Spring 5-20-2016

Air Pollution, Temperature and Cognitive Performance in the Short Run: Evidence from Women's Ability to Recall Dates

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Thesis Submission for the Masters of Science Degree
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May 2016

Abstract: Cognitive performance is important to productivity across many fields and potentially correlated to air pollution and extreme temperatures. We study the effects of daily ambient air pollution and monthly temperature on women's ability of recalling dates across 42 developing countries from 1997 to 2009. We use an estimated natural air pollution data, and calculate the AQI to get an aggregate effect of air pollution. We find that one standard deviation increase in the AQI leads to a statistical decrease in women's probability to recall dates such as birthdays, marriage date or children's birthdays by 0.44 percentage point. Furthermore, there is a nonlinear effect of air pollution with a suggesting AQI threshold 150. We also find each degree day above 30°C increase the probability of women fail to recall children's birthdays by 0.17 percentage point. Moreover, by doing a sub-sample estimation, we find that air pollution and temperature particularly affect uneducated women.

1. Introduction

Ambient air pollution and climate extremes have become two big issues that limit the economic development. According to European Environmental Agency, the annual costs of emissions of air pollutants and carbon dioxide for the European countries is between 60 to 200 billions euro (EEA, 2014). In addition, a growing body of literature documents that exposure to both high ambient air pollution and extreme temperatures have harmful consequences on human health (Kampa and Castanas, 2007; Simkhovich et al., 2008; Tost et al., 2015; Pope, 2000; Huynen et al., 2001; Hocking et al., 2001). Research has found strong evidence that particulate matter can not only penetrate into lungs, but also penetrate into the brain. This could potentially affect human cognitive performance due to its impact on blood flow and brain function (Pope and Dockery, 2006). Other literature has linked the carbon monoxide to illness and hospitalization (Schlenker and Walker, 2011). Medical research has observed symptoms that carbon monoxide leads to headaches, dizziness and confusion (Piantadosi, 2002). On the other hand, recent studies have found that brain is temperature sensitive. High brain temperature particularly impacts the pre-frontal cortex, which is the major part supply the working memory. As a result, high temperature is associated with less effective working memory (Hocking et al., 2001).

However, evidence documenting the link between cognitive performance and air pollution and temperature are limited. To our best knowledge, there is no research study the effects of air pollution and temperature on cognitive performance at the same time, and there is few research targets on developing countries because of the data limitation. This paper attempts to fill this gap by providing the first evidence of short-term cognitive performance to extreme temperatures and air pollution over 42 developing countries. We use survey questions as the measurement of cognitive performance, and use a global survey data on over 720 thousand women between 1997 to 2009. We also test the effect of air pollution and high temperatures on the cognitive performance of particular groups (e.g., uneducated vs. educated, rural vs. urban). In addition, we investigate the nonlinear effects of air pollution on cognition.

Extant literature has found evidence that air pollution and high temperatures have negative effects on cognitive performance and productivity in both the long term and short term. Most research related to this field targets the impact of air pollution on children and infants. Among these papers, children's exposure to high levels of air pollution in their early life has been found to cause the decline of their school performance in their later life (Lavy et al., 2014, Bharadwaj et al., 2014). Moreover, fetal exposure to high temperatures is associated with low income 30 years later (Isen et al., 2015). On the other hand, one study also finds that air pollution has negative effects on adults' cognitive performance, especially elder women (Weuve et al., 2012). Moreover, extant literature has shown that air pollution and temperature have short-term impacts on the cognitive outcomes of adults and children. Students' exposure to high levels of air pollution and temperature before the tests correlate to reduction in their test scores (Lavy et al., 2014; Graff Zivin et al., 2015). There are negative effects of high level air pollution on industrial workers' productivity (Chang et al., 2014; Li et al., 2015). What's more, Pestel (2015) finds strong evidence that high level air pollution decreases professional soccer player's performance. One early study has suggested that high temperatures increase the probability of making mistakes by helicopter pilots (Froom et al., 1993).

