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FRYING THE BRAIN:
The Effect of Prenatal Exposure to Heat on Fetal Brain Development

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Abstract: Due to climate change, temperatures are rising and are expected to keep rising—leading to an increase in exposure to hot temperatures. This paper presents an analysis of the effects of prenatal exposure to heat on fetal brain development and cognitive abilities later-in-life. Using individual-level data from the Indonesian Family Life Surveys (IFLS) and gridded weather data, the main finding is that exposure to days hotter than 29.5°C affects performance on both short-term and working memory tasks. This effect is even stronger during a critical period of fetal brain development—*corticogenesis*—suggesting that heat interferes with fetal brain development which affects cognitive abilities later in life. This effect is also larger in urban areas than rural areas. Using employment data, the analysis is extended to also provide tentative evidence on the potential mechanisms behind these effects. It turns out that a higher share of employment in agriculture reduces the effect, an effect that is exclusive to rural populations, suggesting that high temperatures affect the incomes of workers in agriculture positively allowing them to mitigate the negative effects of prenatal exposure to heat. The results imply a growing cost of climate change to human capital formation and productivity, but importantly they also imply that it is possible to mitigate and avoid the negative effects.

Keywords: Health, Memory, Brain Development, Heat, Climate Change, Human Capital

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Contents

1 Introduction

Climate change is a global phenomenon that is already affecting many aspects of our lives, from the food we eat and the water we drink, to the air we breathe and the weather we experience. As temperatures continue to rise due to the increasing levels of greenhouse gases in the atmosphere, extreme weather events such as heatwaves, droughts, and storms are becoming more frequent and intense (Doblas-Reyes et al., 2021). Both higher temperatures and extreme weather has far reaching consequences for economic growth, development and human health (Henseler and Schumacher, 2019). In addition, climate change can exacerbate existing inequalities and hinder the growth and development of vulnerable communities, particularly in developing countries.

Some of the most vulnerable countries are those that already today have lower incomes, here the effects of changing environments are more salient. The salience comes from a multitude of factors such as more fragile health, so that even small changes in environmental conditions can have large effects on health outcomes (Woodward et al., 2014, Ebi et al., 2021). In India, for example, the mortality of rural populations is adversely affected by higher temperatures, while US rural populations are not affected at all (Burgess et al., 2017). A lower income also often means that there are fewer available coping mechanisms or that the available coping mechanisms become too risky. One example is that while the high-return option of migrating during seasonal famines in Bangladesh exists, many individuals still do not take the option (Bryan et al., 2014).

The combination of a higher *a priori* fragility and fewer options available risks increasing the already existing inequalities between low- and high-income countries. If high income countries are anti-fragile and have access to coping mechanisms, the effects of climate change may be mutable to some extent. The inequalities also extend to the ability for further development and economic growth—especially if the environmental changes have effects on the ability to form human capital, use productive land, and to build a capital stock (Fankhauser and Tol, 2005; Garg et al., 2020; Hertel and Rosch, 2010). Human capital is an important driver of economic growth. And so far, research has shown that environmental factors have an effect on human capital in both high- and low-income countries. With heat, more specifically, it has been shown that heat waves lead to worse mental health and hotter temperatures also affect learning outcomes negatively (Garg et al., 2020; Hansen et al., 2008). Heat is not the only environmental factor that reduces human capital, similar negative findings have been found for the effects of pollution on health and cognitive performance (Landrigan, 2017; X. Zhang et al., 2018).

This paper presents a large-scale analysis of the effects of *in utero* exposure to heat on cognitive abilities in Indonesia. The analysis uses individual-level survey data that spans from 1961 to 2014, giving us a large sample taken born in different years. The survey includes completing a few tasks designed to measure cognitive ability in different forms—respondents answer Raven's progressive matrices, test their numeracy, recall words, and continue number series. I combine the demographic data from the survey with the performance on the cognitive tasks and match it to weather data. The weather, both daily average temperatures and daily precipitation, the individual has been exposed to while *in utero*, is calculated through matching gridded data with the regency the individual was born in. Using this data, I estimate a fixed effects model that allows us to create exogenous variation in temperatures and precipitation. This exogeneity allows me to estimate the causal effect of in utero exposure to heat. This also allows me to test a number of hypotheses about the effect and nature of in utero exposure to heat and the effect on cognitive abilities later in life.

I initially find an effect of heat on cognitive abilities—specifically, there's a large negative effect of exposure to additional days that are hotter than 29.5° degrees on performance in two memory tasks, immediate recall and delayed recall. At the same time, there is no effect on general intelligence, as measured by Raven's progressive matrices. Then, I further investigate a model of heat interfering with the brain development of the fetus by analysing the trimester heterogeneity of the effects. Contrary to previous research on the health outcomes of prenatal exposure to heat, there is no clear evidence of trimester heterogeneity (Hu and Li, 2019). However, when shifting the focus to a critical period of prenatal brain development—corticogenesis—there is strong evidence suggesting that being exposed to heat in utero has a large negative effect on immediate as well as delayed recall. This result also suggest that heat, through some biological mechanism, affects the brain development of the fetus, an effect that is non-reversible.

These results are extended by an analysis of one of the potential mechanisms that creates this effect—the economic mechanism. Comparing rural and urban populations show that urban populations are more adversely affected by heat, a finding that is contrary to previous literature (Hu and Li, 2019). Digging deeper into this finding, by using employment rates in agriculture and manufacturing, I find that the most plausible explanation for this result is that rural populations are able to mitigate the negative effects of heat through higher incomes from agriculture during heat. In rural regencies, a higher employment rate in agriculture in the regency an individual is born in is associated with a lower negative effect of prenatal exposure to heat on cognitive abilities later-in-life. On the contrary, in the same rural regencies, a higher employment rate in manufacturing leads to worse effects from prenatal exposure to heat. Suggesting that households that get their income from manufacturing work are worse off relative to their peers in agriculture. In urban populations, this difference is close to non-existent—suggesting that heat affects these populations directly and that they cannot mitigate it through increased incomes.

This paper therefore contributes to the literature on the effects of prenatal exposure to heat on longer term outcomes. A large number of studies have investigated the health effects, by looking at health outcomes at birth. Deschênes et al. (2009), and more recently Conte Keivabu and Cozzani (2022), McElroy et al. (2022), and Bekkar et al. (2020), find negative effects of prenatal exposure to hot days on birth weight as well as on the likelihood of preterm births and stillbirths.[1] Even more recently, further studies have shown that these birth outcome effects extend to later in life.

The long-term effects of hot weather on income and educational attainment has been shown to be negative by Isen et al. (2017) that use US data to find a negative effect on annual income and by Fishman et al. (2019) that use data from Ecuador to show that a 1° C increase in average temperature during pregnancy reduces both future income and educational attainment for the child. Hu and Li (2019) extend this research by looking at both educational attainment and later-in-life health, they find similar results and they also provide evidence in favor of an income mechanism. So far, there has only been one positive result, Wilde et al. (2017) find that higher average temperatures during conception leads to higher educational attainment and literacy, an effect that likely arises due to fetal selection. This literature weakly suggests negative effects on cognition, since studies have shown that cognition is a strong predictor for educational attainment, however there is little direct evidence of this effect as it may be that the effect on educational attainment arises only from poorer health (Guerra-Carrillo et al., 2017). Adhvaryu et al. (2015) investigate the relationship between in utero exposure to heat and mental health, and find that a higher temperature in the year before birth is positively associated with a higher likelihood of depression later in life.

To this day, little work has been done on the cognitive effects of in utero exposure to heat. Kuate et al. (2021) investigate the relationship between monthly average temperatures experienced while in utero and cognitive aging, they find that there's a relation between temperatures and higher cognitive aging. However, they find that the effect is positive for the lowest and highest temperatures, while average temperatures are negative—leading to a U-shaped effect over temperatures. In comparison, this study uses daily average temperatures, which makes sure that eventual nonlinearities are not left out and allows me to find the effects of short-term exposure to hot temperatures. The more precise data also allows me to pinpoint critical brain development phases, to get more precise estimates of vulnerability. There is also a focus on a younger population in this paper, the mean age in our sample is 26.57 years, which gives valuable insights into the effects on the working population in a period of their life that they are supposed to be at their highest cognitive ability and the most productive.

This paper also contributes to the wider literature on the relationship between early-life conditions in general and later-in-life outcomes.[2] Very rare shocks early in life have been well-studied, such as the effects of the Chernobyl disaster, the spanish influenza pandemic, and the Korean war (Almond, 2006; Almond et al., 2009; Lee, 2014). Less rare events such as famines and hurricanes have also been studied (Chen and Zhou, 2007; Currie and Rossin-Slater, 2013). The effects on long-term outcomes are in most cases negative, even though these shocks are less generalizable due

[1] For a review of the epidemiological literature on heat and birth outcomes, see Y. Zhang et al. (2017)

[2] See Almond and Currie (2011) as well as Almond et al. (2018) for comprehensive reviews of the literature.

to their rareness. More recently, the literature has been starting to study the effects of more common shocks in early life. Using data from Denmark, Schwandt (2018) shows the long-term effects of in utero exposure to the flu and finds that earnings decrease. Similarly, studies using prenatal exposure to pollution find that cognitive ability, educational attainment, and health are all affected adversely (Bharadwaj et al., 2017; Landrigan, 2017). Among the more positive examples, there are Maccini and Yang (2009) who find that early life rainfall increase educational attainment. This analysis complements this rather broad literature by exploring the effects of prenatal exposure to heat on cognitive performance, another critical factor in development, economic growth, and later-in-life outcomes.

Through the focus on cognitive abilities and brain development, the analysis also contributes to the neuroscientific and neuro-developmental literature that has previously been able to show in detail that several species of mammals are negatively affected by prenatal exposure to heat as well as other factors such as influenza and pollution (Hinoue et al., 2001; Short et al., 2010). M. Edwards (1969), M. Edwards et al. (1971), M. Edwards et al. (1974), and Upfold et al. (1989) show that prenatal exposure to heat has a causal effect on the brain weight, brain growth, the risk of microencephaly and learning capabilities of guinea pigs. Similar results have been found for pregnant mice that were exposed to brief hyperthermia, as their offspring were slower to learn than their counterparts (Shiota and Kayamura, 1989). More specifically, Hinoue et al. (2001) found that brief exposure to hyperthermia while in utero led to interference in the production and migration of neocortical neurons. Chang et al. (2011) also find that brief heat exposure leads to increased neuronal apoptosis in the hippocampus. These effects have also been shown to depend on the timing of the exposure (M. J. Edwards et al., 2003; Hinoue et al., 2001). Even though these effects have been established for animals, there is no direct evidence of a similar effect in humans and there is also reason to expect that the effects need not be similar in humans and mice or guinea pigs both due to the brains being too dissimilar and due to the experimental conditions being too far from the type of conditions that most human fetuses experience.

The rest of this paper is organized as follows. Section 2 discusses the background for the hypothesis of the paper as well as some potential mechanisms an effect could arise through. Section 3 describes the data sources, the key variables, and reports summary statistics. Section 4 shows the empirical method our analysis uses and Section 5 reports the main results of the paper. Section 6 extends and discusses the main results and Section 7 concludes.

2 Background

The causal theory that underlines the analyses in this paper is based on the recorded effects of heat on pregnant mothers, the brain development of fetuses, and on the health and human capital outcomes of exposed fetuses. There's evidence of an effect of prenatal exposure to heat on the health of the fetus, leading to reduced birth weight, increased risk of stillbirth, and later-in-life height (Bekkar et al., 2020; Conte Keivabu and Cozzani, 2022; Hu and Li, 2019). There's also solid evidence on the effect of heat on the health and stress of the mother (Beroukhim et al., 2022; Weinstock, 2008; Y. Zhang et al., 2017). Finally, the evidence from the effect of heat exposure on the brain development of mice and guinea pigs suggests a third effect of heat—interference with the brain development of the human.

I therefore hypothesize that prenatal exposure to heat affects the brain development of the human fetus. Further, this interference, due to happening in vital periods of brain formation, may have long-lasting and, potentially, non-reversible effects that affect the cognitive abilities of the exposed fetus when they are adults. The long-lasting and non-reversible effects of brain development interference have been recorded for multiple other factors, such as for prenatal exposure to alcohol and pollution (Welch-Carre, 2005; X. Zhang et al., 2018).

