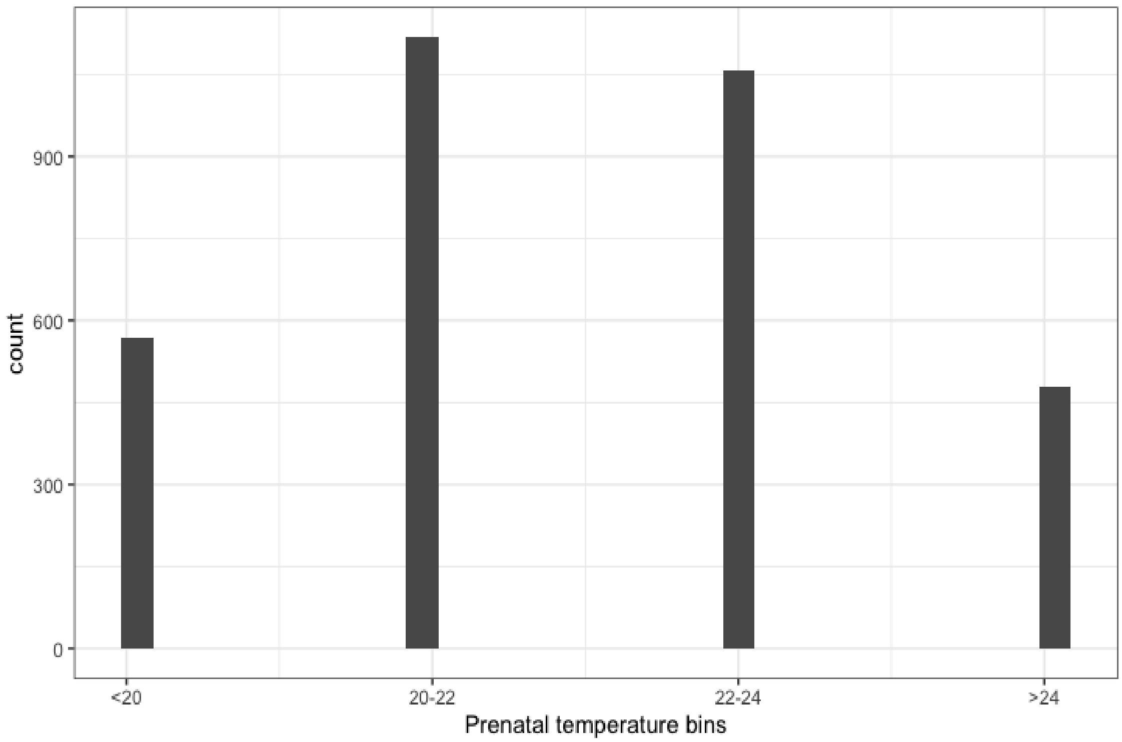
Notes: The figure above represents the distribution of total births by year of birth in our sample. It reveals that most of respondents were born between 1940 and 1970 post apartheid period.

Figure 2-A.4: Distribution of age group in the sample



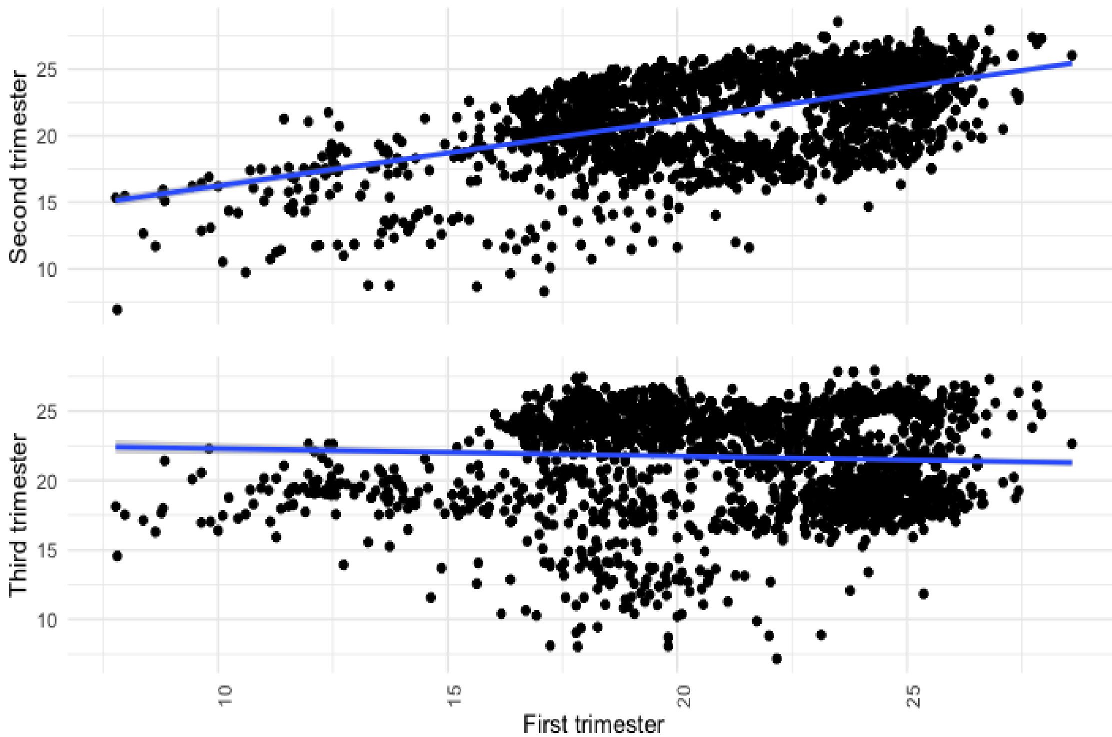
Notes: The figure above represents the distribution of age-group in our sample. We consider four groups: 40-55; 55-65; 65-75; and >75. In our analysis, we compare temperature impacts on cognition score by age-group relative to 40-55.

Figure 2-A.5: 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 2-A.6: 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.

Chapter 3

Labor Market Impacts of Clean Energy Transition: Evidence from Ontario Coal-Fired Phase-Out

By Landry Kuate and Nicholas Rivers

Abstract A large literature seeking to understand the labor market impacts associated with the clean energy transitions broadly finds opposite effects. On the one hand, a net positive impact on the workforce i.e. the new green jobs created in renewable energy sectors will compensate for the jobs lost in fossil-fuel sectors, while on the other hand, the so-called regulated dirty energy sector will reduce the fraction of workers hired. However, empirical and simulation models typically ignore transitional impacts associated with environmental regulations on labour. These relate to how workers adjust over time to environmental regulations, not just the steady state impact that is the focus of prior studies. We evaluate an environmental regulation (Ontario coal-fired electricity generating plants phase-out) regarding its transitional and long-term impacts on employee's outcomes including *(i)* wages; *(ii)* unemployment insurance; *(iii)* sector mobility; and *(iv)* geographic location. Using the Longitudinal Worker File (LWF) and Postal Codes Conversion File (PCCF) maintained by Statistics Canada, we estimate the labor market impacts of clean energy policy by comparing employees from affected coal plants to a comparable group of employees from non-affected plants. We find that, workers exposed to Ontario phase-out coal policy have earned on average 7000 $ CAD yearly less compared to those who weren't exposed. Our findings are consistent across a set of alternative specifications and robustness checks. Moreover, results

from the event study approach suggest that the regulation leads to labor costs with the decline of wages just in transition. We provide supportive evidence on large labor costs due to environmental regulation policy and shed lights on the importance of reforms and training programs to support workers during the transition.