Since the air pollution monitoring data is not available in most developing countries, our analysis uses a newly available air pollution data, which is estimated based on the natural air pollution (e.g., fire activities) by the NASA GISS ModelE climate model. This air pollution data do not take into account industrial air pollution, which is considered the dominant source of global air pollution. Thus, our air pollution is exogenous and does not correlate with individual's characteristics, such as wealth. The model provides the daily average of PM2.5, PM10 and CO on a 55 km by 55 km grid. In order to get an aggregate sense of air pollution, we combine all these three pollutants and calculate the Air Quality Index (AQI)[1] as our major measurement of air pollution. We combine the air pollution data with the ERA-Interim, which is the major source of our climate data on a 55 km by 55 km grid at the global level. Then, we merge the air pollution and climate data with the Demographic and Health Surveys (DHS) by matching each pixel with the DHS cluster. The DHS contains rich information about women and children across 67 developing countries. Interviewees and interviewers are randomly assigned in each DHS countries ("DHS interviewer's manual", 2015). We use the *date flag variables* in the DHS as the main measurements of the cognitive performance. The *date flag variables* are indicators of whether the respondent provides the date of some key events, such as birthdays, marriage date, children's birthdays etc. These dates could be missing or inconsistent with the fact or other records. These events recall questions serve as a simple test of cognition in the short run. In this paper, we consider three date flags, respondent's birthday flag, marriage date flag and children's birthday flag. We think that the ability to recall these three dates test women's concentration (willingness to respond) and their short-term memory[2]. We use the daily level air pollution and monthly level growth degree days 30, which indicates the total days exceeding 30°C in a month to estimate the effects on these three date flags. Since the interview location and date are fixed, we can rule out avoidance behavior and residential sorting issues. We then apply these data to robust econometric models to identify the causal effects of air pollution and temperature on women's ability to recall dates. We also designed a model that allows us to test the nonlinear effects of air pollution on cognitive performance.

Our analysis reveals a statistically significant, positive impact of both AQI and temperature on women's ability of recalling dates. In particular, a one standard deviation increase in the AQI

[1] See details of AQI and AQI calculation in Appendix I.

[2] We consider the ability to recall birthdays as a test of women's willingness to respond. In other word is women's concentration, because a bad effects of air pollution and temperatures cannot make women forget their birthday, but can make them have low concentration to answer the questions. In contrast, children's birthday flag is more likely to test women's ability to remember their children's birthday, especially for women have several children.

raises the likelihood of women not recalling any of those dates by 0.44 percentage point, and also increases the probability of failing to recall women's birthday by 0.48 percentage point. These effects first arise when the AQI exceeds 150 and increases thereafter, which suggests a potential nonlinear effect. Furthermore, we also find that each degree day above 30°C increases the probability of failing to recall children's birthday by 0.17 percentage point, and this finding is consistent with Hocking et al.'s (2001) argument that high temperatures are associated with less accurate working memory. These findings are robust to numerous controls and fixed effects in each specification. In addition, we find both air pollution and temperature are more influential on uneducated women regarding to their cognitive performance with a robust control.

This paper proceeds as follows. Section 2 describes the scientific background on air pollution and temperature, including the potential mechanisms that affect cognitive performance. Section 3 reviews the extant literature of the impact of air pollution and temperature on cognitive performance. Section 4 describes the data that we use, and Section 5 introduces our identification strategies. Section 6 presents our core results along with some robustness checks. Section 7 concludes this paper and explores the potential implications of our results.

2. Scientific Background

2.1 Air Pollution and Health

The major pollutants we considered are carbon monoxide (CO) and particulate matter ($PM_{2.5}$ and PM_{10}). Particulate matter (PM) consists of metals, organic compounds, material of biologic origin, dust particles, reactive gases and particle carbon core (Kampa and Castanas, 2007). In recognition of the growing evidence that only particles less than 10 micrometers (PM_{10}) penetrate into the lungs and damage human's health, further research demonstrated that smallest particles, those less than 2.5 micrometers, can not only penetrate deep into the lungs, but also enter the bloodstream[3]. Particulate matter can be produced from human activities and natural sources (i.e. dust from desert, fire activities and volcanoes). Those human activities include factories, power plants, motor vehicles and construction activity, resulting in major sources of particulate matter. It has been found that particulate matter, especially $PM_{2.5}$, can remain in the air for a long time and can travel hundreds of miles (Chang et al., 2014). Unlike other pollutants, which we can avoid by going indoors, going inside does little to reduce one's exposure to $PM_{2.5}$. Vette et al. (2001) have shown that $PM_{2.5}$ can easily enter buildings. Another important pollutant we are going to use in this study is carbon monoxide (CO), which is an odorless, colorless gas largely generated by automobile emissions, fossil-fuel furnaces and fires (Piantadosi, 2002). Fire activities are the major natural source responsible for a large amount of CO emissions worldwide.