Biologically, there are a few plausible mechanisms through which the negative effect of prenatal exposure to heat on brain development can arise. The first mechanism is a direct interference with cell migration, proliferation, and apoteosis that is caused by increased heat, i.e. heat disturbs the normal functioning of the processes that create and migrate brain cells. This process is what is indicated in the mice and guinea pig studies (Chang et al., 2011; M. J. Edwards et al., 2003; M. Edwards et al., 1974; Hinoue et al., 2001; Shiota and Kayamura, 1989). Cell migration and proliferation start to happen in the human brain development during the beginning of *corticogenesis*—a period starting approximately 7 weeks after conception. This period is critical for the formation of the cerebral cortex, which includes the frontal cortex and the neocortex—both critical for human cognition (Hawkins et al., 2017; Reilly et al., 2015).

Another plausible biological mechanism arises through prenatal stress exposure. A multitude of studies on both animals and humans have shown that increased activation of the hypothalamic–pituitary–adrenal (HPA) axis leads to an increased level of cortisol in both the mother and the fetus. The excess cortisol can affect fetal growth and brain development. More specifically, animal studies have shown that exposure prenatal stress led to higher cortisol levels, interference with neurogenesis, and smaller hippocampuses in the fetuses (Charil et al., 2010; Coe et al., 2003; Weinstock, 2008). Another plausible mechanism involving the HPA axis is the concentration of placental corticotropin-releasing hormone (CRH). Prenatal stress activates the HPA axis, which produces CRH in the placenta. The CRH reaches the fetal brain, activating CRH receptors in the hippocampus and other brain areas rich on CRH receptors, such as the frontal cortex, and thus causing interference in brain development (Charil et al., 2010). Finally, a third plausible biological mechanism is the effect of nutritional deficiencies on brain development. The development of the brain is an expensive process, both in terms of energy and in terms of the material needed. Therefore, nutritional deficiencies during the prenatal period can have negative effects on cognitive ability later in life (Georgieff et al., 2018). A number of nutrients have been shown to be of importance in brain development, such as iron, zinc, folate, and choline (Zeisel, 2006). If heat leads to nutritional deficiencies, then this may be a plausible mechanism through which heat affects the cognitive abilities of fetuses.

Even though all three of these potential biological mechanisms are directly affecting the brain development and brain functioning of the fetus, we can separate them into two separate categories to more easily refer to them. The mechanism of nutritional deficiencies can be characterized by its indirect character—it mainly arises if the mother's income or behavior is affected, which can create insufficient nutrient intake. The effects on cell proliferation, migration, or apoteosis, on the other hand, may arise only through the simultaneous exposure to heat. The prenatal stress mechanism can be classified as both an indirect and a direct effect, as there's evidence that the HPA axis is activated both by psychological stress factors and, potentially, by heat itself (Gaab et al., 2005; Joseph and Whirledge, 2017). Heat can directly create the indirect effects—of prenatal stress and nutritional deficiencies—through either directly increasing the psychological or physiological stress on the mother or through affecting the income of the mother, which can affect the mother psychologically and by reducing her endowment to be spent on nutrition. The direct effects are hard to test for, as the data does not include biological markers such as brain weight or cortisol level measures. However, the economic effect, meaning the effect on prices, incomes, budget constraints, and return, is more salient.

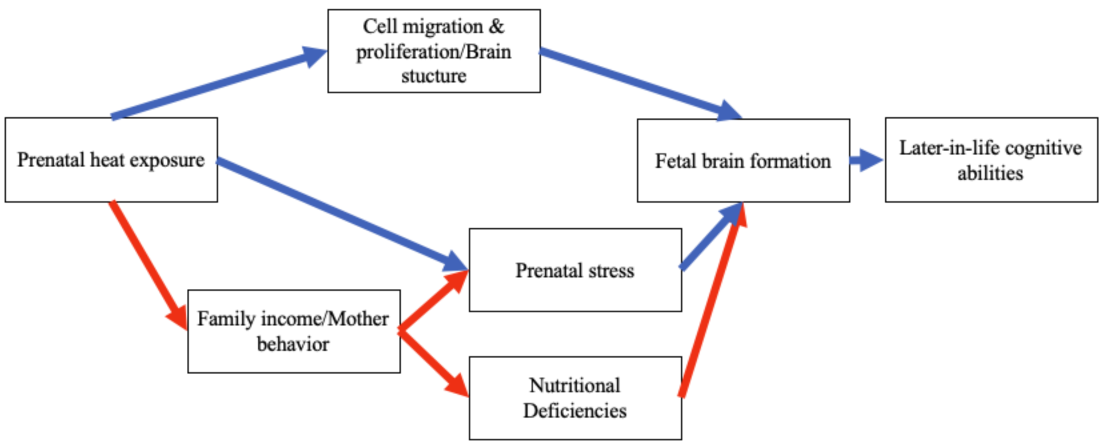

Figure 1: The causal graph of how prenatal exposure to heat affects cognitive abilities

Note: This graph shows the mechanisms through which prenatal exposure to heat can affect later-in-life cognitive abilities. Overall, one can separate the three pathways into direct (blue paths) and indirect paths (red paths). Prenatal stress and nutritional deficiencies arise through heat first affecting the mother. Cell proliferation and migration, as well as prenatal stress are direct effects on the fetus. All three effects affect the formation of the fetal brain, which has negative effects on later-in-life cognitive abilities.

The causal theory is summarized in Figure 1. Based on this model of heat affecting the brain development of the fetus and thus affecting the fetus' cognitive abilities later in life, there are a few hypotheses that are testable. First, the hypothesis that there is a causal link between prenatal heat exposure and cognitive abilities later in life. Second, if this effect is due to interference in the prenatal brain development process then we would expect a larger effect during critical periods of brain development, which is tested through examining the effect of exposure to heat during corticogenesis. These analyses and tests are presented in Section 5 and then complemented with additional analysis in Section 6.

3 Data

To investigate the relationship between heat exposure in-utero and cognitive ability later in life, we created a comprehensive Indonesian individual-level data set for the period between 1961 - 2007. We combined gridded daily average temperature and precipitation data for the 522 regencies and cities in Indonesia with data from the Indonesian Family Life Survey (IFLS) to create a data set with individuals that are born in different periods of time in 229 different regencies. This will allow the analysis to look at the differences between individuals born in the same district at different times.

Indonesia has 4 different administrative levels—Provinces (level 1), Regencies (level 2), Counties (level 3), and Villages (level 4). The second level, regencies, is used for identification. In principle, it could have been possible to use counties as well though that would reduce the power of subsequent regressions by too much. [3]

3.1 Weather

Previous studies have shown that non-linearities are common in the relationship between temperature and health outcomes (Burgess et al., 2017; Hu and Li, 2019). To not exclude these non-linearities *a priori*, daily average temperature data is used in this paper. Monthly or even weekly aggregated data does not suffice for identification of the non-linearities. The ideal setup for the weather data would have been to use data from weather stations in each regency. In reality, it would have been close to impossible to create a large scale complete weather data set from Indonesian weather stations. The weather stations in Indonesia are sparse and they are often missing data from much of the time series we are interested in.

Therefore, I use daily weather data gridded on a $0.25°$ (longitude) $\times 0.25°$ (latitude) grid. The data comes from the Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation of Extreme Events (APHRODITE) project that creates gridded data sets of precipitation and temperatures over all of Asia. The specific data sets used are the Monsoon Asia daily average temperature and precipitation data sets. The gridded fields are defined by interpolating observations that are obtained from meteorological and hydrological stations across the region. This is done on a $0.05°$ (longitude) $\times 0.05°$ (latitude) grid that is then re-gridded to the $0.25°$ (longitude) $\times 0.25°$ (latitude) grid that I use in the analysis (Yasutomi et al., 2011; Yatagai et al., 2012). The data sets start in 1961 and includes data until 2007.

[3] See Table 1 below for summary statistics and Figure 2 for a distribution of daily temperatures.

The gridded datasets do not offer a simple way of connecting individuals with the weather they experience while in-utero, since there is no exact location data in the IFLS surveys. Instead, I use a shapefile of the administrative boundaries. The shapefile contains multipolygon coordinates for each regency in Indonesia, this allows me to match the grid coordinates to the mulipolygon coordinates. From this match, I calculate the daily average temperature in a district by calculating the weighted average of all the grid cells covering the regency. The weights are determined by how much of the grid cell that is covering the regency (Hijmans et al., 2022).

When the data has been interpolated to the regencies, we create a number of variables to be used in analyses. The daily average temperature variable is divided into 6 different bins, $< 21.5°$ C, $21.5-23.5°$ C, $23.5-25.5°$ C, $25.5-27.5°$ C, $27.5-29.5°$ C, and $> 29.5°$ C. For each individual, I count the number of days in each bin in their regency while being in utero. I use these bins to be able to catch as much of the non-linearities as possible without loosing too much power. Further, as previous literature on the relationship between in-utero exposure to heat and health have shown, the trimester in which the exposure happens may matter and thus I also divide the count of days in each bin into the three trimesters (Basu et al., 2010; Bekkar et al., 2020).

I define conception to be 270 days before the birth date. As this is not an exact date, this means that there will be some measurement error in the weather variables as there is a possibility of missing some days in the case of late births or including some days that should not be included in the case of early births. The same problem arises when defining the trimesters. I have defined the first trimester to be from conception until 12 weeks later (84 days) and the second trimester to be from the end of the first trimester until 13 weeks later (94 days).

With precipitation, I create a variable that sums the total precipitation exposed to while in-utero for each individual. Here, I also create a sum for each trimester. I then create the natural log of the sums to use them in the analysis.

3.2 Indonesian Family Life Survey

The IFLS is an on-going longitudinal survey in Indonesia that is representative for 83% of the Indonesian population. The surveys are ran by RAND in collaboration with the Research Population Center, University of Gadhja Mada, and the first wave of the survey was conducted in 1994 and the fifth wave was conducted in 2014-2015. I use data from the final three survey waves, IFLS3-5, as they are the only waves that include data on cognitive abilities (Strauss et al., 2004; Strauss et al., 2016; Strauss et al., 2009).

The surveys obtain data of interest for all adults above 15 years old in the sample. From this main sample, I restrict the data to only include those individuals that have not moved since they were born. This insures that I do not attribute the weather of the regency they currently live in to the weather they were exposed to while in-utero. This still leaves out the possibility that some

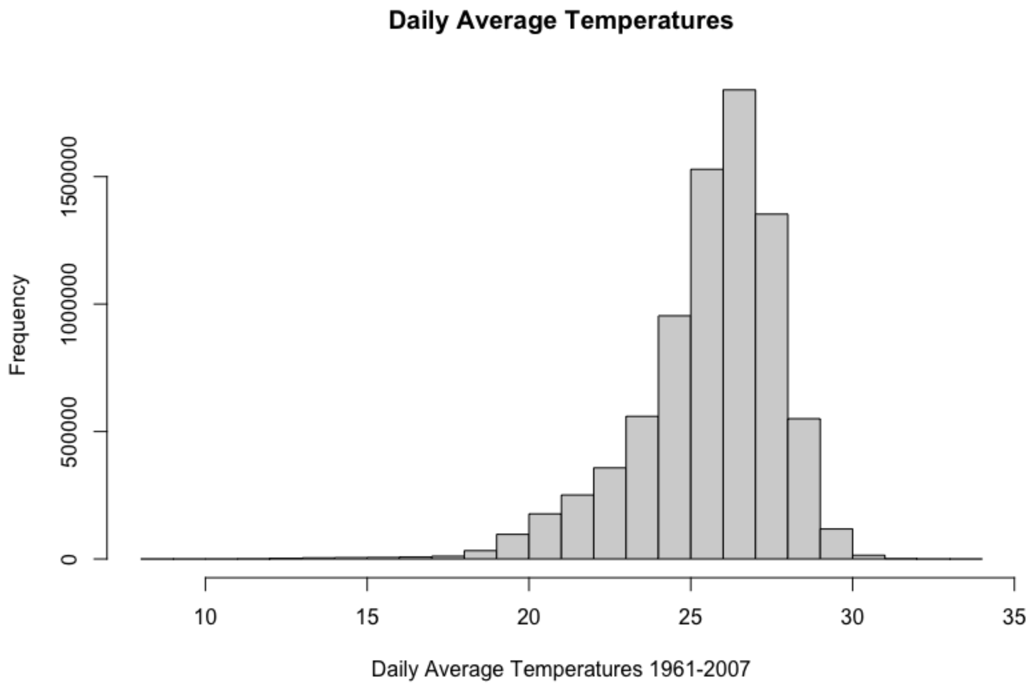

Figure 2: Daily average temperatures in Indonesia between 1961 and 2007

Note: The temperature data is taken from the APHRODITE project (Yasutomi et al., 2011; Yatagai et al., 2012).

mothers may have moved during the pregnancy, though the likelihood of that happening seems negligible. In total, this leaves me with a sample of 17,371 individuals from 229 regencies. The birth years of the sample range from 1961 to 1999. Sample summary statistics are found in Table 1.