3.1 Introduction

A large literature seeking to understand the labor market impacts associated with the clean energy transition broadly finds opposite effects. On the one hand, a net positive impact on the workforce i.e. the new green jobs created in renewable energy sectors will compensate for the jobs lost in fossil-fuel sectors (Yamazaki, 2017), while on the other hand, the so-called regulated dirty energy sector will reduce the fraction of workers hired (Hafstead and Williams, 2018; Yip, 2018). However, empirical and simulation models mostly ignore transitional impacts associated with such regulations on labour. These relate to how workers adjust over time to environmental regulations, not just the steady state impact at the economy wide employment level. Instead, and in line with Walker (2013) the appropriate measure of regulatory costs to the workforce should not be characterized by jobs lost but by any transitional costs associated with reallocating production or workers. Understanding these transitional effects on jobs could help policy makers to better design reforms in order to support workers affected while reducing environmental footprint.

In this paper, we study for the first time the short and long run effects of Ontario's coal phase-out program on labour market outcomes including wages, unemployment, or worker's geographic and sector mobility. We also document heterogeneous impacts among different groups that is, by gender, by age, or marital status. This study builds on the previous research seeking to examine the economic and social costs of environmental regulation such as coal phase-out policy. Coal is a highly abundant and cheap energy resource which has powered the industrialization of many country over history and communities to today. It is a big player in today's energy system, providing 40% of the world's electricity. However, a major concern with coal is related to that it is the most CO2 intensive fossil fuel when combusted because it is composed largely of carbon. Coal also contains other elements that cause pollution problems which can be harmful to human health. In the context of increasing threats of climate change, several countries have committed to significantly reduce their environmental footprint via the level of Greenhouse Gas (GHG) emissions and eliminate coal.

Canada is committed to addressing climate change, in particular by reducing its emissions of GHG. Canada's current commitment involves reducing GHG emissions by 40-45 percent relative to 2005 levels by 2030. To do so, the federal and provincial governments have implemented a large number of policies, including carbon taxes, cap and trade systems, performance standards, policies to promote renewable generated electricity (wind, solar), and regulations to phase out coal-fired power plants, among others. The clean energy transition presents both opportunities and challenges to Canadian workers, as some sectors are likely to contract, and some expand, when GHG policies are applied.[1] An obvious example is in the electricity generation sector, where reducing GHG may involve closure of coal-fired generating plants, and expansion of renewable power generating facilities. For example, in Canada, power generated by coal generating plants has decreased substantially since 2000 especially due to the phase-out of coal generation in Ontario,[2] whereas power generated by wind has increased from near zero in 2005 to 6 percent of Canada's electricity supply as of 2018.[3] In this paper we evaluate the Ontario's coal phase-out policy regarding its impacts on labor market in both short and long-run.

Our interest in transitional labor cost induced by environmental regulation is in part motivated by the growing literature that evaluates trade-offs between jobs and the environment (Yamazaki, 2017; Fullerton and Muehlegger, 2017; Walker, 2013). Numerous studies document that environmental policies lead to small effects on labor outcomes especially jobs loss. For instance, Deschenes (2018) suggests that environmental regulations affect labor demand in a relatively small group of energy-intensive industries while having very small or no effect on employment in service sectors. In addition, regulation typically affects the distribution of employment among industries rather than the economy-wide employment level (Arrow et al., 1996). However, these studies ignore the transition and adjustment costs i.e. the costs related to how workers adapt and reallocate from regulated sector or industry to non-regulated ones.

In addition, the lack of data at the establishment or plant levels at which the regulation occurs, or at the worker level makes it difficult to investigate the true impacts of regulation on workers. Instead, the published literature have long focused on firm or industry as the unit of analysis to research the distributional impacts of a specific climate policy on a given outcomes (Curtis, 2018; Yamazaki, 2017). A paper by Walker (2013) is among the few studies that evaluates this question at the worker level in the context of the 1990 Clean Air Act Amendments (CAAA) in the United States. Using linked worker-firm data, Walker (2013) estimates the transitional costs associated with reallocating workers from newly regulated industries to other sectors of the economy in the context of new environmental regulations. Walker (2013) finds a persistent decline in employment in affected sectors following the strengthening of emissions standards in the early 1990's.

The goal of this paper is to characterize the transitional and long-term implications of

[1] An early assessment of structural changes in the Canadian economy due to climate change policies is presented here: Wigle, Randall Mark. Sectoral impacts of Kyoto compliance. Ottawa, ON: Industry Canada, 2001.

[2] See: https://www.neb-one.gc.ca/nrg/ntgrtd/mrkt/snpsht/2017/04-02cndpwrgnrtn-eng.html

[3] See: https://canwea.ca/wind-energy/installed-capacity/.

environmental regulation at the worker level. We exploit the rapid changes in the electricity sector resulting from policies that aim to reduce emissions, to capture the effects of the phase-out coal-fired generating facilities on employees outcomes including, wages, unemployment insurance, geographic and sector mobility. Ontario's fossil fuel fleet included five coal-fired power plants in Ontario —Nanticoke, Lambton, Lakeview, Thunder Bay and Atikokan. The design of the phase-out coal-fire program implemented in early 2000 in Ontario, makes it unique setting to evaluate this policy. To avoid major supply risks, coal plants needed to be kept in operation until adequate replacement generation and demand reduction measures are in place. It results that the closures of coal fired electricity plants was time varying starting from 2005 to 2014.

To investigate our research questions, we use the Longitudinal Worker File (LWF) and Postal Codes Conversion Files (PCCF) maintained by Statistics Canada, to follow workers in affected facilities over time, in order to gain an understanding of worker-level impacts of environmental regulation. Using the geographic location of Ontario five coal power plants along with the workers' postal code of residence we distinguish among workers whether or not exposed to the policy, that is being employee in the coal plant at the time of policy announcement. In 2003, Ontario announced the closure of all its five coal power plants. A key issue with our data is that while the Ontario coal phase-out targeted particular electricity generating facilities, we cannot directly observe which workers were employed in these facilities with the LWF data. To determine which workers are affected by the coal-plant phase out regulation, we use a method based on the postal code of residence of the individual and the NAICS code of the enterprise to which the individual belongs.

Our empirical strategy relies on a differences-in-differences methodology in two steps. The first step aims to examine the effect of announcement policy on several endpoints such as employee wages, unemployment insurance, sector mobility, and change in geographic location. We expect the announcement to influence the electricity sector through job applications. Workers for reasons of stability will tend to demand less for employment in this sector, which in the medium and long term will lead to an adjustment of wages. Our identification strategy aims to capture this effect.To do so, we compare employees from our treated group directly affected by the coal plant phase-out with similar employees (that form our control group) from the electricity sector living within Ontario a year prior the announcement not directly affected by the closure of the coal plants. For instance, to assess the labor market impacts of Ontario's closure of coal-fired electricity generating enterprises, we would like to compare employees from affected coal plants to a comparable group of employees from non-affected enterprises. The latter includes but not limited to employees from electricity plants not exposed to the policy such as employees from other generating facilities type including, nuclear, wind, or biomass among others, within Ontario.

The second step of the empirical strategy intends to capture the impact at the time of effective closure of the coal power plant. We would like to know whether closure itself had an impact on labour outcomes of interest. Furthermore, in supplementary analyses, we validate our main results by conducting an event-study approach to capture the time varying in exposure to the treatment. Moreover, we show that our results are not sensitive to alternative specifications including additional controls and alternative clustering.

We find that, workers exposed to Ontario coal plant phase-out policy have earned on average 7000 $ yearly less compared to those who weren't exposed. This impact is mainly driven by the announcement effect since the coefficient associated with closure is not statistically significant. Consistent with the effects on wages, our findings indicate that both policy announcement and closure are positively associated with unemployment insurance. Regarding the sector mobility, our results suggest that exposed workers are more likely to change the sector compared to unaffected ones. Heterogeneity results reveal that female, older, and single exposed workers experienced wages loss compare to their peers. Our findings are consistent across a set of alternative specifications and robustness checks. Using event study approach, we find that while environmental regulation is negatively associated to earnings in the short run, in medium and long-term, earnings tend to go back to their initial levels. This implies that in the long run earnings return to their original trajectory, so that any regulation impact is transitory. Our study provides supportive evidence on large labor costs due to environmental regulation policy and shed lights on the importance of reforms and training programs to support workers during the transition.