A large body of evidence has associated PM and CO with various health issues. Specifically, inhaling a certain amount of $PM_{2.5}$ can be toxic to lungs and cardiovascular tissue (Simkhovich et al., 2008), and cross the blood-air barrier of the lungs, gaining access to peripheral circulation and the brain (Muhlfeld et al., 2008). In addition, multiple cell types in the brain are sensitive to air pollution, and there is research claims that PM can even enter the brain and may be related to neurodegenerative pathology (Tost et al., 2015; Thomson et al., 2007; Peters et al., 2006). Classic studies of the lungs and cardiovascular system have indicated inflammation and oxidative stress as the common mechanisms that damage human health (Mills et al., 2009; Riedl, 2008). On the other hand, CO binds to the iron in hemoglobin, inhibiting the body's ability to deliver oxygen to vital organs and tissues. This reduction in oxygen availability can affect the function of those vital organs and tissues, (particularly for high oxygen-consuming organs such as the brain and the heart), leading to impaired concentration, slow reflexes and confusion (Kampa and Castanas, 2008).

[3] Particulate matter is categorized by its size. For any particles with an aerodynamic diameter of 2.5 to 10 um are defined as coarse particles(PM_{10}), fine particles of less than 2.5 um($PM_{2.5}$), and ultrafine particulate matter of less than 0.1 um(UFPM).

Exposure to high levels of ambient air pollution in the long run is associated with increases in human morbidity and mortality, especially to infants (Currie and Neidell, 2005). Despite the impact on children's health outcome, air pollution can also have negative effects on adults' health (Schlenker and Walker, 2011). Short-term exposure to PM may associate with respiratory diseases, for instance asthma attacks and also cardiovascular events, such as heart attacks (Pope, 2000). Scientists have also observed symptoms such as change in blood pressure, irritation in the ear, nose, throat and lungs, and mild headaches after a few hours' exposure to PM, especially for sensitive groups of people with cardiovascular and respiratory diseases (Pope, 2000; Auchincloss et al., 2008). In addition, short-term exposure to CO may also result in heart attack and stroke (Dockery and Pope, 1996). Although there is no direct evidence showing whether either of these air pollutants affect cognition, it is clear that these two air pollutants can affect the function of important organs, especially the brain. Since the brain consumes a large amount of oxygens, any deterioration in oxygen quality can, in theory, affect cognition (Clark and Sokoloff, 1999). Hence, those short-term symptoms can be the main reasons that result in the decline of people's cognitive performance and productivity.

2.2 Temperatures and Health

We also investigate the impact of heat on cognition. How can temperature impact human's cognitive performance? The various heat regulation systems in the body can cope with both high and low temperatures. Under certain limits, thermal comfort can be maintained by appropriate thermoregulatory responses such that physical and mental activities can be processed without any detriment to health or performance (Huynen et al., 2001). However, when temperature exceeds certain limits, the capacity of the body's heat regulation systems may overload so that damage occurs. Particularly, extreme hot temperatures are generally associated with increases in blood viscosity and blood cholesterol levels, which can lead to cardiovascular stress (Huynen et al., 2001).

Moreover, extant literature has shown that the brain's chemistry, electrical properties, and functions are temperature sensitive (Yablonskiy et al., 2000; Hocking et al., 2001), and the brain's performance can be influenced by rising temperatures. Under normal conditions, excessive heat diffuses into the bloodstream, and our body transports the heat to either the skin or lungs, and then transfers it to the environment. As environmental temperatures increase, heat transfer through the skin and lungs slows, which reduces the flow of cool blood to the brain. As a result, the brain's temperature can temporarily increase (Graff Zivin et al., 2015). This is the main way that high temperature affects cognitive performance in the short term. In particular, working memory is less effective when the brain's temperature is high[4] (Graff Zivin et al., 2015).

Previous research has documented that heat is associated with morbidity and mortality. In one early study, Semenza et al. (1999) reported that the heat wave in Chicago in 1995 resulted in large increases in hospital admissions among all age groups. In addition, Deschenes and Greenstone (2011) found that climate change increases the overall annual U.S> mortality rate, particularly in infants.

3. Literature Review

Negative effects of air pollution and heat on human health have been well documented in economics literature. Hence, one could believe that the negative consequences can not only damage a population's health, but also indirectly affect human productivity and cognitive performance. In extant literature, people's cognitive performance is usually measured as their productivity in different occupations. For example, economists use school outcomes (e.g. test scores), as the major measurement of students' cognitive performance. For adults, cognitive performance is measured

[4] Hocking et al. (2001) state that the pre-frontal cortex is the major part that supply the working memory, which stores data in neural circuits. As Graff Zivin et al., (2015) explain, "Performing tasks that utilize working memory when core body temperature is elevated increases neuronal activity in the pre-frontal cortex for any given level of performance, suggesting that working memory is less effective when brain temperature is high."

through people's verbal memory, category fluency, working memory, attention and workplace productivity. Most of these studies have shown negative consequences of air pollution and excessive heat on human cognitive performance in both the long term and short term.