The outcome variables of interest are those that measure cognitive abilities in some way. Starting from IFLS3, the surveys include a module called EK. This module is completed by all 7-24 year olds in the sample and it is a test with 22 questions that tests pattern-matching and mathematics, I remove the mathematics-questions and create a variable only based on pattern-matching skill. Appendix section A shows a sample of the type of questions asked in module EK. The questions asked are akin to Raven's progressive matrices, which means it tests fluid intelligence (Strauss et al., 2016).

Further, IFLS4 and IFLS5 include a module on memory in Book B3B which each individual older than 15 is supposed to complete. In the module, the individual is given a list of 10 words which are then repeated back to the interviewer. (See appendix section A for the word list in IFLS5) First directly and then with a delay, consisting of completing another module of the survey. This gives us a measure of both direct memory and long-term working memory for each individual above 15 that completed IFLS4 or IFLS5. This measure helps me highlight another aspect of cognitive performance that affects human capital formation and productivity. Engle et al. (1999) argue that word recall, especially delayed word recall, can be used to determine working memory (WM) capacity. They also find that WM predicts fluid intelligence, as measured by Raven's progressive matrices and Catell Culture Flair Test. Additionally, theories of memory and learning, such as the cognitive load theory, suggest that working memory is a key component in the ability to learn and acquire skills and knowledge (Sweller, 2010). A large literature suggests that improving working memory also improves learning outcomes and educational outcomes, though I could find no studies suggesting that regular education causally increases working memory (Cowan, 2014). If that is the case, then memory measures serves as a good outcome variable that is not mediated by educational attainment.

Finally, in IFLS5 an additional cognitive capacity test was included in Book B3B. In this version, the respondents were given sequences of 4 numbers with one number left out. The respondents had to fill in the missing number. The test was created in collaboration with Dr. John McArdle, who also created a scoring algorithm that scored each respondent based on their result on this module (Strauss et al., 2016). This gives me two alternative measures of pattern-matching ability. Since this module was only included in IFLS5, the number of observations for this measure are low and all analyses using these measures are reported in the Appendix (See Table B.1).

From the IFLS I also obtain data for control variables such as parents' level of education, parents' age at birth, age, birth year and month, location, education, ethnicity, gender, and the number of siblings.

3.3 Indonesian Census

The Minnesota Population Center (2020) provides the Integrated Public Use Microdata Series, a set of census microdata from all over the world.[4] The Indonesian data includes censuses made in 1976-2010, in five year intervals. Full censuses are performed only every tenth year, and in between inter-censal surveys are performed. In total, the sample includes more than 55 million people. In each census, respondents are chosen randomly in each strata and then they are asked questions about family situation, employment, and more. In the analysis of potential mechanisms, I use the employment data from each census. More specifically, each respondent in the census records their occupational status. The occupation the respondent has is recoded, roughly, according to the International Standard Industrial Classification (ISIC). This allows me to construct variables of employment rate in key industries in each regency of our sample.

I match each individual with the employment statistics of the regency they were born in. Due to the censuses only being performed every 5 years, I match the employment statistics taken closest in time to the birth year of the individual. In this way, the employment variable comes as close as possible to representing the state of the labor market at the time of birth.

[4] I also wish to acknowledge the statistical offices that provided the underlying data making this research possible: BPS Statistics Indonesia, Indonesia.

3.4 Summary Statistics

Table 1 summarizes the data used in the analysis. The main outcome variables used are *immediate recall, delayed recall*, and *EK score*. The average individual in the sample recalls just under 5.8 (out of 10) words directly after having heard them and after a slight delay (on average 2 minutes) they recalled just under 4.9 (out of 10) words. In the EK cognitive assessment, the average sample respondent had 6.3 correct answers out of 8 possible. On the cognitive assessment with number series, COB Score, the average individual in our sample answers correctly 3.2 times out of 7.

In regards to the exposure to temperatures, the summary statistics show us that there is quite little variation. Most of the prenatal days are spent in temperatures ranging between $23.5 - 27.5$°C. On average, an individual in the sample is only exposed to *one* day hotter than 29.5°C and the median individual exposure is zero days above 29.5°C.[5] Across the entire weather sample, from 1961 - 2007, the daily average temperature was 25.57°C and the daily average precipitation was 4.78 millimeters.[6]

The individual characteristics show us that the sample skews younger, with an average age of 24. Further, the average individual has close to 3 siblings and has attended at least 6 years of school.[7]

4 Empirical Method

To identify the causal effect of in utero exposure to heat on cognitive ability later in life, the model exploits the plausibly random variation in temperature for any given regency and year. There are some potentially confounding variables in the unobserved differences between regencies and years, but these are accounted for by using using the following fixed effects specification:

$$Y_{irym} = \sum_{j=1}^{6} \beta_j Days_{jiry} + \gamma Precip_{iry} + X_i'\delta + \lambda_{ry} + \eta_{rm} + \theta_{ym} + \varepsilon_{irym} \tag{1}$$

This specification captures the presumed heterogeneity in the effect of temperatures on cognitive abilities, where Y_{iry} denotes the outcome variable (e.g., measures of cognitive ability) for individual i, in regency r, born in year y. The variables of interest here are the six $Days_{jiry}$ that count the number of in-utero days in each of the eight temperature bins in regency r within year y. I use $Precip_{iry}$, the natural logarithm of precipitation while in-utero in regency r within year y, as a weather control. Including precipitation, which likely correlates with temperature and that may also have an effect on cognitive ability (Maccini and Yang, 2009), is necessary to avoid bias in the variables of interest, though I will not take any particular interest in the effect of rainfall

[5] This is quite low, e.g the individuals in the sample of Hu and Li (2019)) experience approximately 53 days over 29.5°C on average.

[6] See Figure 2 for the entire distribution of temperatures

[7] Primary school for 6 years was made fully mandatory in Indonesia in 1984, by 1994 this was extended to include secondary school for a total compulsory education of 9 years (Lewis and Nguyen, 2020).

during pregnancy on cognitive abilities. X_i' is a vector of control variables including the age of the parents at birth, the parents' educational attainment, the age of the individual, the ethnicity of the individual and the number of siblings the individual has.

The specification uses three two-way fixed effects to control for unobserved variables—Regency-by-year, regency-by-month, and year-by-month. λ_{ry} denotes regency-by-year fixed effects which control for nonlinear changes that may affect the human capital formation of individuals born in the regency. For example, Indonesia adapted the 1970s Sekolah Dasar INPRES program during our sample, which affected human capital formation in regencies nonlinearly (Duflo, 2001). η_{rm} denotes regency-by-month fixed effects which control for factors that may be correlated with both temperature and early development such as seasonal employment. These factors are most likely county- and month-specific. And θ_{ym} denotes year-by-month fixed effects that control for year-specific shocks that affect all counties. An example of this type of shock is the Asian economic crisis in the 1990s, which affected Indonesia severely. These three sets combined with the precipitation controls isolates the plausibly random fluctuations in temperatures in a given regency for each year and month. This random fluctuation is what gives identification to the study.

The main specification for the overall effects during the entire pregnancy is eq. (1). However, previous studies on the relationship between health and temperature exposure in utero have shown that there may be considerable heterogeneity in the timing of the temperature shocks as well. Therefore, I complement the main results with an additional specification making use of the pregnancy trimesters.

$$Y_{irym} = \sum_{a=1}^{3}\sum_{j=1}^{6}\beta_{ja} Days_{jairy} + \sum_{a=1}^{3}\gamma Precip_{airy} + X_i'\delta + \lambda_{ry} + \eta_{rm} + \theta_{ym} + \varepsilon_{irym} \tag{2}$$

This is essentially the same specification as eq. (1), but now each bin has three instances, one for each trimester a of the pregnancy. The same goes for the precipitation variable. Further, previous neuroscience and biology research on the negative effects of different conditions on brain development have shown that the period of corticogenesis, i.e the period where the cortical regions of the brain are formed, is especially sensitive to different stressors (Kostović and Judaš, 2015). Therefore, I run a third specification where I divide the pregnancy into two periods a, corticogenesis and non-corticogenesis.

Despite these specifications and the set of three twoway fixed effects, there is still some concerns abut coefficient bias that remain in the data. First, there's a concern about migration. Even though the sample is made up of individuals whose families have not moved outside of their regency since their first child was born, it is still possible that some pregnant mothers have moved during pregnancy or spent significant time outside of the regency where the family is living during pregnancy. This we cannot control for, but it may affect the results slightly. Second, the dates of birth in the sample are inaccurately measured, due to many families in Indonesia not having access to their birth certificates. This inaccuracy leads to coefficient bias if the inaccuracies are not randomly distributed in the sample. Unfortunately, there is no way of testing this possibility.[8] Another factor related to birth dates that may lead to coefficient bias is the recorded issue of high temperatures affecting the length of the gestation period (Basu et al., 2010). These effects also seem to be larger in the third trimester, though the evidence is somewhat inconclusive (Conte Keivabu and Cozzani, 2022). If that is the case and pre-term delivery is correlated with worse cognitive abilities later in life, then this would bias the estimated coefficients on temperature shocks in the later stages of the pregnancy downwards. At the same time, this would make me set the time of conception too early, effectively making me over-count the exposure to heat while in utero—leading to an over-estimation of the effects during early pregnancy. There is unfortunately no way to measure the true gestation length from the data, and therefore one should interpret the results with these limitations in mind.

5 Results

This section reports the estimated effects of in utero exposure to heat on cognitive ability. The main outcome variables are referred to as *Fluid Intelligence* (EK Score), *Immediate Recall*, and *Delayed Recall*. The main results, using Equation (1) as specification, are presented in Figure 3. All three of these models are estimated with the full set of controls and the standard errors are clustered at the Regency-level throughout. These initial estimates show that the exposure to an additional day with temperature above 29.5°C has a negative effect on immediate as well as delayed word recall—the effect on fluid intelligence, on the other hand, is slightly positive.

5.1 Fluid Intelligence

The first outcome of interest is the fluid intelligence measure from Book EK in IFLS. Table 2 reports the results from the regressions with the standardized number of correct answers on the eight common Raven's progressive matrices. Column (1) and (2) reports the effect when only taking exposure to the hottest days into account. The point estimates are slightly positive, but very inaccurately estimated. Common to all specifications is that including the individual characteristics controls decreases the estimates slightly, while having very small effects on the standard errors. When all of the bins are included, with bin 3 ($23.5 - 25.5$°C) as a reference point, in column (3) and (4) the estimates for the hottest days increase slightly. These results show the non-linear nature of temperature exposure, where the temperature bins that are below 29.5°C have much smaller effects. This corroborates previous results from Burgess et al. (2017), Hu and Li (2019), and Adhvaryu et al. (2015) that also show the non-linearity of the effect of temperature exposure. Finally, in the last two columns, (5) and (6), the estimates show that there is a positive effect

[8] A priori, it seems unlikely that the measurement error is randomly distributed.

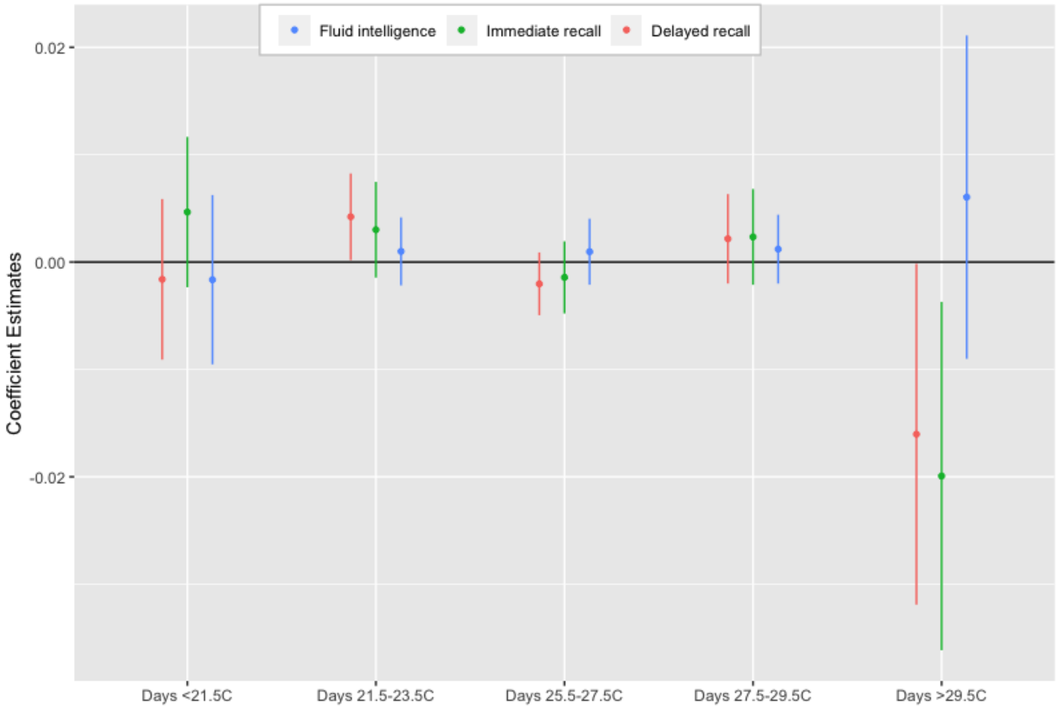

Figure 3: Total effects

of exposure to hotter days in all the trimesters—though without controls exposure in the second trimester has a larger effect. I also estimate the same specification, but using the score on COB and the W-ability score as outcomes instead. The results of these estimations are found in Table B.1, and they are very similar to the results in Table 2.