The remainder of the paper proceeds as follows. Section 3.2 discusses the Ontario coal phase-out policy background. Section 3.3 describes the data and variables pertaining to this study. Section 3.4 outlines the empirical strategy. Our findings are then presented in section 3.5, while sections 3.6 presents robustness checks. We conclude and discuss in section 3.7.

3.2 Ontario Coal Phase-out Program

Historically, Ontario has largely relied on hydro power for its electricity supply. In the 1960s Ontario invested heavily in coal-fired power plants for base load supply. In the 1970s the government also began an extensive nuclear power construction program, building 20 reactors over the next 20 years. By the end of the 20th century, Ontario's fossil fuel fleet included five coal-fired power plants in Ontario —Nanticoke, Lambton, Lakeview, Thunder Bay and Atikokan generating stations. Ontario's five coal-fired electricity-generating plants accounted for nearly a third of Ontario Power Generation's output (see table 3-1). In early 2000s, Canada committed to addressing climate change, e.g., by signing the Kyoto Protocol. Ontario decided to phase out coal fired power in 2003, largely to reduce air pollution/smog emissions (but also to address GHG emissions) [4]. Ontario implemented the coal phase-out program with the objective to close by 2010 its five coal power plants. The elimination of coal-fired electricity was a shared effort between the Ontario Ministry of Energy and two of its agencies: the Ontario Power Generation (OPG), the largest generator of electricity in the province and the Independent Electricity System Operator (IESO). The timeline action of the Ontario coal-fired phase out was as follows [5]

- In 2003, Ontario announces that it will stop burning coal at Lakeview GS. Ontario appoints the Select Committee on Alternative Fuel Sources to make policy recommendations on alternative power sources.
- In 2005, Ontario announces the planned closure of the Lakeview Generating Station and commits to closing the province's four remaining coal-fired power plants.
- Lakeview generating station closes.
- In 2006, Ministry of Energy instructs former Ontario Power Authority (OPA now IESO) to plan for coal phase-out at the earliest practical time, but still ensure adequate system capacity and reliability.
- In 2007, Cessation of Coal Use Regulation directs end date of December 31, 2014.
- In 2012, Atikokan generating station closes.
- In 2013, Nanticoke and Lambton generating station close.
- In 2014, Thunder Bay generating station closes.
- In 2015, Atikokan and Thunder Bay generating station reopen, fueled by biomass.

The decision of phase-out coal in Ontario has in part motivated by its human health and environmental benefits. However, there is an ongoing discussion of whether its benefits have outweighed its costs. The latter costs include but are not limited to unemployment, additional costs in pollution abatement equipment, reducing productivity, and increased in electricity prices. Moreover, eliminating coal-fired electricity in Ontario coincided with the need to restructure the electricity sector following the failed period of deregulation and privatization from 1998 to 2002. The sector suffered from under-investment, aging generation facilities

[4]See: https://www.ontario.ca/page/end-coal
[5]For details, please see, https://www.ontario.ca/page/end-coal

and soaring rates. The restructuring of the sector as well as the establishment of the Ontario Power Authority (OPA) in 2004 were undertaken with certain objectives in mind: phasing out coal, ramping up conservation and promoting renewable energy technologies by means of multiple support mechanisms (Rosenbloom and Meadowcroft, 2014). This may have helped to facilitate the introduction and successful implementation of the phase-out. Given this context of restructuring of electricity sector, it is possible that the direct effects of coal phase-out program overlapped with development of other renewable sources of energy.

3.3 Data and Descriptive Statistics

3.3.1 Sample construction and key variables

This study uses the Longitudinal Worker File (LWF) database combined with the Postal Code Conversion Files (PCCF) maintained by Statistics Canada. The LWF is an administrative database combining information at job and person levels and designed to provide information on employment dynamics in Canada. From the linked administrative tax data sources, information on worker's demographic characteristics, the jobs they hold, the business enterprises in which they work, and the earnings they receive can be identified. The LWF is a longitudinal file of 100% sample of workers, providing information on a year-by-year basis from 1997 to 2015 (the 2019 vintage). This database is particularly well-suited to studying our research question on the earnings dynamics and workers mobility following the clean energy transition.

Our key variables of interest focus on labour outcomes including wages, unemployment insurance, sector mobility, and geographic location. In addition to wages and unemployment insurance variables, sector and geographic mobility are relevant outcomes to consider when analyse the effect of regulation on workers decisions. Regarding sector mobility and geographic location we generate these variables. The sector mobility (geographic location) is a dummy variable equal 1 if the individual is not in the same industry (postal code of residence) as they were in 2002, and 0 otherwise. The LWF includes data on the enterprise of employment for individuals, and provides a 4 digit NAICS code associated with that enterprise. We use this to establish treatment status. This reflects an important limitation of our study, since we only observe the enterprise (company) and not the establishment (plant) of employment. In Ontario, the same enterprise (Ontario Power Generation) held both coal plants as well as other electricity generation plants, and we are not able to directly determine from the LWF which individuals were affected by the coal-plant phaseout. In addition, we observe 4-digit NAICS codes, which allow us to identify workers in the electricity sector, but not more detailed sub-sectors of the electricity sector, which require 6-digit NAICS codes.

A key issue with our data is that while the Ontario coal phase-out targeted particular electricity generating facilities, we cannot directly observe which workers were employed in these facilities with the LWF data. To determine which workers are affected by the coal-plant phase out regulation, we use a method based on the postal code of residence of the individual and the NAICS code of the enterprise to which the individual belongs. We assume that all individuals living within a certain radius around a generating station and belonging to the electricity sector are part of our target population. Below we describe the steps for building our database:

- We begin by linking job and person files of the LWF for the year 2002, that is the year prior to the policy announcement using the unique employee code. Based on the 4-digit NAICS code of the enterprise in which the job is held, we restrict our sample to workers employed in enterprises in the electricity generation sector in 2002. We merge the resulting dataset to PCCF files using individual postal codes of residence. Finally, we compute the distance from each postal code of residence to any of the five coal plants in Ontario as well as the other plants we consider for our analysis.

- Next, we identify the population of workers that forms our treated and control units from the sub-database built in the first step, using NAICS code. The treated group is formed by those workers employed in electricity sector and living in a certain radius [6] of each of the five coal plant in Ontario during the year 2002. While we require all individuals selected in 2002 to be employed, we do not exclude the possibility that over time their employment status might change as we follow them back and forward around the year 2002.

  Regarding the control groups, this paper considers two ways of defining the control group. The first definition supposes that any individual within the electricity sector working in Ontario during year 2002 and living at a distance greater than 25km from any of each five coal plants, to form our control unit. An alternative control group consists of people working in the electricity sector in Ontario during 2002, but living 25 km or less to selected control electricity plants. The latter plants includes a subset of electricity generating stations based on nuclear and hydroelectric fuel— which account for more than 50 percent of the province total electricity supply. Two factors were used to selected these plants: First, *(i)* the plants should generate electricity based on nuclear or hydroelectric since they account for around 57 % as of September 2003 as shown in

[6] We consider as a centroid the location of the coal plant and compute a radius around it. In our baseline analysis, radius equals to 25 kilometers while we later vary it to test the robustness of our results.

table 3-1. Second, *(ii)* we require the selected facilities to stay open during the sample period, that is from 1997-2015 and to operate under the Ontario Power Generation (OPG), the government utility that generates about three-quarters of the province's electricity. In total, our set of this alternative control group consists into workers from the following plants: Bruce Nuclear, Darlington nuclear, Pickering nuclear, Manitou, Ear falls, Otto Holden generating stations.[7]

- Once we have formed our three groups of interest–treated and the two different control groups–we append the LWF person files from 1997 to 2015 restricted to the individuals that belong to our three groups as build in step 2. This approach allows us to follow treated and control workers forward and backwards in time even if they move to a different sector or move to a different geogaphic location (within Canada).

The final dataset allows to track an individual whether exposed to the policy and examine its economics and mobility outcomes over time.