3.1 Air Pollution

3.1.1 The Long-Term Impact

In most extant research, children, especially infants, are used as the major research participants of their studies, because most important organs of children are not well developed. Hence, children are more sensitive to the damage of air pollution. Bharadwj et al. (2014) examine the impact of fetal exposure to air pollution on 4^{th} grade test score in Santiago, Chile. Their research uses sibling fixed effect to control family characteristics and avoid the residential sorting issues[5]. The authors also exploit data on air quality alerts to help address concerns related to avoidance behavior[6]. Bharadwj et al.'s paper found a strong and robust negative effect on fetal exposure to high levels of CO on math and language test scores in their later life.

There is little research indicating that air pollution has long-term effects on adults' cognitive performance. One study by Weuve et al. (2012) investigated the impact of particulate matter on older women's cognitive performance in the long run. The author tested older women's verbal memory, category fluency, working memory, and attention three times at two-year intervals via telephone assessments, and he found that higher levels of long-term exposure to particulate matter were associated with significantly faster cognitive decline for women over 70.

3.1.2 The Short-Term Impact

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[5] Residential sorting refers to individuals choosing residential locations based on the attributes of the area, which cause to a non-random assignment of pollution (Graff Zivin and Neidell, 2013).

[6] Avoidance behaviors are actions that people take to avoid exposure to ambient air pollution (e.g. indoor), without considering such avoidance behaviors, the effects of air pollution could be underestimated.

Some literature in this field pays particular attention to the short-term effects of air pollution on people's cognitive performance. Lavy et al. (2014) estimate the relationship between air pollution and teenagers' cognitive performance. Lavy et al.'s study indicates the significant negative consequences of both CO and PM2.5 on teenagers' high school test scores in the short run. The authors use both PM2.5 and CO levels in Israel at a specific time before the high school testing was to start, to examine if there is a short-term effect of air pollution on students' test performance. Israel's unique high school test system allows the authors to control each individual's characteristics as well as the difficulty of the tests[7]. The results show that a 10-unit increase in the ambient concentration of fine particulate matter reduces the test scores by 0.46 points, and increasing the amount of CO decreases test scores by 0.85 points.

The negative effects of air pollution on adults' productivity in the short run have also been documented. Estimating the impact of air pollution on labor productivity is particularly difficult, because pollution is more tightly related to industrial production, which may have reverse causality. Chang et al., (2014) presented evidence on the impact of outdoor pollution on the productivity of indoor workers. The paper focuses on the effect of PM2.5 on the efficiency of pear packers in a pear packing facility in Northern California. To solve the endogeneity of pollution, the authors use a large wildfire as a natural experiment, which increases the overall level of PM2.5. The result suggests that an increase in PM2.5 of 10 micrograms per cubic meter reduces the productivity of workers by $0.41 per hour, which is equivalent to 6 percent of average hourly earnings. The paper also finds evidence that PM2.5 has a non-linear effect on worker productivity.

However, one can argue that the indoor work environment in the Chang et al. (2014) study is naturally ventilated, and without the temperature, any variation in temperature might lead to the

[7] High school students in Israel are allow to the high-stakes exit exams more than once and start from grade 10, and students will get reward points depends on the difficulty of the exams.

change of PM2.5. Without controlling temperature, the estimation will be biased. In order to address these concerns, Li, Liu and Salvo (2015) provide a more valid method to estimate the impact of air pollution on labor productivity for manufacturing workers. They used the daily PM2.5 concentrations to estimate the impact on worker output in a Beijing's textile mill. In their study, all laborers work in an environment that is indoor, temperature controlled, and sheltered from rain and wind. This rules out other factors (e.g. heat, extreme weather conditions) that affect labor productivity. The major finding of this paper is that every additional 10 ug/m^3 of exposure to PM2.5 leads to 4.3 meters of fabric reduction for each worker. The paper also finds a huge non-linear effect of PM2.5 on labor productivity.