Under the assumption that there is a negative effect on cognitive ability, these first results are somewhat surprising. Especially as Kuate et al. (2021) find that their measure of cognition is negatively affected by an increase in average ambient temperatures while in utero. However, their z-score variable is constructed from a number of different tasks, such as immediate word recall, delayed word recall, number skips, and orientation questions, i.e their cognition measure does not include a measure for fluid or general intelligence. Raven's matrices are generally seen as a good way to measure intelligence without too many disturbing factors such as cultural differences (Brouwers et al., 2009). However, as shown in Section 2, there may be brain region specific effects of prenatal exposure to heat, meaning that some cognitive capacities are affected by the exposure, while others remain unaffected.

5.2 Memory

Another important part of cognitive ability and performance, and certainly of human capital formation, is memory (Cowan, 2014; St Clair-Thompson et al., 2010). Importantly, Chang et al. (2011) find that prenatal exposure to heat in mice leads to increased neuronal cell death in the hippocampus—a brain area that is important for memory functions—and worse performance on learning tasks (Eichenbaum et al., 1999). There is thus a precedence in studies on animals for a

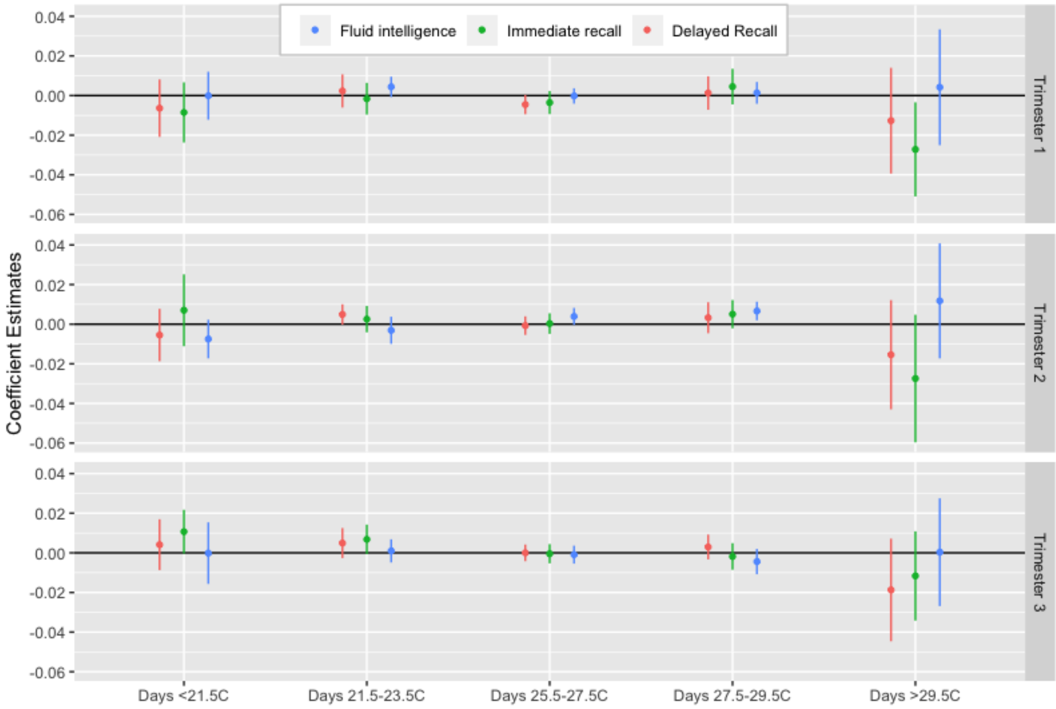

Figure 4: Trimester effects

negative effect on memory, though generalizations across species are not sure to hold.

Table 3 reports the estimated effects of prenatal exposure to heat on the normalized performance in the immediate word recall test. The performance on the immediate word recall test is measured by having a list of 10 words read to each individual and right after the initial reading the individual is going to repeat as many of the words as possible. Thus this measure reasonably measures the short-term memory capacity of each individual. In column (1) and (2) the estimated effect of the total number of days over 29.5°C degrees exposed to while in utero is shown. The effect is more negative and significant with controls and it shows that one additional hot day while in utero decreases performance on the immediate word recall by .016 standard deviations. The effect size is similar when comparing all of the temperature bins in columns (3) and (4). The nonlinear effect of temperature is shown in that it is only the hottest days that have a significant effect, the other bins are not significant and the effects are very close to 0. In column (5) and (6) the hottest days in each trimester are compared to each other. Column (6), where controls are included, shows tentative evidence that the effects of exposure to hot days is larger in the first two trimesters but the estimates are not very accurately estimated.

The estimates for Equation (2), where all bins from all three trimesters are included, are reported in Figure 4. The plot shows a central problem when using this dense specification, where the full set of 15 bins are included. The variation in the data is not enough to estimate the parameters with sufficient accuracy. The immediate and delayed recall estimates show negative effects for additional days in the 6th bin, while other estimates are close to zero.

Though short-term memory likely has some implications for human capital formation and productivity, there are stronger links between working memory and human capital formation (Cowan, 2014). Short-term memory differs from working memory, in most accounts, by only being about information storing—typically only for a few seconds. Working memory, on the other hand, involves both information storing and an attention component—which allows working memory to store and use information over a longer period of time (Baddeley, 2012; Engle et al., 1999). Therefore, working memory seems to be a more important component to activities such as planning, creating strategies, and solving complex problems, than only short-term memory. Table 4 reports the effects of prenatal exposure to heat on the standardized score on delayed word recall, a commonly used task to measure working memory capacity (Engle et al., 1999).

Broadly, the results in Table 4 are similar to the results in Table 3 with slightly smaller effect sizes across the board. In columns (1)-(4), the estimates for the 6th bin are all negative. The estimate in column (4), where controls are included, implies that exposure to one additional day hotter than 29°C leads to getting a .017 standard deviations lower score on the delayed word recall. In column (5) and (6), the hottest days in each trimester are compared. None of the estimates are significant, but all effects are negative. Further, the estimate for the hottest days in the third trimester is larger than the other estimates—this is contrary to the point estimates in columns (5) and (6) in Table 3 which suggest that exposure in the first and second trimesters have larger effects.

Overall then, the results when using the two word recall tasks as outcomes indicate a negative effect of prenatal exposure to heat. The results imply that prenatal exposure to one week of days hotter than 29.5°C lead to a 0.14 standard deviation decrease in immediate recall performance and a 0.11 standard deviation reduction in delayed recall performance. Compared to Kuate et al. (2021), who find that moderate temperatures are worst for cognition when aging, we find that the hottest temperatures have negative effects. Though, it is important to note that Kuate et al. (2021) only have average temperatures in the range of $17 - 25$°C, which means that they miss the nonlinear effects of hotter temperatures and they also use average temperatures during the entire pregnancy rather than daily average temperatures. Instead, these results are more similar to Hu and Li (2019) and Adhvaryu et al. (2015) who find that the effects on health and mental health are larger the hotter the temperatures. Hu and Li (2019) also find that the effects on health outcomes is largest during the first trimester, while for educational outcomes the effects are larger in the second trimester. The results presented here indicate a similar importance of the first trimester for immediate recall, while the third trimester has the largest coefficients for delayed recall. The effects are not significant though, and therefore I cannot draw any strong conclusions about trimester heterogeneity. However, under the hypothesis that heat exposure affects cognitive abilities through affecting brain development, using trimesters to gauge timing heterogeneity may not be the best method. Therefore, I now turn to investigating the effects of being exposed to heat while in the critical period corticogenesis.

5.3 Corticogenesis

As previously discussed, in Section 2, one of the potential mechanisms through which a negative effect on cognitive ability may appear is the direct effect of increased heat on the brain formation of the fetus. This is hard to test for directly, as I have no measures of brain weight or the like. Yet if there's increased damage on the brain from heat exposure during critical brain formation stages, then one would expect hotter days to have a larger negative effect during those development stages than when less critical brain formation is happening. Therefore, I estimate Equation (2) but with corticogenesis and non-corticogenesis as periods rather than the trimesters of the pregnancy. Corticogenesis is a period roughly between the gestational weeks 7 and 18 during the fetal development in which the structure and neuronal content of the cerebral cortex is formed through neural proliferation and migration. Between postconceptional weeks 7 and 14, the cortical plate is formed. It is through this plate, or mold, that radial glial cells and neurons can form and, later, migrate from. The period from week 14 until week 18 is characterized by the addition of more neurons and the initial formation of synaptic connectivity (Kostović and Judaš, 2015). Towards the end of corticogenesis, in mid-gestation, the hippocampal and entorhinal areas start to differentiate—two areas that are important for memory (Eichenbaum et al., 1999; Takehara-Nishiuchi, 2014). Due to this important developmental period, which forms the base of subsequent cerebral cortex development, and the evidence that neuronal proliferation and migration can be damaged by heat stress from Hinoue et al. (2001) and M. J. Edwards et al. (2003), investigating this period more closely can give evidence of potential direct effects.

The coefficients from the estimation using cortogenesis and non-cortogenesis as periods are presented in Table 6. Columns (1) and (2) use EK score as the outcome variable. The coefficients here are similar to the coefficients in Table 2, no significant results and the estimated effects for the hottest days are slightly positive. In column (2), there's a slightly larger effect on fluid intelligence during corticogenesis than outside of corticogenesis. The positive, though quite small, effect on fluid intelligence is surprising and it may indicate that the fetal brain development is interfered with in some regions of the brain and aided in other regions of the bran at the same time by heat exposure.

Columns (3) and (4), on the other hand, use immediate recall as the outcome variable. The coefficient on days in bin 6 during corticogenesis is significantly negative, both in terms of effect size and it is statistically significant at the .1% level. A cleaner comparison to exposure to heat outside of corticogenesis is given in column (4), where both periods are included. Exposure to hot days has a significantly larger negative effect if it occurs during corticogenesis, the effect is more than 4 times as large compared to exposure outside of corticogenesis. The estimated coefficients in columns (5) and (6), where delayed recall is used as the outcome, are very similar. Again, the coefficients imply that exposure to one additional day above 29.5° degrees has a large negative effect, as long as the exposure occurs inside the period of corticogenesis. When the fetus is exposed outside of corticogenesis, the effect is still negative but much smaller and not statistically significant. The estimates imply that exposure to a week f days with average temperatures above 29.5°C, while in utero and during corticogenesis, leads to a 0.37 standard deviation decline in performance on immediate recall and a 0.27 standard deviation decline in performance on delayed recall. To facilitate comparisons between the estimates on the hottest days from both inside and outside corticogenesis, from columns (2), (4), and (6), are plotted in Figure 5.