3.3.2 Summary Statistics

Table 3-3 below reports the main variables pertaining this study. We report the average measure of our labour outcomes during the sample period 1997-2015 while distinguishing between treated and non treated workers. The treated group is derived from the above definition and the control group is based on the first definition presented in the previous section. We use the alternative definition of the control group to perform a robustness checks to validate our effects. Our data includes on average 24,526 workers in 2002, with 3,677 treated and 20,849 untreated workers. In total, our sample consists into 415,800 observations with 61,421 from the treated group and 354,379 from the control group over the sample period 1997-2015. One might be concerned about the rate of missing observations in the sense that our analysis would not capture individuals who have retired earlier in the period or left the labor market for reason other than job losses or layoffs. Table 3-2 shows that over years, the number of workers in our sample slightly change (decrease) suggesting that this is a minor concern. On average, we count 3,000 workers employed in coal sector in Ontario at the time of policy announcement. We also acknowledge that because of the way we define our treatment status, this number probably count employees not necessarily in the coal sector as treated. So that, 3,000 workers employed in the coal plants corresponds to an overestimate of the true number given that LWF (the 2019 vintage) represents a 100 % sample of Canadian workers. This suggests that the method used to form our treated and

[7] We use the list presents at the following link: https://openinframap.org/stats/area/Canada/plants; to select our plants.

control units is somehow appropriate.

Labor cost of the regulation can be assessed through its direct impacts on wages —a key component of individual welfare —and/or on other induced adjustment costs. The latter include the cost of worker's sector reallocation or geographic mobility to adjust from job lost. To account for these employment costs, and given data limitation, we consider wages; unemployment insurance; sector and geographic mobility as relevant outcomes to study. Figure 3-2 depicts the change over the sample period (1997-2015) of our key variables in the treated and the control groups. Specifically, we look at the variation before and after the coal phase-out regulation was implemented in 2003 in Ontario. Overall, wages seem to follow an increase pattern up to 2010s where its started decline in the two groups as show in panel (a). Regarding the unemployment insurance plots in panel (b), it has followed the similar unstable trend around the mean of 365$. Since, we are interested in knowing where workers have moved following the regulation, we add panel (c) and (d) on sector and geographic migrations. They both show a considerable decrease trend after the regulation meaning that worker have moved from electricity sector and outside of Ontario irrespective of receiving or nor the treatment.

Our sample indicates that treated and unaffected workers average years is almost the same (47 vs. 46 for the control group), while the treated group tends to earn more (90,000 vs. 84,000 $) compared to their counterparts in the control group. Regarding the sector mobility, our data reveals that workers exposed to the policy were more likely to move to another sector (different from electricity NAICS code of "2211") compared to the unaffected individuals. Similarly, treated group of workers used to change their geographic location, that is moving to a different postal code of residence than the one prior the policy was implemented. Credible identification requires avoiding selection issues i.e. having workers different in their specific-skills such that they tend to be in a given sector. Unfortunately, despite the richness of the data which permit to flexibly control for most unobserved shocks, we do not have information on education or technical skills of workers. To solve the latter concern, we add individual fixed effects in our specification.

3.4 Empirical Strategy

3.4.1 Identification Strategy

We propose to compare outcomes of employees that are directly impacted by environmental regulations with a control group of employees who are not directly affected by the transition. Our primary identification strategy aims to capture the effect of environmental policy on workers' outcomes. To do so, we proceed by the difference-in-differences approach which relies on the parallel trend assumption. We investigate the impacts of Ontario's closure of coal-fired electricity generating plants, which took place between 2003-2014. Our empirical strategy relies on a differences-in-differences methodology in two steps. The first step aims to examine the effect of announcement policy on several endpoints such as employee wages, unemployment insurance, sector mobility, and change in geographic location. We expect the announcement to influence the electricity sector through job applications. Workers for reasons of stability will tend to demand less for employment in this sector, which in the medium and long term will lead to an adjustment of wages. Our identification strategy aims to capture this effect

Let $COAL\_WORKER_i(p)$ be a dummy equals to 1 if the worker i living at a distance less or equal to 25 km to any of the Ontario five coal plants p, in year α_p —the year of the plant effective closure —, with $\alpha_p \in 2005, 2010, 2012, 2013, 2014$, and 0 otherwise. Let $POST\_ANNOUNCEMENT_t$ be a dummy equals to 1 for years equal or greater than 2003 –the year of policy announcement— and 0 otherwise. We estimate the following equation:

$$Y_{it} = \sum_p 1COAL\_WORKER_i(p) \times 1POST\_ANNOUNCEMENT_t + \theta_i + \lambda_t + \epsilon_{it} \quad (3.1)$$

where Y_{it}, measures individual i outcomes (wages unemployment insurance, sector mobility, employment status, and geographic location) in year t, θ_i individual fixed effects, λ_t, year fixed effect and the error term ϵ_{it} which represents unobserved shocks to outcomes and assumed to be uncorrelated with the regressor of interest.

The second step of the empirical strategy intends to capture the impact at the time of effective closure of the coal power plant. We would like to know whether at the time of plant closure there was an impact on the labor outcomes of interest.

Let $POST\_CLOSURE_t(t >= \alpha_p)$ be a dummy equals 1 if for a given individual i living less or at 25km from any of the Ontario five coal plants p at the time and after their closure in a given year α_p, and 0 otherwise. The subscript α_p captures the time varying nature of the treatment given that plants used to shutdown at different point of time. For instance $POST\_CLOSURE_t(t >= 2005)$ equals 1 if worker i lives at 10 km from the Lakeview generating station during or after 2005, when the plant shutdown. To derive our causal impacts, we estimate the following equation:

$$Y_{it} = \sum_p 1COAL\_WORKER_i(p) \times 1POST\_CLOSURE_t(t >= \alpha_p) + \theta_i + \lambda_t + \epsilon_{it} \quad (3.2)$$

By doing so, we intend to capture any effect following the effective closure of any of our five coal plant. We also evaluate a version of the specification which combines the two equations above as the following:

$$\begin{aligned} Y_{it} = &\sum_p 1COAL\_WORKER_i(p) \times 1POST\_ANNOUNCEMENT_t + \\ &\sum_p 1COAL\_WORKER_i(p) \times 1POST\_CLOSURE_t(t >= \alpha_p) + \\ &+ \theta_i + \lambda_t + \epsilon_{it} \end{aligned} \tag{3.3}$$

For the rest of the paper, discussions focus mainly on the announcement effect, given that impact at the time of closure might resulted from what anticipation and strategies workers made earlier when regulation was announced.

We generalize equation (3.1) to allow for an event-study regression, in order to understand trends in the treated vs control groups in the years leading up to the coal fired station phase-out announcement as well as following the announcement.

$$\begin{aligned} Y_{it} = &\sum_p \sum_{k=-m}^{M} \beta_k 1COAL\_WORKER_i(p) \times 1POST\_ANNOUNCEMENT_t \times 1(\tau = k) \\ &+ \theta_i + \lambda_t + \epsilon_{it} \end{aligned} \tag{3.4}$$

where equation (3.4) is simply a generalization of a difference-in-difference estimator that allows any regulatory effects to evolve over time as opposed to assuming that the effect occurs immediately and lasts forever. τ denotes the year before or after the policy was announced. The excluded time category is $k = -1$, so that estimates are measured relative to the year before the announce of the regulation.

We perform several additional exercises to confirm the robustness of our results. We begin by changing the length of radius from 10 to more than 30 km around the coal plant location. We expected that, as we move away from a given coal power plant, workers should not be impacted by the environmental regulation. This exercise ensures that our results are actually induced by the implementation of the policy. In addition, we repeat our equation (3.1) while considering the alternative definition of the control group.