Pestel (2015) argues that a very detailed data of individuals' short-run productivity is missing for a lot of occupations. He estimates the causal effect of ambient air pollution on individuals' productivity by using the information on the universe of professional soccer players and teams in the German Bundesliga in 2,956 matches and 32 different stadiums throughout the country over a twelve-year period. Since professional sports data offer very detailed information of each match, it allows the author to measure individuals' short-run productivity consistently. Because the match schedule is fixed, the ambient air pollution could be considered as exogenous to each player, which overcomes the concerns of residential sorting and avoidance behavior. The results indicate that one percent increase in the concentration of particulate matter leads to a 0.02 percent reduction in the number of passes. The negative effects increase with players' age over 30.

3.2 Heat and Temperature

3.2.1 The Long-Term Impact

Similar to the air pollution, there is little evidence that shows high temperatures have long-term consequences on cognitive performance. Isen et al. (2015) investigate how exposure to extreme temperatures in utero and early childhood affects adults' earnings 30 years later. By controlling country by day of year by race by sex and year fixed effects, it isolates other factors that may affect later life outcomes. Since temperatures are different across different years on the same day, this technique allows the authors to quantify any differences in the later life outcomes of two children of the same gender and same race, who are born in the same country on the same day, but in different years. This paper finds that an extra day with mean temperature above 32°C (89F) in utero and in the first year of life is associated with a 0.2 percent reduction in average annual income 30 years later.

Some literature has linked the negative effects of temperature on productivity in the long run. Dell et al. (2012) find evidence that higher temperatures substantially reduce economic growth in developing countries. Not just developing countries, Deryugina and Hsiang's (2014) paper investigates the effects of daily temperature on annual income in U.S. counties over 40 years, and they indicate that total personal income per capita is highest if the 24-hour average temperatures are between 9-15°C (48-59F), and it will decline as the temperature increases. In addition, high temperature can also decrease the productivity at firm level. Somanathan et al. (2014) look at the impact of temperature on firm productivity for manufacturing firms in India. They find that, above 25°C (77F), the overall firm output decreases 5.6 percent as one additional degree increases. Particularly, they show that temperature has more effects in plants with a high labor share and low electricity intensity. Although there is no direct evidence supporting that high temperature affects an individual's productivity, the literature we list above suggests that high temperature can cause a decline in countries' and firms' productivity due to the reduction of labor productivity[8].

3.2.2 The Short-Term Impact

[8] Deryugina and Hsiang (2014) examine the impact of temperature on both farm and non-farm income losses, and they conclude high temperature reduces the productivity of both workers and crops. Somanathan's et al. (2014) paper uses the daily output of a manufacturing unit as the measurement of the firm productivity, and they find that temperature affects more in plants with a high labor share. Therefore, one can believe high temperature can impact a country's and firm's productivity through the decline of laborers' productivity.

There is little extant literature focused on analyzing the relationship between weather and cognitive performance in the short run. One paper written by Graff Zivin et al. (2015) provides the first estimates of the impact of temperature on children's cognitive performance in the short run. They use assessments of cognitive ability from the children included in the National Longitudinal Survey of Youth and link it with temperature. By doing the child fixed effects, they can capture all other children's characteristics that may affect their cognitive performance, and they exploit the exogenous interview date and daily fluctuations in temperature across the same children over time to find any causal effects. The results imply that math performance declines above 21°C (70F), and becomes significant beyond 26°C (79F). Moreover, early research has linked heat with adults' cognitive performance. Froom et al. (1993) provide evidence that helicopter pilots are more likely to make mistakes if the ambient temperature is above 25°C(77F). What's more, Pilcher et al. (2002) use a meta-analysis[9] to summarize the effects of hot temperature exposure on cognitive performance. Based on 22 original studies, hot temperature negatively impacts performance on different cognitive-related tasks. Specifically, if the temperature is above 32°C (89F), it will lead to the greatest decrement in cognitive performance.

4. Data

We use three major data sources, the Demographic and Health Surveys, air pollution and ERA- Interim in this study. We use the *pixel ID* to match with the DHS cluster. *Pixel ID* is the geographic code of air pollution, which is measured in a 0.5-degree spatial resolution. The size of the DHS cluster is smaller than the size of *pixel ID*. DHS cluster is a geographic identification that DHS use for interviewing. There are 28 women, on average, who took surveys in each DHS cluster each year. We combine these three data by using *pixel ID*, DHS cluster and interview dates. This section

[9] Meta-analysis is a statistical technique for combining and summarizing the findings from different independent studies.

briefly describes these data and points out key summary statistics. Table 1 lists the detailed summary statistics.