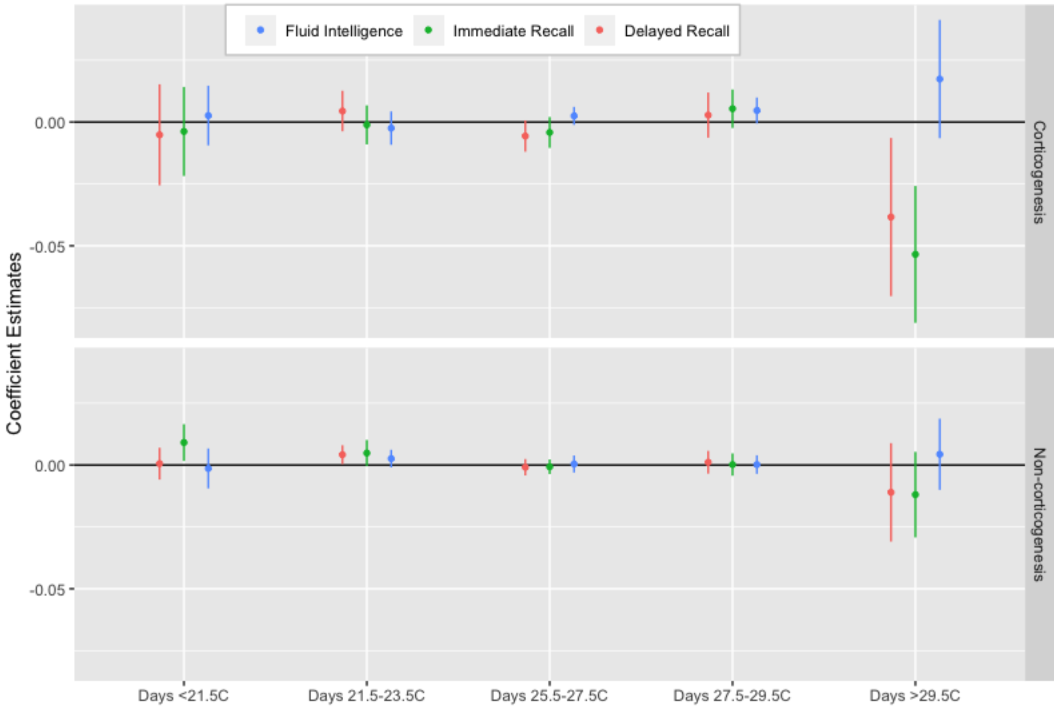

Figure 5: Corticogenesis

This final set of results provide evidence in favor of the hypothesis that the brain development of the fetus is harmed when the mother is exposed to heat while pregnant.[9] However, it may still be that the negative effect arises as a result of economic effects during corticogenesis. It may be that reduced incomes lead to psychological stress or a reduction in nutritional intake, which can affect brain development, and this possibility still exists even though we have shown that the negative cognitive effects are larger during corticogenesis. That is why I in the next section try to provide some evidence on some potential mechanisms and heterogeneities in the effects.

6 Discussion

In this section I present additional evidence and robustness checks for the previous results. Despite the above evidence on the cognitive effects of prenatal exposure to heat, a few question remains. First, I provide some evidence on one of the potential mechanisms—the economic mechanism. Un-

[9]It is important to note that corticogenesis necessarily overlaps with many other important processes in brain development and we should not immediately conclude that heat affects or interferes with corticogenesis.

fortunately, the data does not permit me to further explore the direct biological mechanism nor the indirect biological mechanism. After that, I provide some robustness checks and an investigation of the possibility that cognitive ability is affected by exposure to heat before conception and after birth.

6.1 Potential Mechanisms

I have no data on the incomes and economic changes in each regency when there's a hot day—however, using the rural-urban distinction as well as employment in different industries across regencies, I investigate the economic pathway. (See Figure 1 for the causal graph) Previous research has shown that urban populations are less affected by heat, plausibly due to having better opportunities to mitigate and avoid heat as well as being richer in general. Crucially, many in the urban environment also work in industries that are not affected much by weather (Hu and Li, 2019). On the other hand, rural populations often work in agriculture which is more affected by weather. If heat affects the economic situation, one would then expect that rural populations are more affected.

Comparing the effect of prenatal exposure to heat between rural- and urban-born individuals can thus provide a test of the expectation that rural populations are more strongly affected by heat-exposure. This test is carried out by estimating eq. (1), with additional interactions between each bin and the indicator variable for being born in a rural-regency. Since previous results have shown that there are no clear effects of prenatal exposure to heat on fluid intelligence, I limit the further investigation to immediate and delayed recall. The results of the estimations are presented in Table 6. To facilitate comparisons with previous results, column (1) and (3) are reproductions of column (3) in Table 3 and Table 4. Thus, the new results are presented in columns (2) and (4) in Table 6.

On *immediate recall*, the effect of being prenatally exposed to another day in bin 6 is associated with a .0222 standard deviation decline in *immediate recall* score. This is the effect on the urban population. The effect on *immediate recall* on the rural population, on the other hand, is only -0.005 standard deviations. In other words, based on the point estimates, the rural population on average experiences no negative effects on *immediate recall* from exposure to heat while in utero. The effect on *delayed recall* for the rural population, based on point estimates, is also slightly positive, at 0.0027 standard deviations.

Compared to the results of a similar exercise done by Hu and Li (2019), where they use health outcomes, educational attainment, and illiteracy as outcomes, these results are completely opposite to what they find. They find that rural-born individuals experience larger and statistically significant negative effects on literacy and adult height, while the effect is small and statistically insignificant for urban-born individuals. The opposite results from my estimation is therefore somewhat surprising, however there are several plausible explanations. For example, it may be that coping mechanisms are more readily available in rural areas, such as access to shadowy areas or water structures that one can cool down in. Another potential explanation may be heat islands in cities. These heat islands lead to higher temperatures in cities as well as stagnant air that leads to higher concentrations of toxic air pollution (Piracha and Chaudhary, 2022). Thus it may be that the urban environment in combination with heat is a particularly dangerous combination.

Overall though, these results indicate that direct effects is not the only mechanism through which the effects of prenatal exposure to heat is propagated. If that were the case, the expectation would be that urban and rural populations would not differ in any way except for their exposure to heat.

To further explore this difference between rural and urban populations, I investigate heterogeneous effects based on employment rates in different industries. From the IPUMS database, I obtain census data from Indonesia which I use to create regency-specific employment rates in three different industries—agriculture, manufacturing, and services (Minnesota Population Center, 2020). These are matched to each individual, based on the census closest to the birth year of the individual. Thus I can estimate Equation (1) with additional interactions between the temperature bins and the employment rate in industry x. The results of this estimation are reported in Table 7. The first three columns report these estimations using *Immediate Recall* as the outcome variable and the final three columns use *Delayed Recall* as the outcome. In column (1), the coefficient on the interaction term is positive for agricultural employment rates and the hottest temperatures, implying that higher employment rates in agriculture help negate part of the negative effect of exposure to heat. The result is similar but the effect is stronger in column (4)—implying that at 50% employment in agriculture, the effect of one additional day of exposure to a day above 29.5°C on delayed recall is negated. Interestingly, exposure to days in the two lowest bins leads to decreased performance on memory tasks when employment in agriculture is increasing. The most plausible explanation for this effect is that rice and corn is the most important and common crop in Indonesia. Rice, contrary to many other crops, thrives in average temperatures between $22-28$°C(Krishnan et al., 2011). Therefore, temperatures below that may reduce the yield of rice and thus affect the incomes of households negatively, leading to prenatal stress or nutritional changes that affect the fetal brain development negatively.

The opposite effect appears in columns (2) and (5), where increased employment in manufacturing leads to decreased performance on the memory task during days above 29.5° degrees. A plausible explanation for this effect is that it is harder to avoid or mitigate high temperatures when one works in manufacturing. However, another plausible explanation is that most manufacturing jobs are located in urban areas—meaning that the effect of manufacturing is rather an effect of something else in the urban environment. I investigate this potential explanation by estimating an extension of the above estimation, where I add one more interaction-level—the rural-urban distinction.

The results of this estimation are presented in Table 8. The results for the days above 29.5° degrees are also presented in Figure 6. The uppermost panel of the table presents the effects of exposure to days in each temperature bin interacted with the employment rate in either agriculture or manufacturing. The lower panel presents the coefficients when we add the rural indicator to that interaction. This way, we see the differences between employment in rural and urban areas.

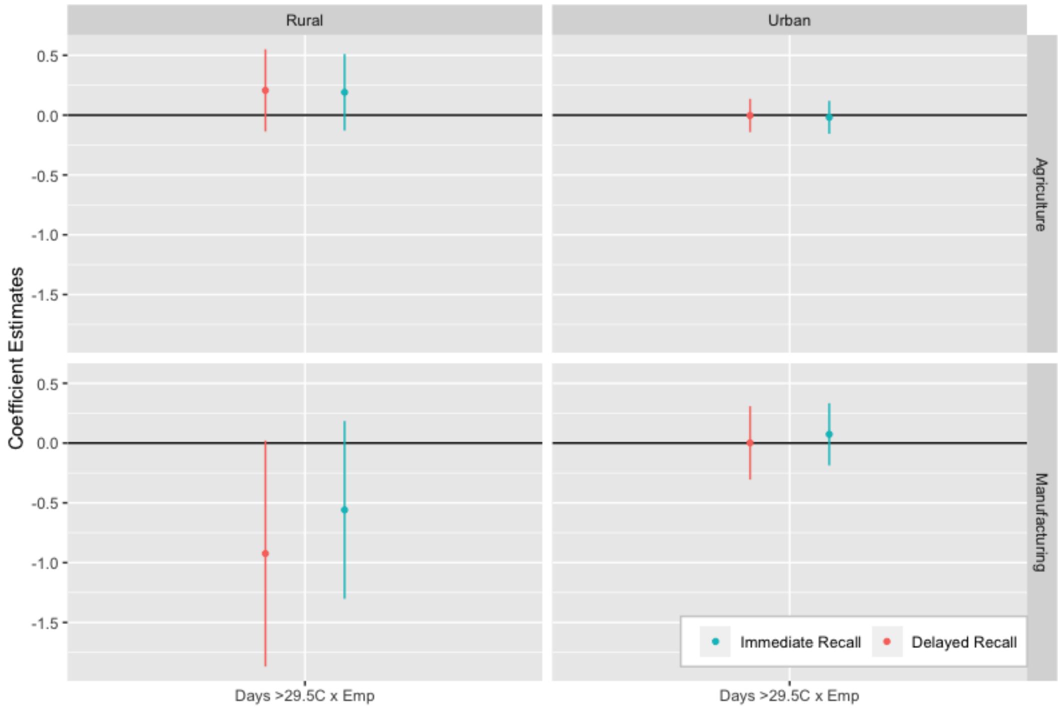

Figure 6: Employment effects, Rural v. Urban

The pattern that emerges from this estimation is easy to spot—the coefficients on the days above 29.5° degrees in the lower panel are one or two orders of magnitude larger than the estimated coefficients in the upper panel. This indicates that the effects coming from different employment rates in different industries is mainly coming from the effects this has on the rural population. These results imply that the reason that the effect of prenatal exposure to heat on cognitive abilities is larger in urban areas is because a larger part of the population is employed in non-agriculture—meaning that they cannot counteract the negative effects of heat through an increased income. Rural populations are mainly employed in agriculture, and thus hotter days plausibly improve crop yields, mainly rice and corn yields, and thus they have a positive economic effect that counteracts the negative effects of exposure to heat. Corn is a C4-crop, and those are generally more resistant to heat stress than C3-crops such as wheat, and the literature on the response of rice to heat has shown that damage to rice mainly arise at temperatures above 33°C[10] (Krishnan et al., 2011). Therefore it is plausible that the higher temperatures improve yield and thus affect the incomes

[10]See e.g Figure 1 in Krishnan et al. (2011) for an overview of optimal and critical temperatures in the growth of rice.

of rural populations positively. This effect is very likely nonlinear in nature as well, meaning that there is some temperature where this improvement in yield breaks. This potential mechanism is similar to what Hu and Li (2019) propose for their results. The important difference being that they compare provinces that have a higher fraction of C4-plants in their crop production to those that do not. C4-plants are plants that are more resistant to heat and they find that provinces with higher rates of C4-plant production are less affected by prenatal heat exposure, presumably due to less heat-caused damage to crop yields.

From this perspective, the large negative effect on the interaction between manufacturing employment and the hottest days in the rural population (as seen in the lower left panel of Figure 6) arises due to the employed in manufacturing being worse off in real terms compared to their peers working in agriculture.

Overall, these results point to the importance of the economic pathway—an indirect effect of prenatal heat exposure—as it allows individuals to mitigate the negative effects. At the same time, for urban populations it seems like economic effects have little effect. Instead they are more directly affected, as shown in Table 6. Unfortunately, since the census only covers 269 unique regencies (out of more than 500 total) I loose quite a few observations, leading to less power and though the estimates give an indication, they are by no means conclusive evidence. Further studies on these effects are needed.

6.2 Pre-conception and Post-birth Effects

Investigating the pre-conception and post-birth effects is interesting for a couple of reasons. First, there is the question of the impreciseness of the conception and birth date variables. The imprecision means that I may discard or miss some variation or effect. Exploring the time before and after birth is also interesting in that it can give an idea about the magnitude and importance of the in utero effects. Brain development continues after birth, and it may be that there's a larger effect on cognitive ability after birth than while in utero, which has implications for coping mechanisms and behavioral changes. Therefore, I estimate a version of the specification in Equation (2), where I use the 3 months before birth, the pregnancy, and the 6 months after birth as the periods instead of the pregnancy trimesters.