3.5 Results

3.5.1 Baseline results

We summarize the results of our baseline regression –equation 3.1 outlined above in tables 3-4 and 3-5, corresponding to the effects of the policy announcement on (i) wages and unemployment insurance and (ii) sector mobility and geographic location, respectively. In table 3-4, column (1) and (2) report the point estimates of the isolated effects of the policy announcement on average wages and unemployment insurance. Our findings indicate that on average, the announcement of regulation have negatively affected the earnings of those workers from specific coal electricity sub-sector and living in Ontario. Estimates in column (1) of table 3-4 suggest that compared to workers unaffected by the announcement, those concerned by the policy experienced on average a wage decrease of 7,000 $ on yearly basis. Column (2) shows that unlike wages, unemployment insurance received by the concerned workers have been greater than 50 $ yearly compared to unaffected workers. These results are consistent given that the wage loss was compensated by the increase in unemployment insurance.

The announcement of the regulation seems to be anticipated by the market in that it would have influenced the preferences of the workers who move in order to avoid a loss of income due to the coal plants closure. As a result of this anticipation, workers may review the allocation of their time between work and training to remain competitive on the market after regulation. This reduction in working time would explain the drop in wages observed when the policy was announced. Another explanation would come from the migration of workers to other sectors or geographical locations to avoid job loss due to regulation. Table 3-5 examines this evidence.

Table 3-5 reports estimates of the impact of the announcement of coal fired phase-out regulation on sector mobility and change in geographic location, that is, moving outside of their postal code of residence. It reveals that compared to unaffected workers, the concerned ones are more likely to move from electricity sector and outside of their postal code of residence. In terms of magnitude, our results suggest that announcement increase by 5.2 percentage points the rate of workers moving out of the coal electricity sub-sector. This migration in both sector electricity and geographic location might be due to rigidity in sector specific skills, so that workers are seeking jobs either in the same electricity sub-sector but outside Ontario or remain in Ontario but in different sector.

Next, we are interested in knowing whether there is an impact at the effective time of plant's closure. To do so we run the regression expressed in equation 3.2 where we define the treatment which is time varying, based on the coal plants closure. We consider

$COAL\_WORKER_i(p)$ and $POST\_CLOSURE_t(t >= \alpha_p)$ dummies. The results of the latter specification are reported in tables 3-6 and 3-7. Our findings suggest that only Unemployment insurance and sector mobility are sensitive to the effective closure. Indeed, closure leads to and increase (decrease) of unemployment insurance (sector mobility) of those workers affected by the regulation compared to the unaffected ones in the control group.

3.5.2 Event study approach

Central to our paper is to capture both the transitional and the long run effect of the Ontario coal phase-out policy on the employees labor outcomes. To do so, we examine an alternative specification of the baseline above, where we allow for the dynamic in the impacts as shown in equation 3.4. Figure 3-4 depicts the dynamic of the impact of Ontario Coal phase-out policy on our four variables of interest represent in panels (a), (b), (c), and (d). The graphs also indicate in red the time of each coal plant closure, that is, 2005 ($k = 2$) for Lakeview generating station; 2012 ($k = 9$) for Atikokan generating station; 2013 ($k = 10$) for Nanticoke and Lambton generating stations and 2014 ($k = 11$) for Thunder Bay generating station. It appears that the trend of earnings since the policy was announced goes from decreasing in the short run to slightly increase in medium and long run. However, the loss observed right after the announcement of the policy was compensated by the gain that benefits the regulated workers.

The event-study approach highlights the transitional or permanent costs associated to the regulation. Figure 3-4 plots the coefficients from a version of Equation 3.4 for the 5 years prior and 12 years after the regulation was announced. Specifically, the plotted coefficients are the difference in event time indicators for the workers concerned by the regulation relative to those unaffected by the policy. There are two important features from this figure in terms of immediate costs on wages and reallocation costs due to sector and geographic mobility. First, the trends in wages and mobility of workers from regulated coal plants for the years prior to the policy announcement are remarkably similar (as reflected by the zero pre-trend differences). Secondly, beginning with the year post the policy announcement, compared to the unaffected workers, the wages of affected workers slightly jump in the short-run (one year) before begin to fall for the next 12 years to an average of 7,000 \$ CAD yearly relative to their levels a year prior the policy announcement. This graph summarizes the main finding of the paper and suggests that the regulation leads to labor costs with the decline of wages. However, we also describe evidence that the latter labor costs occurred in transition as earnings increased after the closure of the last coal plant unit.

3.5.3 Heterogeneous results

So far we have produced evidence that the policy of regulating the polluting coal plant sector has had an effect on workers in this electricity sub-sector. To advance the analysis, we examine how this impact varies according to the socio-demographic characteristics of the workers. Specifically we analyze the effects according to sex; age; and the worker's marital status. First, gender has been proven to have a singular impact on the labor market participation of individuals by sector of activity. This analysis aims to estimate the cost of regulation by gender. Second, age group may influence the impact of regulation insofar as the worker may or may not have the flexibility to relocate easily to another province or train in new skills demanded by the sector. Finally, marital status (married or single) affects workers' decisions and preferences in response to regulation. For example, a single worker can easily change his place of residence in order to adjust to the adverse effects of the policy unlike more geographically constrained married workers.

Results of the heterogeneous analysis are reported in tables 3-8, 3-9, 3-10, and 3-11, corresponding to the effects on wages, unemployment insurance, sector mobility and geographic location, respectively. In each table, column (1) reports the effects conditional on gender, colum (2) on age and column(3) on individual marital status, that is, being or not single. Below we discuss the results and the rationale behind each heterogeneous analysis.

Gender. Our coefficient of interest is the one associated to the interaction term COAL_WORKER, POST_ANNOUNCEMENT, and being male. Our findings indicate that compared to female, male exposed to the policy have received on average 99 $ less in term of unemployment insurance. They also tend to stay in the electricity sector compared to female as shown in column (1) of table 3-10.

Age. We examine how the Ontario coal phase-out policy affected employees labor outcomes conditional on their age group. Column (2) of tables 3-8, 3-9, 3-10, and 3-11, reports the estimated coefficients on the interaction terms of age and treatment. We find that older worker exposed to the policy tend to leave the electricity sector. The rationale behind is that older workers have less incentive to move in another sector, despite the regulation, given that they have rigidity in their sector specific skills. Our results confirm the latter hypothesis.

Marital status (single). Finally, we are interesting in knowing how the effect of the policy affect single worker compared to others with another marital status. The rationale behind this analysis is that being single can allow worker to easily reallocate to another province or different area to seek a similar job. Therefore, for these category of workers, one might expect the cost of adjustment to be low. Our findings are somehow supportive for the latter argument, i.e. single tends to receive less amount of unemployment insurance compared to their counterparts married or in union.

3.6 Robustness Checks

3.6.1 Change the radius

We consider to vary the radius that represent the distance between workers postal code of residence to coal power plant location. In the baseline specification we consider radius equals to 25km. We arbitrary choose the different radius, greater or equal to 10km, 20km, and more than 30km. We anticipate that as the radius increased, our estimate become less precised conditional on the fact that workers share the similar labor market or community, which is not necessarily true. Table 3-12 reports the point estimates of the effect of the policy on our four main outcomes. While the effect on earning remain positive, the magnitude tends to decrease and become not statistically significant when the radius is greater than 30km. Surprisingly, the effect on number of jobs is positive, as we increase the radius. This switch in sign might be due to the difference in local labor market. Finally, as we increase the radius, the effect on pension plans contribution is not statistically significant.

3.6.2 Change the control group

As the second robustness checks exercise, we change the control groups and consider the alternative definition of the control group as mentioned in section 3.3. Tables 3-13 and 3-14 repeat our baseline regression where the control group is now form by people working in the electricity sector in Ontario during 2002, but living closed by distance less or equal to 25km to selected electricity plants. The latter plants includes Bruce Nuclear, Darlington nuclear, Pickering nuclear, Manitou, Ear falls, Otto Holden generating stations. Our estimate are consistent with the main findings of the paper. Indeed, using this control group, we find that compared to workers unexposed to the policy, our treated groups earned on average 7,000 $ less. This impact is closed to the one obtained when using our baseline specification.