4.1 Air Pollution and Temperature

Our air pollution data is generated by the Ruth Defries' Lab at Columbia University. It is an estimating data based on the natural resource, such as global fire emissions (e.g., forest fires, savanna fire, burning agriculture waste and peat fires). They used the MODerate resolution Imaging Spectrooradiometer (MODIS) sensor on satellites to detect the burned area of different fire activities. They use a revised version of GISS-E2-PUCCINI, which is the latest version of the NASA GISS ModelE climate model[10] to estimate the pollution emissions of global fires from 1997 to present on a 0.5 degree (55km) spatial resolution[11] at the daily level(Marlier et al., 2014; Van der Werf et al., 2010). We encode each of this 0.5-degree spatial resolution as one pixel. This means the pollution will vary across different pixel. This pollution data does not take into account industrial air pollution and only estimate the air pollution based on natural activities, which means the air pollution could be considered as exogenous. The model can simulate the PM, CO and Ozone level at each pixel conditional on the certain fire activity. Figure 1 shows the overall estimation of daily average PM2.5 emissions from 1997 to 2008. It is clear that the variation of air pollution in Afican countries is very high, and countries with high forest density, for example Indonesia, also associate with high PM2.5.

PMs (PM2.5 and PM10) in our data are reported as a 24-hour moving average (ug/m^3). CO data is measured as an 8-hour moving average (ppm). We exclude Ozone from our pollution data

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[10] "The climate modeling program at GISS is primarily aimed at the development of coupled atmosphere-ocean models for simulating Earth's climate system. Primary emphasis is placed on investigation of climate sensitivity —globally and regionally, including the climate system's response to diverse forcings such as solar variability, volcanoes, anthropogenic and natural emissions of greenhouse gases and aerosols, paleo-climate changes, etc" (Global Climate Modeling, 2015).
[11] Spatial resolution specifies how large (in degrees of latitude and longitude or in km or miles) the grid cells in a model are.

because the Ozone emission from fire activity is too small compared with CO and PM. In order to find the aggregate effect of air pollution on cognition, we combine all pollutants (PM2.5, PM10, CO) and calculate a daily Air Quality Index (AQI) according to the Guidelines for the Reporting of Daily Air Quality, which is conducted by the U.S. Environmental Protection Agency (Mintz, 2006). The AQI is a composite measurement of air pollution, which ranges from 0 to 500 and a consistent unit. Another advantage of using the AQI is that the EPA clearly defines the AQI standard, and ranks air quality based on various health risks. We can take this advantage to estimate the non-linear effects of air pollution. Figure 2 presents the total number of days that the AQI falls to the different categories. The six AQI categories (Good, Moderate, Unhealthy for Sensitive Group, Unhealthy, Very Unhealthy and Hazardous) corresponds to a different level of health concern.

We combine our air pollution data with the climate data using information on the DHS cluster and exact date. Our climate data are from the ERA-Interim, by the European Centre for Medium-Range Weather Forecasts, which produce a reanalysis of the global atmosphere start from 1979 to present. In this study, we look at the growing degree days (GDD) and precipitation. Particularly, we use monthly GDD-30, which is an indicator of the total days exceeding 30°C in a month, and the precipitation is a monthly average in millimeters. Based on Table 1, the average GDD-30 of the whole sample is 5.25, and the mean of the monthly precipitation is 1108 mm.

4.2 The Cognitive Performance Data

The main data source for measuring the cognitive performance comes from the Demographic and Health Surveys (DHS). The DHS collects primary data, which contains rich information on the health of children and women as well as household characteristics. In a majority of DHS, only women between 15 and 50 are eligible to take the surveys. The data are available from 1986 to 2011, and it includes over 1.7 million women from 67 developing countries, and most of these countries are located in tropical areas ("Description of the Demographic and Health Surveys", 2010).

We use the *date flag variables* in the DHS as the main measurement of cognitive performance. *Date flag variables* are indicators of whether or not the woman can recall important dates. In DHS, there are some dates of key events in respondents' lives, which are missing. It is either because they do not provide the date information when they responded to the surveys or the dates the respondents provide are inconsistent with the facts or the official record. These events include respondents' birthday, marriage date, children's birthday, conception dates of the current pregnancy, the start date of using birth control method, and the interview date. Since these dates are very important to the surveys, DHS has to impute these missing dates according to respondents' age, official records and other information. The date flag variables indicate what format the information was in prior to imputation, and what basis was used for the imputation.