The estimated coefficients on each of the outcomes are reported in Table 9 and they are visualized in Figure 7. Beginning with the three months before conception, the estimates show that there's an opposite effect of exposure to hotter days. On immediate recall, the coefficient on days in the hottest bin, Days $> 29.5°$C, is positive and implying that one additional day of hot temperatures increase the immediate word recall score by 0.0159 standard deviations. A similar, but larger effect is estimated for delayed word recall, where the estimate implies that an additional day of exposure to hot temperatures increase the score by 0.0224 standard deviations. These pre-conception results run contrary to the results of Hu and Li (2019) and Kuate et al. (2021) that do not find evidence of a pre-conception effect. Even though this pre-conception effect is quite surprising, it is not the first time such an effect has been recorded. Wilde et al. (2017) find a positive effect of higher temperatures around conception on educational attainment and the likelihood of being literate later in life.[11] Their preferred explanation for the result is that fetal loss is a likely driver of the higher health and human capital outcomes later in life—this effect arises due to fetuses being very sensitive in the very early days of gestation, the weakest fetuses do not survive harsher conditions and thus the fetuses that do survive the harsher conditions are stronger, on average, than fetuses that do not experience the harsher conditions. This effect varies between genders, as male fetuses are more vulnerable than female fetuses (Wilde et al., 2017).

This effect might similarly be a driver in our results, as otherwise it seems unlikely that pre-conception weather has an effect on the cognitive abilities of the fetus. One of the pieces of evidence that Wilde et al. (2017) use to pin down the fetal loss hypothesis is to explore the differential effects on genders. I investigate the pre-conception effects in a similar way to them in Table B.2. In short, the results from this estimation with *Immediate Recall* as the outcome are very similar to the results Wilde et al. (2017) find—males in the sample drive this effect, while females have no pre-conception effect. However, when it comes to *Delayed Recall*, there is no gender heterogeneity in the pre-conception effect—further suggesting that there is a qualitative difference in the brain functions used to perform *Immediate Recall* and *Delayed Recall*.

The post-birth effects of exposure to heat on cognitive effects are very similar to the effects while in utero, they imply that an additional day of exposure to a day in the hottest temperature bin in the six months after birth decrease immediate recall score by .0125 standard deviations and delayed word recall score by 0.0180 standard deviations. Though only the estimate for the delayed word recall score is statistically significant. These results are not very surprising, given that brain development keeps going long after birth [12] (Kostović and Judaš, 2015). Given that the effects are similar during and after pregnancy, further research should aim to establish more granular estimates for when the damage to cognitive ability and brain development is largest since this could determine where mitigation strategies might be most efficient.

The main focus in this paper is not on pre-conception or post-birth effects, but if there are gender heterogeneity effects in pre-conception effects there may as well be for the in utero effects as well. The next subsection will therefore investigate gender heterogeneity of the in utero effects.

[11]It is important to note though, that Wilde et al. (2017) use average monthly temperatures as their explanatory variable. This difference may be important.

[12]See e.g. Figure 1 in Kostović and Judaš (2015) for an overview of the development processes in the cerebral cortex that continue post-birth.

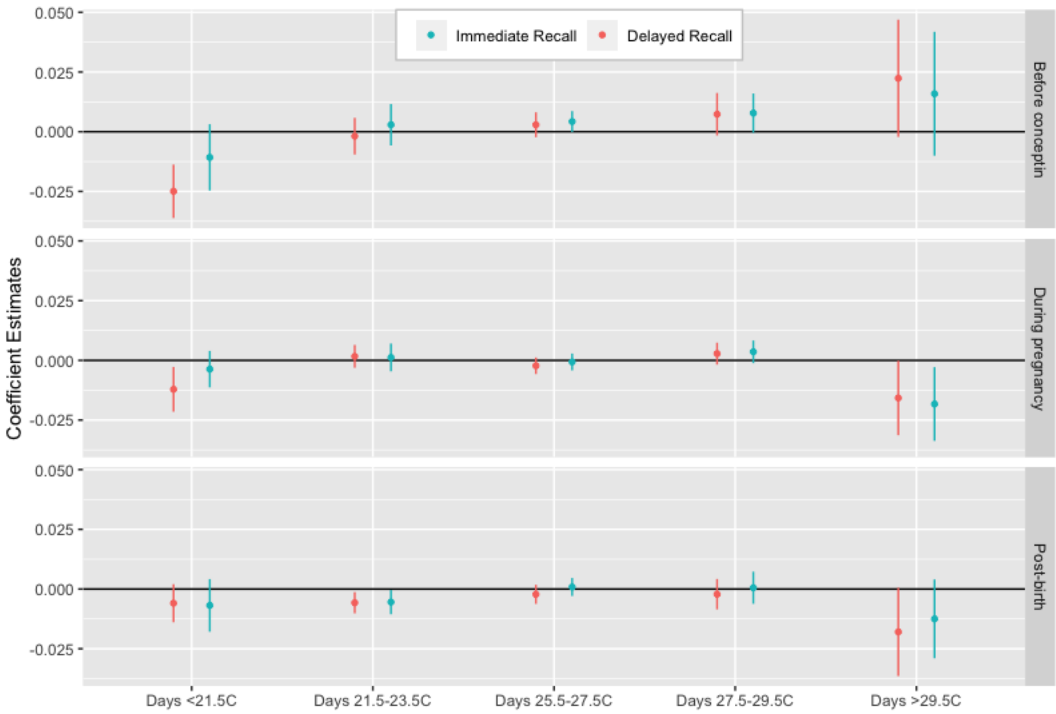

Figure 7: Pre-conception & Post-birth effects

6.3 Gender Heterogeneity

As Wilde et al. (2017) have shown, gender heterogeneity can give important insights into the mechanisms of the negative effects on cognitive ability. Other previous results have also established that males require more maternal resources and are more fragile in utero compared to females. Therefore, the gender ratio skews female during periods of fetal stress (Basu et al., 2010). To my knowledge, the only evidence on gender heterogeneity in the effect of heat on brain development comes from Kuate et al. (2021), who find that there is no large difference between males and females in the effect of exposure to higher average ambient temperatures during the entire prenatal period on cognition when aging. Animal studies, such as Hinoue et al. (2001) or M. Edwards et al. (1971) have not reported any such differences either. However, there is more evidence from studies that show that the effect of exposing pregnant mice to stress has different effects on the fetus depending on whether the fetus is a female or a male. Stress for the pregnant mother increases corticosterone in the fetal brain, for males it also decreases fetal testosterone and brain aromatase, while for females it alters brain catecholamine activity. Further, this difference in brain chemistry effect leads to "learning deficits, reductions in hippocampal neurogenesis, LTP and dendritic spine density in the prefrontal cortex" being more prevalent in male mice that have been prenatally exposed to stress. In female mice, increased anxiety, depression, and increased response of the HPA axis to stress is more prevalent after being exposed, prenatally, to stress (Weinstock, 2007). Thus a gender differential in the effect of in utero exposure to heat may arise from the different effects of increased stress in the pregnant mother. Therefore, if the evidence shows a gender difference that would be some evidence (though not conclusive) in favor of the indirect biological pathway. The opposite case, wherein different genders have similar effects, would weakly provide evidence in favor of the direct biological pathway.

To investigate these hypotheses, I estimate a version of Equation (1), where I also include interaction terms between each temperature bin and an indicator for females. The results of this estimation are presented in Table 10. Columns (1) and (3) are previous the results of previous estimations with no interaction between the temperature bins and the female indicator. In column (2) the outcome variable is *immediate recall*, and the coefficients of interest are the coefficients on the interaction terms. The coefficients show that there is no difference between males and females in the effect of exposure in utero—the coefficient on the hottest bin interacted with the female indicator is -0.0074 standard deviations and it is statistically insignificant. The result is similar for *delayed recall* in column (4), the coefficients on the interaction terms are all very small and insignificant indicating there's no difference between males and females in the effect of prenatal exposure to heat.

These results differ from some of the previous literature showing that males are more fragile in utero than females (Catalano et al., 2008; Pongou et al., 2017). It may thus be that the health and mortality of fetuses are differently affected based on gender, while brain development is not. The evidence is not strong enough to draw any strong conclusions though, since the coefficients for our interaction terms are not significant.

7 Conclusion

Using individual-level survey data from the Indonesian Family Life Survey (IFLS), combined with weather data, this paper shows that prenatal exposure to heat affects cognitive abilities later in life. More specifically, in utero exposure to heat has a negative effect on memory, leading to worse performance on word recall—both direct recall and with a delay. On the other hand, there is no strong effect on performance on Raven's progressive matrices, suggesting that fluid intelligence is not adversely affected. The strong effect on memory and the non-existent effect on fluid intelligence measures suggests that exposure to heat damages specific structures in the brain or interferes with very specific development processes. The effects are larger during corticogenesis, a critical period for brain formation, which points to the interference with some development process in that period—establishing where the timing of the exposure has the largest effect can help narrow down the potential processes that are affected by heat.

Beyond that, I also try to provide some tentative and suggestive evidence about the potential mechanisms—I find that a higher rate of employment in agriculture has a positive effect on memory, counteracting the negative effects of heat. This effect is also only visible in rural areas, suggesting that agriculture affects incomes positively in rural areas which allow them to mitigate the effects of heat. This surprising result, that is contrary to previous research, is not strong evidence in favor of the mechanism—due to having few observations in the analysis. Even though one should be careful in drawing strong conclusions from the analysis on mechanisms—it suggests a potential path for future research towards understanding the mechanisms. This can help design policies to mitigate and avoid the potential damage of prenatal exposure to heat.

Apart from lacking power in some of the analyses, there is a general lack of more cognitive tests that test other cognitive abilities apart from pattern-matching á la Raven's matrices and simple memory tasks. It may be that heat exposure specifically damages the parts of the brain that handle memory, and thus that no other cognitive abilities are harmed, however we cannot rule out alternative hypotheses without testing other cognitive capabilities.

The results, as presented, imply that efforts that target pregnant mothers has the potential to improve productivity, human capital formation, and ultimately economic development. The results also imply another harmful aspect of climate change, that populations all over the world may need to adapt to and mitigate. Further, that the fact that memory is affected but not fluid intelligence, combined with attention being an important part of memory—especially working memory—leads me to predict that prenatal exposure to heat increases the likelihood of developing attention disorders, such as ADHD. I'm not aware of any research investigating this potential link—researching that link would be a good way to extend and validate the research presented in this paper.

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Tables

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Immediate Recall	15,232	5.836	1.576	0	10
Delayed Recall	15,232	4.916	1.769	0	10
W Score	11,794	531.137	57.116	299	635
EK Score	17,371	6.363	1.760	0	8
COB Score	11,794	3.168	1.297	0	7
Educational attainment	17,012	10.968	2.897	6	21
Trimester 1					
ln(Precipitation)	17,371	5.650	1.123	−5.661	7.614
Days $< 21.5°$C	17,371	2.596	12.013	0	85
Days $21.5 - 23.5°$C	17,371	8.515	18.582	0	84
Days $23.5 - 25.5°$C	17,371	23.114	25.067	0	84
Days $25.5 - 27.5°$C	17,371	34.504	26.804	0	84
Days $27.5 - 29.5°$C	17,371	11.607	18.478	0	82
Days $> 29.5°$C	17,371	0.339	2.119	0	58
Trimester 2					
ln(Precipitation)	17,371	5.769	1.175	−13.378	7.685
Days $< 21.5°$C	17,371	2.965	13.538	0	94
Days $21.5 - 23.5°$C	17,371	9.332	20.280	0	93
Days $23.5 - 25.5°$C	17,371	25.651	27.516	0	92
Days $25.5 - 27.5°$C	17,371	38.540	29.535	0	94
Days $27.5 - 29.5°$C	17,371	12.485	19.786	0	88
Days $> 29.5°$C	17,371	0.348	2.075	0	43
Trimester 3					
ln(Precipitation)	17,371	5.627	1.287	−7.768	7.550
Days $< 21.5°$C	17,371	2.909	13.382	0	92
Days $21.5 - 23.5°$C	17,371	9.223	19.894	0	88
Days $23.5 - 25.5°$C	17,371	24.976	27.181	0	91
Days $25.5 - 27.5°$C	17,371	37.446	29.073	0	92
Days $27.5 - 29.5°$C	17,371	12.677	19.968	0	88
Days $> 29.5°$C	17,371	0.317	1.861	0	71
Controls					
Age	17,371	24.078	8.974	15	53
Siblings	17,051	2.848	2.002	0	25
Age at birth, Father	16,945	32.493	8.719	15	97
Age at birth, Mother	16,441	27.235	7.261	15	50
Educational attainment, Father	16,973	8.407	3.239	6	21
Educational attainment, mother	17,111	7.723	2.772	6	18
Rural	17,371	0.414	0.493	0	1
Female	17,371	0.520	0.500	0	1
Weather					
Daily temperatures	7,869,812	25.569	2.179	8.025	33.499
Daily precipitation	8,953,130	4.783	6.778	0.000	238.206