3.7 Conclusion and Discussion

This paper investigates the transitional and long-term labor market costs of environmental regulations. We examine this relation in the context of the Ontario coal phase-out program implemented in early 2000s among the five coal fired electricity facilities. Our conceptual framework which guides the analysis hypothesizes that an environmental regulation on a targeted sector leads ultimately to two opposite effects. On the one hand, regulation has a direct effect on the reduction of local air pollutants like sulfur dioxide and oxides of nitrogen and GHG emissions with significant improve in the quality of air, labor productivity, and finally the hiring rates or the earnings. On the other hand, the introduction of the environmental regulation is perceived as a cost to firms which require to reorganize its internal production. As part of this restructuring, firms would increase the demand of green skills as well as clean and could either reduce the hiring rates or the earnings to support the cost of the acquisitions of this new factors of production.

The novelty of our paper results from that in our setting the regulation of coal plants lead to their closure instead of just the restructuring as in other contexts[8]. Although our setting is unique, we answer our research question using the above conceptual framework.

We construct a unique database based on the Longitudinal Worker File (LWF) database combined with the Postal Code Conversion Files (PCCF) maintained by Statistics Canada. The lack of information on establishments makes it difficult to identify our targeted groups–treated and control groups, given that the policy targets the establishments and not the enterprises. Moreover, missing information on the 6-digits NAICS codes adds additional issue, that is, not only to determine the sector of activity of a worker but also to which establishment he belongs to. To remedy this problem we use the approximation method based on the postal code of residence of the individual and the NAICS code of the enterprise to which he belongs. Concretely, we assume that all individuals living within a certain radius around a gener- ating station and belonging to the electricity sector as part of our target population. The final dataset allows to track over years workers whether exposed or not to the Ontario coal phase-out policy and examine its economics and demographics characteristics as well as post-displacement outcomes.

To investigate our research question, our empirical strategy proposes to compare outcomes of employees that are directly impacted by environmental regulations with a control group of employees who are not directly affected by the transition. Our primary identification strategy aims to capture the effect of environmental policy on workers' outcomes, such as wages, unemployment insurance, number of jobs, and pension plans. To do so, we proceed by the difference-in-differences approach which relies on the parallel trend assumption. We find that, workers exposed to Ontario phase-out coal policy have earned on average 7000 $ yearly less compared to those who weren't exposed. This effect is prevented for female,

[8]In the context of Clean Air Act in the USA, the regulation of polluting sectors did not necessarily leads to the closure of firms operating there

older, and single workers compare to their peers. Our findings are consistent across a set of alternative specifications and robustness checks. Using event study approach, we find that while environmental regulation is negatively associated to earnings in the short run, in medium and long-term, earnings tend to go back to their initial levels. Therefore, our study provides supportive evidence on small labor costs due to environmental regulation policy and shed lights on the importance of reforms and training programs to support workers during the transition

Our findings offer several policy recommendations. First, the employment and earnings effects of regulations are concentrated among a certain category of workers and within energy-intensive industry. Therefore, policymakers should include program which support labor reintegration and protection of these workers. These include but are not limited to job training programs, support to firm in acquisition of green skills and clean technologies. Second, this study highlights the importance of aligning the reforms on the timing, considering both labor market adjustments in short and long-run. Finally, from a climate change perspective, this study speaks to the broadly literature seeking to provide solutions in order to adapt (and mitigate) from the harmful effects of climate change on labor market.

Figures and Tables

Table 3-1: Ontario total electricity supply in 2003

Type of fuel	Capacity (MW)	Share (%)
Hydroelectric	6,796	30
Green Power	134	0.4
Nuclear	6,103	27
Gas-fired	2,200	9.6
Coal-fired	7,500	33

Notes: Ontario's five coal-fired electricity-generating plants account for nearly a third of Ontario Power Generation's output. See the link: https://www.theglobeandmail.com/news/national/ontarios-five-coal-fired-plants-to-shut-down-within-four-years/article995631/

Table 3-2: Total workers by treated and control groups over 1997-2015

Year	Control	Treated	Total
1997	19,093	3,306	22,399
1998	19,336	3,362	22,698
1999	19,813	3,435	23,248
2000	19,967	3,486	23,453
2001	20,291	3,553	23,844
2002	20,849	3,677	24,526
2003	19,855	3,490	23,345
2004	19,230	3,356	22,586
2005	18,877	3,262	22,139
2006	18,497	3,226	21,723
2007	18,236	3,157	21,393
2008	17,784	3,077	20,861
2009	17,350	3,007	20,357
2010	16,762	2,937	19,699
2011	16,524	2,905	19,429
2012	15,733	2,742	18,475
2013	14,948	2,566	17,514
2014	14,272	2,401	16,673
2015	13,481	2,238	15,719

Notes: The table reports the total workers by group over the sample period 1997-2015. Treated group refers to workers living at 25km or less to any of each of the five coal-plants and working within the electricity sector in Ontario a year prior the policy announcement (2002).

Table 3-3: Summary Statistics

Statistic	N	Mean	St. Dev.
		Treated group	
Wages	61,421	90,365.28	1,890
Unemployment Insurance	61,421	365.52	1,874.207
Sector Mobility[9]	61,421	0.796	0.403
Geographic Location[10]	61,421	0.62	0.097
Male	61,421	0.727	0.445
Age	61,421	47.63	10.257
		Control group	
Wages	354,379	84,110.08	6,797
Unemployment Insurance	354,379	432.983	1,959.839
Sector Mobility	354,379	0.816	0.387
Geographic Location	354,379	0.75	0.086
Male	354,379	0.788	0.401
Age	354,379	46.499	10.281

Notes: The table reports the key variables pertaining this study. The sample covers the period 1997-2015 with around 597,271 observations. The treated group is formed by those workers employed in electricity sector and living in a certain radius 5 of each of coal plant in Ontario on year 2002, the year of policy announcement. Regarding the control group several workers are considered as a comparable group. On average, we count 3,000 workers per given year employed in coal sector in Ontario at the time of policy announcement.

Table 3-4: Main Results: Effects on Wages and Unemployment Insurance

	Dependent variable:	
	Wages	Insurance
	(1)	(2)
POST_ANNOUNCEMENT$_t$	48123.28***	-11.716
	(1266.693)	(20.795)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	-7435.885^{**}	50.723**
	(3042.87)	(22.385)
Year FE	Yes	Yes
Individual FE	Yes	Yes
Observations	415,800	415,800
R-squared	0.3652	0.3196

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on average annual wages and unemployment insurance in that sector over time. In all regressions, standard errors are clustered at the individual level.

Table 3-5: Main Results: Effects on Sector and Geographic Mobility

	Dependent variable:	
	Sector mobility	Geographic location
	(1)	(2)
POST_ANNOUNCEMENT$_t$	0.0457***	$-$0.00385***
	(0.00412)	(0.00102)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	$-$0.0528***	$-$0.00267*
	(0.00659)	(0.00155)
Year FE	Yes	Yes
Individual FE	Yes	Yes
Observations	415,800	415,800
R-squared	0.559	0.477

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on average annual mobility by sector and province of residence over time. In all regressions, standard errors are clustered at the individual level.

Table 3-6: Effects of Closure on Wages and Unemployment Insurance

	Dependent variable:	
	Wages	Insurance
	(1)	(2)
POST_CLOSURE$_t(t >= \alpha_p)$	-1296.562	57.096
	(2879.959)	(36.1301)
COAL_WORKER_i(p)) $\times POST\_CLOSURE_t(t >= \alpha_p)$	-2663.583	10.934
	(4126.564)	(36.961)
Year FE	Yes	Yes
Individual FE	Yes	Yes
Observations	415,800	415,800
R-squared	0.3652	0.319

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on average annual wages and unemployment insurance in that sector over time. In all regressions, standard errors are clustered at the individual level.