We categorize the date flag variables into three groups: 1) respondents provide correct and full date information for the event; 2) respondents do not provide correct and full date information, but the respondent's age is not missing, and DHS imputed these dates according to respondent's age; 3) respondents do not provide correct and full date information for the event, and respondent's age information is also missing. In this research, we exclude the third group because women in this group may not know the date of the event at all. Therefore, there is no way for this group of women to recall the date when they respond to the survey.

We consider three date flag variables in our study, the flag of respondents' birthdays, the flag of respondents' marriage date and the flag of respondent's children's birthday, referring to them as *birthday flag*, *marriage date flag* and *children's birthday flag*. We only use these three date flag variables because these dates are more likely to be remembered, and it is easy to find a record and to impute it accurately. We only include women who are married when we look at the marriage date flag, and exclude those who do not have children when we use children's birthday flag as the cognitive measurement. We think these three date flag variables test both respondents' willingness to complete the survey questions and their short-term memory. The birthday flag is testing women's willingness to respond to the question. On the other hand, the children's birthday flag is more likely to test women's short-term memory, especially for those who have several children. This children's birthday flag is the average child's birthday flag per child, which is equal to the total children's birthday flags divided by total children the mom has. The marriage date flag is kind of testing both characteristics. We also create two aggregate date flag variables to test their effects of the whole sample: 1) *any flag* is a dummy variable that turns to 1 if any of those three dates flags pop up. 2) *total flag* is the sum of those three dates flags. We use these five date flags as our measurements of women's cognitive performance in all of the specifications. The average of any flag is 0.347 for the whole sample. Women who have not been educated and live in rural have higher probability to have date flags than women who have been educated and live in urban area.

After we merge our DHS data with air pollution data and ERA data, we have 736,160 women across 42 countries left in our sample. Figure 3 shows the countries left in our sample. The interview interval is from 1997 to 2009. Since the DHS is conducted once a year, the sample in each year is different. Thus, our final data is a cross-sectional data. According to the DHS interviewer guidelines, all interviewees are randomly selected each year. The interviewers are also randomly assigned to each country, and only the best-qualified interviewers in the training are allowed to go in the field. All interviews are finished in one month. Based on this information, we can assume all of our sample have been randomly selected. Table 1 reports the average daily AQI is higher in rural area than it in urban area, which is not consistent with the situation in real world. However, what we observe is totally making sense for our air pollution data since our pollution data does not take the industrial pollution into account. On the other hand, rural area is more likely to have fire activities (e.g., burning agriculture waste). Thus, the air pollution in rural area should be higher than urban area in our data.

5. Empirical Strategies

Our goal is to estimate the effects of air pollution and heat on women's cognitive performance, particularly on women's ability to recall dates. We estimate linear fixed effects regression models of following form:

$$\mathbf{DateFlags_{i,t,j} = \beta AQI_{t,j} + \gamma GDD\text{-}30_{t,j} + \vartheta\ Prec_{t,j} + \eta X_{i,t} + Country * Year + M_t + C_j + \varepsilon_{i,t,j}} \quad \textbf{(1)}$$

where DateFlags are five date flags (total flags, any flag, birthday flag, marriage date flag and children's birthday flag) of women *i* at DHS cluster *j* at the interview date *t;* $AQI_{t,j}$ is our measurement of air pollution (daily average AQI) at DHS cluster *j* at the interview date *t*. In our regressions, we calculate the z score of the AQI, and use it as the independent variable. $GDD\text{-}30_{t,j}$ is the monthly mean of growing degree days over 30°C at DHS cluster *j* at the interview month *t*. It is the primary measurement of heat; $Prec_{t,j}$ $X_{i,t}$ is a vector of women's characteristics possibly related to date flags. We control women's age, age square and total fertility. We also control women's education level and whether women live in a rural or an urban area. The education indicator report women's highest education level, which is indicated as uneducated, primary school, secondary school or higher education. Instead of including education dummy and rural dummy in our controls, we interact the education dummy and rural dummy with the country. By doing so, we control the effects of women's education level and living area on their cognitive performance differently across different countries[12], which yield a robustness effects of air pollution and heat on date flags. Moreover, we include the country by year fixed effects to control country and year trends. It also can be considered as a "survey"

[12] Including country * education and country * rural means each country gets its own coefficient on education variables and rural dummy. By doing so, we control for average date flag by women's education level and living area for each country differently. We rule out some country specific effects of education level and living area on date flags.

fixed effects, which controls all the effects caused by the DHS taking place in a certain country in a certain year. M_t is the month fixed effect, which captures all month invariant effects; C_j is the DHS cluster fixed effects, which controls for all time invariant characteristics of each cluster. Since the interview schedule and location are fixed, we can rule out any avoidance behavior and residential sorting issues, and identify the causal effects of air pollution and temperature on performance. $\boldsymbol{\varepsilon}_{i,t,j}$ is an idiosyncratic error term.