Note: The full sample contains 17,371 individuals from 229 regencies in Indonesia. The weather data is obtained from the APHRODITE project (Yasutomi et al., 2011; Yatagai et al., 2012). The individual-level data is obtained from IFLS, survey waves 3-5 (Strauss et al., 2004; Strauss et al., 2016; Strauss et al., 2009). Immediate recall and delayed recall is the number of words remembered. W Score is a score based on the answers in module COB. EK Score is the number of correct answers in the EK cognitive assessment, a mix of numeracy and Raven's progressive matrices. Female and Rural are indicators for the individual being a female and living in an rural region, respectively. The temperature bins are defined as follows: Bin 1: $< 21.5°$C, Bin 2: $21.5 - 23.5°$C, Bin 3: $23.5 - 25.5°$C, Bin 4: $25.5 - 27.5°$C, Bin 5: $27.5 - 29.5°$C, Bin 6: $> 29.5°$C

Table 2: Fluid Intelligence

	Dependent variable:					
	EK					
	(1)	(2)	(3)	(4)	(5)	(6)
Entire pregnancy						
Days > 29.5°C	0.0063	0.0049	0.0079	0.0060		
	(0.0070)	(0.0071)	(0.0077)	(0.0077)		
Days 27.5 − 29.5°C			0.0012	0.0012		
			(0.0016)	(0.0016)		
Days 25.5 − 27.5°C			0.0012	0.0010		
			(0.0016)	(0.0016)		
Days 21.5 − 23.5°C			0.0006	0.0010		
			(0.0017)	(0.0016)		
Days < 21.5°C			-0.0024	-0.0016		
			(0.0042)	(0.0040)		
Trimester 1						
Days > 29.5°C					0.0038	0.0047
					(0.0133)	(0.0133)
Trimester 2						
Days > 29.5°C					0.0101	0.0064
					(0.0136)	(0.0138)
Trimester 3						
Days > 29.5°C					0.0067	0.0050
					(0.0143)	(0.0140)
Observations	15,907	15,907	15,907	15,907	15,907	15,907
Controls	No	Yes	No	Yes	No	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.64569	0.65226	0.64577	0.65232	0.64587	0.65247
Within R^2	0.00013	0.01866	0.00034	0.01884	0.00064	0.01927

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variable *EK*, is a standardized measure of the number of correct answers on 8 questions of Raven's progressive matrices. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 − 23.5°C, Bin 3: 23.5 − 25.5°C, Bin 4: 25.5 − 27.5°C, Bin 5: 27.5 − 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 3: Immediate Recall

	Dependent variable:					
	Immediate Recall					
	(1)	(2)	(3)	(4)	(5)	(6)
Entire pregnancy						
Days > 29.5°C	-0.0151**	-0.0160**	-0.0192**	-0.0199**		
	(0.0075)	(0.0076)	(0.0080)	(0.0083)		
Days 27.5 – 29.5°C			0.0022	0.0023		
			(0.0023)	(0.0023)		
Days 25.5 – 27.5°C			-0.0016	-0.0014		
			(0.0017)	(0.0017)		
Days 21.5 – 23.5°C			0.0026	0.0030		
			(0.0023)	(0.0023)		
Days < 21.5°C			0.0053	0.0047		
			(0.0041)	(0.0036)		
Trimester 1						
Days > 29.5°C					-0.0189*	-0.0196*
					(0.0107)	(0.0110)
Trimester 2						
Days > 29.5°C					-0.0173	-0.0219
					(0.0147)	(0.0152)
Trimester 3						
Days > 29.5°C					-0.0084	-0.0072
					(0.0109)	(0.0109)
Observations	14,090	14,090	14,090	14,090	14,090	14,090
Controls	No	Yes	No	Yes	No	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.59290	0.59758	0.59374	0.59844	0.59319	0.59801
Within R^2	0.00134	0.01283	0.00340	0.01493	0.00206	0.01387

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variable *Immediate Recall*, is a standardized measure of the number of correctly recalled words from a 10 word long list. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 4: Delayed Recall

	Dependent variable:					
	Delayed Recall					
	(1)	(2)	(3)	(4)	(5)	(6)
Entire pregnancy						
Days > 29.5°C	-0.0105	-0.0115	-0.0152*	-0.0160**		
	(0.0081)	(0.0081)	(0.0080)	(0.0081)		
Days 27.5 – 29.5°C			0.0021	0.0022		
			(0.0022)	(0.0021)		
Days 25.5 – 27.5°C			-0.0022	-0.0020		
			(0.0015)	(0.0015)		
Days 21.5 – 23.5°C			0.0039*	0.0042**		
			(0.0021)	(0.0021)		
Days < 21.5°C			-0.0010	-0.0016		
			(0.0037)	(0.0038)		
Trimester 1						
Days > 29.5°C					-0.0031	-0.0042
					(0.0132)	(0.0137)
Trimester 2						
Days > 29.5°C					-0.0065	-0.0101
					(0.0127)	(0.0131)
Trimester 3						
Days > 29.5°C					-0.0197	-0.0190
					(0.0137)	(0.0135)
Observations	14,090	14,090	14,090	14,090	14,090	14,090
Controls	No	Yes	No	Yes	No	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.59110	0.59454	0.59230	0.59576	0.59120	0.59470
Within R^2	0.00050	0.00888	0.00343	0.01188	0.00072	0.00928

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variable *Delayed Recall*, is a standardized measure of the number of correctly recalled words, after a short delay, from a 10 word long list. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 5: Corticogenesis

	Dependent variable:					
	EK		Immediate Recall		Delayed Recall	
	(1)	(2)	(3)	(4)	(5)	(6)
Corticogenesis						
Days > 29.5°C	0.0131	0.0146	-0.0511***	-0.0535***	-0.0367**	-0.0384**
	(0.0120)	(0.0131)	(0.0137)	(0.0141)	(0.0167)	(0.0163)
Days 27.5 – 29.5°C	0.0041	0.0042	0.0051	0.0054	0.0022	0.0028
	(0.0026)	(0.0026)	(0.0040)	(0.0040)	(0.0047)	(0.0047)
Days 25.5 – 27.5°C	0.0020	0.0022	-0.0043	-0.0042	-0.0058*	-0.0056*
	(0.0017)	(0.0018)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Days 21.5 – 23.5°C	-0.0025	-0.0022	-0.0010	-0.0011	0.0046	0.0045
	(0.0036)	(0.0036)	(0.0040)	(0.0040)	(0.0042)	(0.0042)
Days < 21.5°C	0.0016	0.0002	-0.0025	-0.0038	-0.0019	-0.0051
	(0.0067)	(0.0068)	(0.0089)	(0.0092)	(0.0108)	(0.0104)
Non-corticogenesis						
Days > 29.5°C		0.0025		-0.0120		-0.0110
		(0.0074)		(0.0088)		(0.0101)
Days 27.5 – 29.5°C		-0.0003		0.0002		0.0011
		(0.0020)		(0.0023)		(0.0023)
Days 25.5 – 27.5°C		0.0002		-0.0007		-0.0009
		(0.0018)		(0.0027)		(0.0019)
Days 21.5 – 23.5°C		0.0022		0.0048*		0.0042**
		(0.0018)		(0.0027)		(0.0019)
Days < 21.5°C		-0.0022		0.0091**		0.0006
		(0.0049)		(0.0038)		(0.0033)
Observations	15,907	15,907	14,090	14,090	14,090	14,090
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.65250	0.65260	0.59949	0.59995	0.59625	0.59682
Within R^2	0.01934	0.01963	0.01751	0.01864	0.01307	0.01446

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. *Corticogenesis* is defined as the period between 7 and 18 weeks of gestation, *Non-corticogenesis* is negatively defined as the gestational period that is not in corticogenesis. The outcome variables *EK, Immediate Recall, Delayed Recall*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 6: Rural and Urban Populations

	Dependent variable:			
	Immediate Recall		Delayed Recall	
	(1)	(2)	(3)	(4)
Entire pregnancy				
Days > 29.5°C	-0.0199**	-0.0220**	-0.0160**	-0.0181**
	(0.0083)	(0.0087)	(0.0081)	(0.0079)
Days 27.5 – 29.5°C	0.0023	0.0023	0.0022	0.0023
	(0.0023)	(0.0024)	(0.0021)	(0.0022)
Days 25.5 – 27.5°C	-0.0014	-0.0015	-0.0020	-0.0017
	(0.0017)	(0.0018)	(0.0015)	(0.0015)
Days 21.5 – 23.5°C	0.0030	0.0031	0.0042**	0.0044**
	(0.0023)	(0.0025)	(0.0021)	(0.0021)
Days < 21.5°C	0.0047	0.0049	-0.0016	-0.0014
	(0.0036)	(0.0034)	(0.0038)	(0.0039)
Days > 29.5°C × Rural		0.0198		0.0220
		(0.0190)		(0.0256)
Days 27.5 – 29.5°C × Rural		0.0005		0.0002
		(0.0013)		(0.0011)
Days 25.5 – 27.5°C × Rural		0.0006		0.0003
		(0.0007)		(0.0007)
Days 21.5 – 23.5°C× Rural		-0.0002		-0.0006
		(0.0009)		(0.0008)
Days < 21.5°C × Rural		0.0001		-0.0005
		(0.0017)		(0.0014)
Observations	14,090	14,090	14,090	14,090
Controls	Yes	Yes	Yes	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
R^2	0.59844	0.59875	0.59576	0.59605
Within R^2	0.01493	0.01570	0.01188	0.01258

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variables *Immediate Recall, Delayed Recall*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 7: Employment

	Dependent variable:					
	Immediate Recall			Delayed Recall		
	(1)	(2)	(3)	(4)	(5)	(6)
Entire pregnancy						
Days > 29.5°C	-0.0493	-0.0070	-0.0169	-0.0590	0.0105	-0.0311
	(0.0321)	(0.0213)	(0.0568)	(0.0390)	(0.0289)	(0.0625)
Days 27.5 – 29.5°C	0.0126**	0.0046	0.0034	0.0066	0.0059	0.0036
	(0.0050)	(0.0044)	(0.0060)	(0.0070)	(0.0037)	(0.0054)
Days 25.5 – 27.5°C	0.0009	-0.0033	0.0009	0.0038	-0.0016	-0.0044
	(0.0048)	(0.0029)	(0.0039)	(0.0046)	(0.0030)	(0.0037)
Days 21.5 – 23.5°C	0.0306***	-0.0042	-0.0104	0.0181*	-0.0004	-0.0057
	(0.0081)	(0.0070)	(0.0069)	(0.0098)	(0.0057)	(0.0060)
Days < 21.5°C	0.0366**	-0.0037	0.0109	0.0398	-0.0104	0.0050
	(0.0162)	(0.0115)	(0.0130)	(0.0256)	(0.0149)	(0.0250)
Industry	**Agri**	**Manu**	**Serv**	**Agri**	**Manu**	**Serv**
Days > 29.5°C	0.0820	-0.0703	-0.0331	0.1043	-0.1718	0.0716
× Employment	(0.0702)	(0.1338)	(0.4325)	(0.0756)	(0.1406)	(0.4316)
Days 27.5 – 29.5°C	-0.0196	0.0002	0.0090	-0.0073	-0.0209	-0.0059
× Employment	(0.0119)	(0.0171)	(0.0420)	(0.0127)	(0.0217)	(0.0398)
Days 25.5 – 27.5°C	-0.0056	0.0086	-0.0265	-0.0138	-0.0095	0.0117
× Employment	(0.0095)	(0.0174)	(0.0260)	(0.0105)	(0.0150)	(0.0250)
Days 21.5 – 23.5°C	-0.0515***	0.0668	0.1093**	-0.0269	0.0389	0.0770
× Employment	(0.0146)	(0.0562)	(0.0464)	(0.0170)	(0.0509)	(0.0478)
Days < 21.5°C	-0.0580*	0.0771	-0.0268	-0.0809*	0.0692	-0.0388
× Employment	(0.0303)	(0.0745)	(0.0948)	(0.0485)	(0.1012)	(0.1887)
Observations	9,423	9,423	9,423	9,423	9,423	9,423
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.60762	0.60662	0.60709	0.60925	0.60882	0.60870
Within R^2	0.01873	0.01623	0.01740	0.01505	0.01398	0.01367