Table 3-7: Effects of Closure on Sector and Geographic Mobility

	Dependent variable:	
	Sector mobility	Geographic location
	(1)	(2)
POST_CLOSURE$_t(t >= \alpha_p)$	-0.0031	0.00052
	(0.0058)	(0.001602)
COAL_WORKER_i(p) $\times POST\_CLOSURE_t(t >= \alpha_p)$	-0.0509^{***}	-0.00249
	(0.0079)	(0.00221)
Year FE	Yes	Yes
Individual FE	Yes	Yes
Year FE	Yes	Yes
Individual FE	Yes	Yes
Observations	415,800	415,800
R-squared	0.559	0.477

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on average annual mobility by sector and province of residence over time. In all regressions, standard errors are clustered at the individual level.

Table 3-8: Heterogeneous Impacts by Group: Effects on Wages

	Dependent variable:		
	Wages		
	(1)	(2)	(3)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	-2392.414^{*}	-7544.611^{**}	-8496.293^{**}
	(1276.997)	(3761.86)	(3737.38)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Male$	-6526.717		
	(4335.833)		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Age$		1494.583	
		(3876.008)	
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Single$			2562.436
			(4120.148)
Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	415,800	415,800	415,800

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on the average annual earnings per worker in that sector over time conditional on individual being male, at certain age, or single.

Table 3-9: Heterogeneous Impacts by Group: Effects on Unemployment Insurance

	Dependent variable:		
	Insurance		
	(1)	(2)	(3)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	124.852**	35.807*	57.099**
	(53.108)	(20.020)	(22.413)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Male$	−99.494*		
	(58.345)		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Age$		98.295	
		(109.818)	
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Single$			−137.1413**
			(65.405)
Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	415,800	415,800	415,800

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on the average annual unemployment insurance in that sector over time conditional on individual being male, at certain age, or single.

Table 3-10: Heterogeneous Impacts by Group: Effects on Sector Mobility

	Dependent variable:		
	Sector Mobility		
	(1)	(2)	(3)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	-0.0868^{***}	-0.03878^{***}	-0.0395^{***}
	(0.1385)	(0.006702)	(0.00691)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Male$	0.04641^{***}		
	(0.01574)		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Age$		-0.05745^{***}	
		(0.01996)	
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Single$			-0.0891^{***}
			(0.01818)
Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	415,800	415,800	415,800

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on the average annual sector mobility over time conditional on individual being male, at certain age, or single.

Table 3-11: Heterogeneous Impacts by Group: Effects on Geographic Location

	Dependent variable:		
	Geographic Location		
	(1)	(2)	(3)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	−0.001585	−0.00050	−0.00157
	(0.002981)	(0.00128)	(0.001297)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Male$	−0.001381		
	(0.0035)		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Age$		−0.01195	
		(0.007944)	
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t \times Single$			−0.003005
			(0.00546)
Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	415,800	415,800	415,800

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on the average annual geographic location over time conditional on individual being male, at certain age, or single.

Table 3-12: Robustness checks by distance to the plant

Radius >=	*Dependent variable:*			
	Baseline (25km)	10km	20km	30km
		Wages		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	-7435.885^{**}	-9706.637^{***}	-3880.687^{**}	-6314.389^{***}
	(3042.87)	(2904.238)	(1853.225)	(2479.167)
		Insurance		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	50.723^{**}	-60.674	37.703	34.424^{*}
	(22.385)	(44.069)	(25.094)	(20.334)
		Sector Mobility		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	-0.0528^{***}	-0.0348^{**}	-0.0540^{***}	-0.0513
	(0.00659)	(0.123)	(0.0074)	(0.00604)
		Geographic Location		
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	-0.00267^{*}	-0.00447	-0.00329^{*}	$-$ 0.00157
	(0.001558)	(0.0028)	(0.001773)	(0.00141)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	415,800	415,800	415,800	415,800

Notes: *p<0.1; **p<0.05; ***p<0.01. Table 3-12 reports the point estimates of the effect of the polic on our four main outcomes–wages, unemployment insurance, sector mobility and geographic location.

Table 3-13: Robustness checks using the alternative definition of the control group –(1/2)

	Dependent variable:	
	Wages	Insurance
	(1)	(2)
$\text{POST\_ANNOUNCEMENT}_t$	55606.13***	−105.7684***
	(1722.853)	(29.5546)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	−82031.69**	101.4894***
	(3433.203)	(25.933)
Year FE	Yes	Yes
Individual FE	Yes	Yes
Observations	169,143	169,143
R-squared	0.3353	0.2845

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on average annual wages and unemployment insurance in that sector over time. In all regressions, standard errors are clustered at the individual level.

Table 3-14: Robustness checks using the alternative definition of the control group –(2/2)

	Dependent variable:	
	Sector mobility	Geographic location
	(1)	(2)
POST_ANNOUNCEMENT$_t$	0.00909	0.000179
	(0.00676)	(0.001639)
COAL_WORKER_i(p) $\times POST\_ANNOUNCEMENT_t$	-0.04816^{***}	-0.00526
	(0.00783)	(0.00178)
Year FE	Yes	Yes
Individual FE	Yes	Yes
Observations	169,143	169,143
R-squared	0.550	0.470

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports point estimates of the impact of Ontario Coal phase-out policy on average annual mobility by sector and province of residence over time. In all regressions, standard errors are clustered at the individual level.

Figure 3-1: Ontario coal plants' location in early 2000s

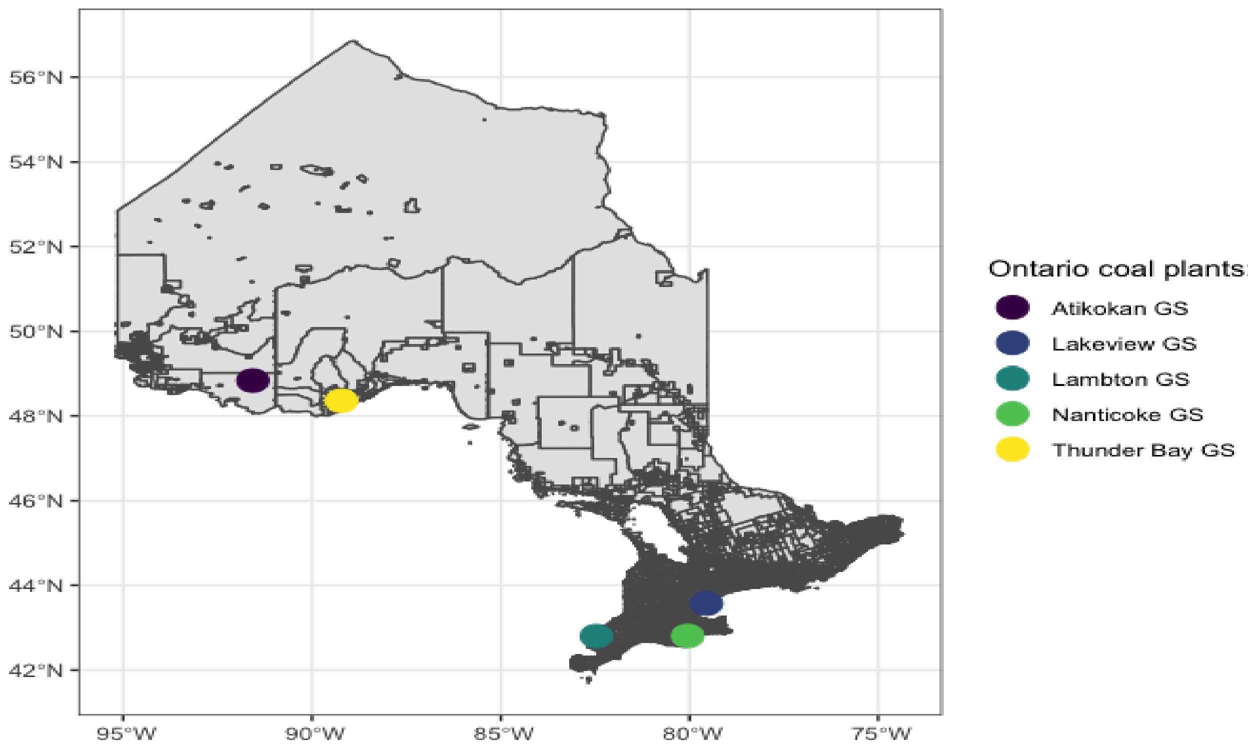
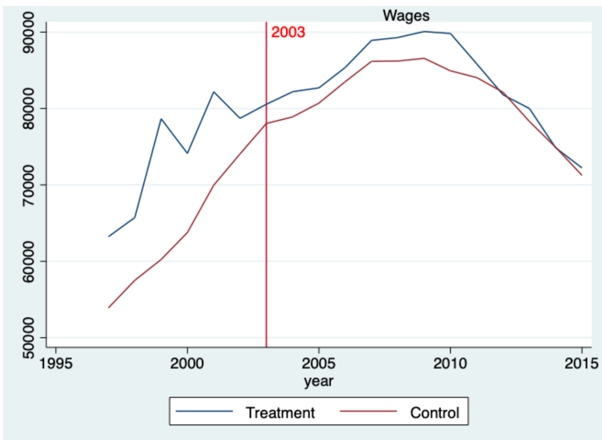
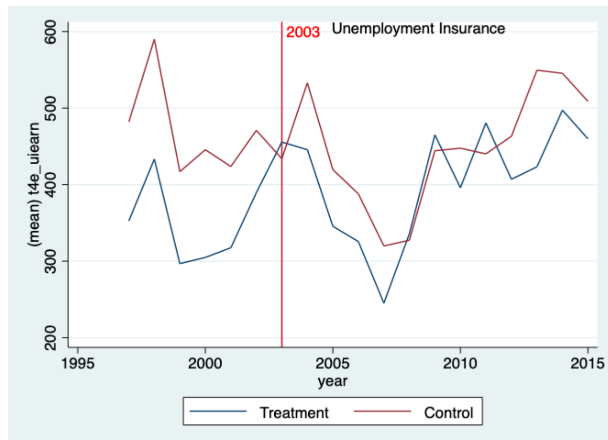


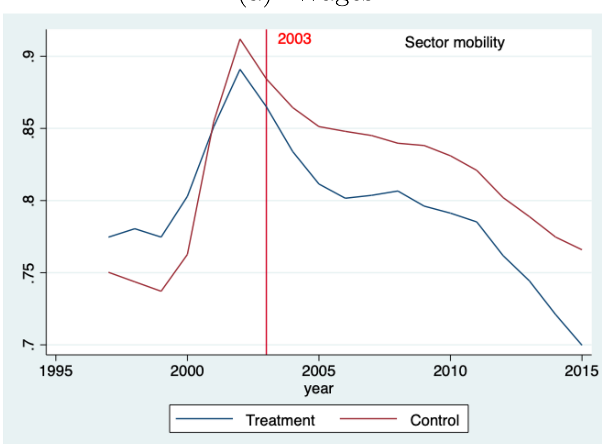
Figure 3-2: Data visualization over sample period 1997-2015



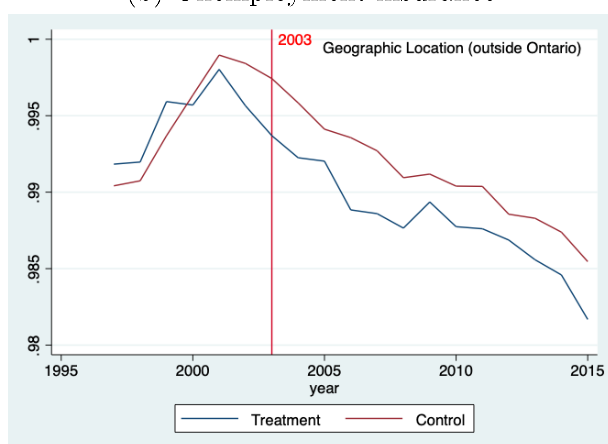
(a) Wages



(b) Unemployment insurance



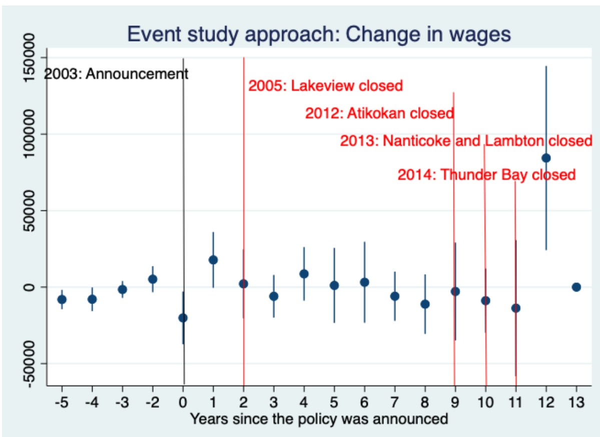
(c) Sector mobility



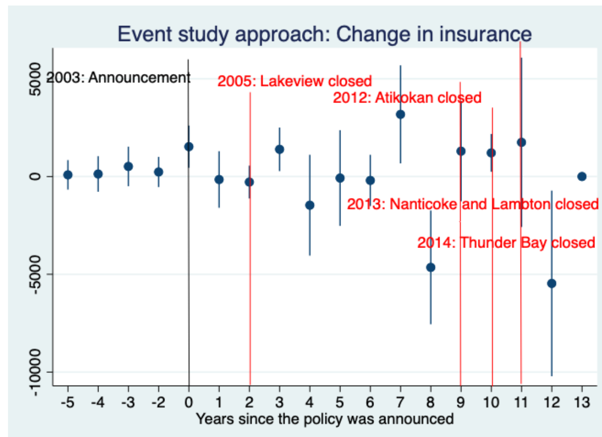
(d) Geographic location

Notes: This figure depicts the trends of our key variables among the group of interest. Specifically, we look at the variation before and after the coal phase-out regulation was implemented in Ontario.

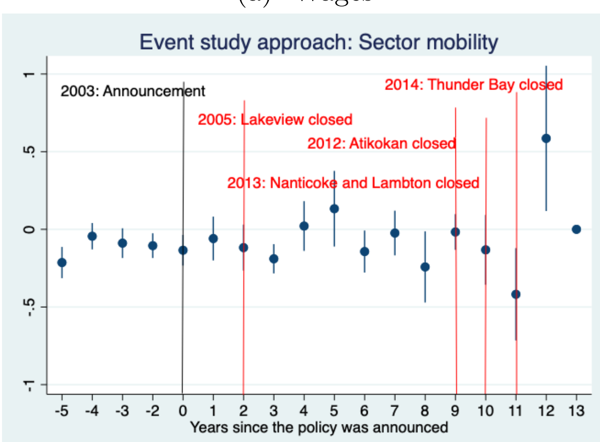
Figure 3-4: Event study approach



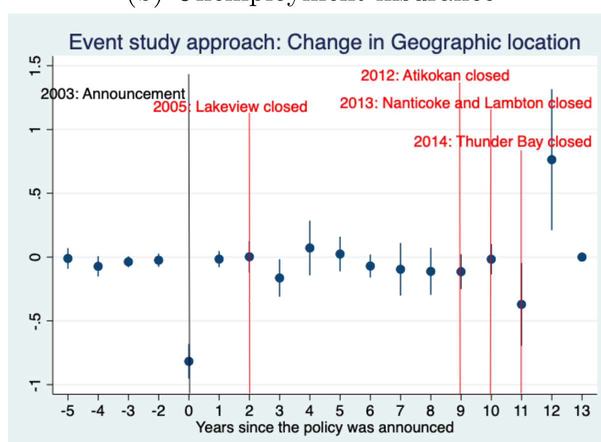
(a) Wages



(b) Unemployment insurance



(c) Sector mobility



(d) Geographic location

Notes: This figure depicts the change in trends of our key variables since the policy was implemented. We also indicate the time of closure of any of each coal-fired electricity plant.

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