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variables *Immediate Recall, Delayed Recall*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 8: Employment pt.2

	Dependent variable:			
	Immediate Recall		Delayed Recall	
	(1)	(2)	(3)	(4)
Heat × Employment, Urban	**Agri**	**Manu**	**Agri**	**Manu**
Days > 29.5°C × Emp	-0.0181	0.0732	-0.0028	0.0016
	(0.0702)	(0.1327)	(0.0709)	(0.1566)
Days 27.5 – 29.5°C × Emp	-0.0133	0.0019	-0.0054	-0.0185
	(0.0123)	(0.0177)	(0.0141)	(0.0213)
Days 25.5 – 27.5°C × Emp	-0.0044	0.0214	-0.0160	-0.0020
	(0.0095)	(0.0183)	(0.0111)	(0.0160)
Days 21.5 – 23.5°C × Emp	-0.0432***	0.0863	-0.0234	0.0540
	(0.0095)	(0.0553)	(0.0111)	(0.0480)
Days < 21.5°C × Emp	-0.0494	0.0855	-0.0775	0.0774
	(0.0305)	(0.0761)	(0.0494)	(0.0983)
Heat × Employment, Rural	**Agri**	**Manu**	**Agri**	**Manu**
Days > 29.5°C × Emp × Rural	0.1912	-0.5587	0.2068	-0.9236*
	(0.1631)	(0.3791)	(0.1752)	(0.4818)
Days 27.5 – 29.5°C × Emp × Rural	-0.0139	0.0040	-0.0047	0.0067
	(0.0089)	(0.0143)	(0.0096)	(0.0175)
Days 25.5 – 27.5°C × Emp × Rural	-0.0036	-0.0266***	0.0036	-0.0176*
	(0.0047)	(0.0074)	(0.0060)	(0.0094)
Days 21.5 – 23.5°C× Emp × Rural	-0.0125*	-0.0258**	-0.0052	-0.0207
	(0.0069)	(0.0109)	(0.0066)	(0.0167)
Days < 21.5°C × Emp × Rural	-0.0176***	0.0097	-0.0065	0.0087
	(0.0046)	(0.0085)	(0.0074)	(0.0149)
Observations	9,423	9,423	9,423	9,423
Controls	Yes	Yes	Yes	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
R^2	0.60885	0.60810	0.61024	0.61051
Within R^2	0.02180	0.01995	0.01756	0.01822

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variables *Immediate Recall, Delayed Recall*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 9: Pre-conception & Post-birth effects

	Dependent variable:	
	Immediate Recall	Delayed Recall
	(1)	(2)
Pre-conception		
Days > 29.5°C	0.0159	0.0224*
	(0.0132)	(0.0125)
Days 27.5 – 29.5°C	0.0078*	0.0073
	(0.0042)	(0.0045)
Days 25.5 – 27.5°C	0.0042*	0.0029
	(0.0022)	(0.0027)
Days 21.5 – 23.5°C	0.0029	-0.0019
	(0.0044)	(0.0039)
Days < 21.5°C	-0.0107	-0.0250***
	(0.0071)	(0.0057)
Pregnancy		
Days > 29.5°C	-0.0183**	-0.0158**
	(0.0079)	(0.0080)
Days 27.5 – 29.5°C	0.0036	0.0028
	(0.0024)	(0.0023)
Days 25.5 – 27.5°C	-0.0007	-0.0023
	(0.0018)	(0.0018)
Days 21.5 – 23.5°C	0.0012	0.0017
	(0.0030)	(0.0024)
Days < 21.5°C	-0.0037	-0.0121**
	(0.0039)	(0.0048)
Post-birth		
Days > 29.5°C	-0.0125	-0.0180*
	(0.0084)	(0.0094)
Days 27.5 – 29.5°C	0.0005	-0.0022
	(0.0034)	(0.0032)
Days 25.5 – 27.5°C	0.0009	-0.0022
	(0.0019)	(0.0020)
Days 21.5 – 23.5°C	-0.0055**	-0.0057**
	(0.0026)	(0.0023)
Days < 21.5°C	-0.0069	-0.0059
	(0.0056)	(0.0041)
Observations	14,090	14,090
Controls	Yes	Yes
Regency-by-Year FE	Yes	Yes
Regency-by-month FE	Yes	Yes
Year-by-month FE	Yes	Yes
R^2	0.59971	0.59736
Within R^2	0.01804	0.01580

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variables *Immediate Recall, Delayed Recall*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. *Pre-conception* is defined as the three months before conception. *Post-birth* is defined as the six months after birth. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table 10: Gender Heterogeneity

	Dependent variable:			
	Immediate Recall		Delayed Recall	
	(1)	(2)	(3)	(4)
Entire pregnancy				
Days > 29.5°C	-0.0199**	-0.0156	-0.0160**	-0.0155
	(0.0083)	(0.0122)	(0.0081)	(0.0115)
Days 27.5 – 29.5°C	0.0023	0.0023	0.0022	0.0023
	(0.0023)	(0.0024)	(0.0021)	(0.0022)
Days 25.5 – 27.5°C	-0.0014	-0.0015	-0.0020	-0.0017
	(0.0017)	(0.0018)	(0.0015)	(0.0015)
Days 21.5 – 23.5°C	0.0030	0.0031	0.0042**	0.0044**
	(0.0023)	(0.0025)	(0.0021)	(0.0021)
Days < 21.5°C	0.0047	0.0049	-0.0016	-0.0014
	(0.0036)	(0.0034)	(0.0038)	(0.0039)
Days > 29.5°C × Female		-0.0087		-0.0009
		(0.0129)		(0.0115)
Days 27.5 – 29.5°C × Female		0.0001		-7.33×10^{-5}
		(0.0009)		(0.0008)
Days 25.5 – 27.5°C × Female		6.25×10^{-5}		-0.0006
		(0.0006)		(0.0005)
Days 21.5 – 23.5°C× Female		-0.0002		-0.0004
		(0.0008)		(0.0005)
Days < 21.5°C × Female		-0.0002		-0.0004
		(0.0005)		(0.0006)
Observations	14,090	14,090	14,090	14,090
Controls	Yes	Yes	Yes	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
R^2	0.59844	0.59856	0.59576	0.59587
Within R^2	0.01493	0.01523	0.01188	0.01215

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variables *Immediate Recall, Delayed Recall*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Appendices

A Samples from IFLS

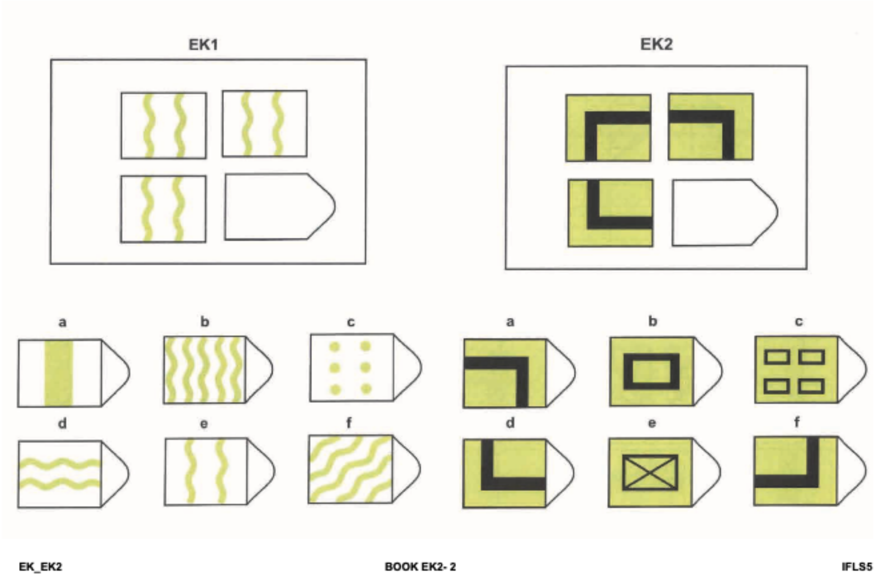

Figure A.1: Example of questions in the Cognitive Measurement in Book EK of IFLS5

LIST A	LIST B	LIST C	LIST D
A01. HOTEL	B01. SKY	C01. MOUNT	D01. WATER
A02. RIVER	B02. OCEAN	C02. STONE	D02. MOSQUE
A03. TREE	B03. FLAG	C03. BLOOD	D03. DOCTOR
A04. SKIN	B04. RUPIAH	C04. CORNER	D04. CASTLE
A05. GOLD	B05. WIFE	C05. SHOES	D05. FIRE
A06. MARKET	B06. MACHINE	C06. LETTER	D06. GARDEN
A07. PAPER	B07. HOUSE	C07. GIRL	D07. SEA
A08. CHILD	B08. EARTH	C08. HOUSE	D08. VILLAGE
A09. KING	B09. SCHOOL	C09. VALLEY	D09. BABY
A10. BOOK	B10. BUTTER	C10. CAR	D10. TABLE

Figure A.2: The word lists used for word recall in Section CO in Book B3B of IFLS5

B Tables

Table B.1: Alternative measures of fluid intelligence

	Dependent variable:			
	COB Score		W Ability Score	
	(1)	(2)	(3)	(4)
Entire pregnancy				
Days > 29.5°C	0.0046		0.7260	
	(0.0109)		(0.5594)	
Days 27.5 – 29.5°C	0.0056*		0.2335	
	(0.0029)		(0.1458)	
Days 25.5 – 27.5°C	0.0017		0.0924	
	(0.0021)		(0.0964)	
Days 21.5 – 23.5°C	0.0023		0.0947	
	(0.0031)		(0.1572)	
Days < 21.5°C	0.0062		0.3247	
	(0.0140)		(0.7285)	
Trimester 1				
Days > 29.5°C		-0.0003		0.5608
		(0.0132)		(0.8777)
Trimester 2				
Days > 29.5°C		-0.0035		0.1112
		(0.0144)		(0.9062)
Trimester 3				
Days > 29.5°C		0.0150		1.217
		(0.0155)		(0.8606)
Observations	10,784	10,784	10,784	10,784
Controls	Yes	Yes	Yes	Yes
Regency-by-Year FE	Yes	Yes	Yes	Yes
Regency-by-month FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
R^2	0.69626	0.69547	0.69369	0.69339
Within R^2	0.03257	0.03005	0.02006	0.01911

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variables *COB Score, W Ability Score*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.

Table B.2: Gender heterogeneity in pre-conception

	Dependent variable:	
	Immediate Recall	Delayed Recall
	(1)	(2)
Pre-conception		
Days > 29.5°C	0.0468***	0.0414***
	(0.0142)	(0.0131)
Days 27.5 – 29.5°C	0.0055	0.0061
	(0.0045)	(0.0046)
Days 25.5 – 27.5°C	0.0044**	0.0038
	(0.0022)	(0.0028)
Days 21.5 – 23.5°C	0.0033	-0.0021
	(0.0041)	(0.0040)
Days < 21.5°C	-0.0071	-0.0182***
	(0.0067)	(0.0054)
Days > 29.5°C × Female	-0.0369***	-0.0098
	(0.0127)	(0.0117)
Days 27.5 – 29.5°C × Female	0.0014	-0.0003
	(0.0018)	(0.0020)
Days 25.5 – 27.5°C × Female	-0.0011	-0.0014
	(0.0013)	(0.0013)
Days 21.5 – 23.5°C × Female	-0.0008	-0.0010
	(0.0019)	(0.0018)
Days < 21.5°C × Female	-0.0015	-0.0010
	(0.0014)	(0.0015)
Observations	14,090	14,090
Controls	Yes	Yes
Regency-by-Year FE	Yes	Yes
Regency-by-month FE	Yes	Yes
Year-by-month FE	Yes	Yes
R^2	0.59862	0.59550
Within R^2	0.01538	0.01124

*p<0.1; **p<0.05; ***p<0.01

Note: All standard errors are clustered at the Regency-level. The outcome variables *Immediate Recall, Delayed Recall*, are standardized measures of the number of correct answers on different tests, see Section 3 for detailed descriptions. Control variables are the natural log of precipitation, an indicator for females, an indicator for rural-born individuals, the mother's educational attainment, the mother's age at birth, and the number of siblings. The temperature bins are defined as follows: Bin 1: < 21.5°C, Bin 2: 21.5 – 23.5°C, Bin 3: 23.5 – 25.5°C, Bin 4: 25.5 – 27.5°C, Bin 5: 27.5 – 29.5°C, Bin 6: > 29.5°C. Bin 3 is used as the reference bin in models including the full set of bins.