Our second specification test effects whether air pollution and temperature can reduce women's cognitive performance for those who belong to a specific group. Since we observe in Table 1 that women in rural areas and with low education levels are more likely to have to date flag, we will compare the effects between women who have been educated and not, and also, between women who live in rural areas and urban areas. The models we estimate are of the following form:

$$\mathbf{DateFlags_{i,t,j} \mid Group = \boldsymbol{\beta} AQI_{t,j} + \boldsymbol{\gamma} GDD\text{-}30_{t,j} + \boldsymbol{\vartheta}\ Prec_{t,j\,+}\ \boldsymbol{\eta} X_{i,t} + Country * Year + M_t + C_j + \boldsymbol{\varepsilon}_{i,t,j}} \quad \mathbf{(2)}$$

where we retain all the date flag measurements, air pollution and temperature treatments the same, and keep all controls and fixed effects in the first model. The only difference is we estimate the sub-sample effects, in which we only include women who belong to each group in our sample (e.g., educated, uneducated, rural and urban). The main purpose of testing this model is we want to check if air pollution and heat have more effects on women who have relatively low levels of human capital.,

Extant research has found non-linear effects of air pollution on adults' productivity in the short run (Chang et al., 2014; Li et al., 2015). Our last estimation will test whether air pollution has non-linear effects on women's cognitive performance. We are not able to test the non-linear effects of temperature because we cannot find a clear temperature standard, and GDD-30 is already a high temperature. The models of testing non-linear effects of air pollution are formed as follows:

$$\textbf{DateFlags}_{i,t,j} = \boldsymbol{\beta}_1\,\textbf{Moderate}_{t,j} + \boldsymbol{\beta}_2\,\textbf{Sensitive}_{i,j} + \boldsymbol{\beta}_3\,\textbf{Unhealthy}_{t,j} + \boldsymbol{\beta}_4\,\textbf{VeryUnhealthy}_{t,j} + \boldsymbol{\beta}_5\,\textbf{Hazardous}_{t,j} + \boldsymbol{\gamma}\textbf{GDD-30}_{t,j} + \boldsymbol{\vartheta}\,\textbf{Prec}_{t,j} + \boldsymbol{\eta}\textbf{X}_{i,t} + \textbf{Country * Year} + \textbf{M}_t + \textbf{C}_j + \boldsymbol{\varepsilon}_{i,t,j} \qquad \textbf{(3)}$$

With the same date flag measurements, controls and fixed effects, we change our air pollution treatment to five dummy variables, which indicate whether the AQI at interview day t falls in the correspondent AQI health category. The coefficient of each of these health categories indicates the marginal effects of the AQI in the category relating to women's ability to recall dates compared with a good AQI day.

6. Empirical Results

6.1 Main Results

In Table 2, we present our baseline results of the relationship between the AQI, GDD-30 and five date flag variables. All of our results are controlled with country by year fixed effects, month fixed effects and DHS cluster fixed effects. In Columns (1) and (2), we report the correlation between the AQI, temperature and two aggregate date flag measurements. In Column (1), we estimate that one standard deviation increase of the AQI is associated with a 0.44 percentage point increase in women's probability to not complete any of these three dates (birthday, marriage date and children's birthday), and the coefficient is significant at the 5% level. Moving from Column (1) to Column (2), it illustrates a one-standard deviation increase in the AQI significantly increase 0.007 total date flags. However, we do not see any significant effect of temperature on these two date flags. In Column (3) to (5), we estimate the effects of air pollution on each of the three date flags, e.g., birthday flag, marriage date flag and children's birthday flag. As mentioned earlier, we only take into account women who have married and have children when we look at the marriage date flag and children's birthday flag. The estimate of 0.0048 in the first row of Column (3) implies that one standard deviation increase in the AQI rise the birthday flag 0.48 percentage point. We do not see any significance of the AQI on marriage date flag and children's birthday flag, and it suggests that the effects of the AQI on aggregate date flags are driven by the birthday flag. On the other hand, we only observe significant coefficient of temperature on children's birthday flag. In the second row of Column (5), the coefficient indicates that each degree day above 30°C increase the probability of failing to recall children's birthday by 0.17 percent. This result is consistent with Hocking et al.' (2001) finding that is high brain temperature is mostly affect ability of memory.

Table 3a is comparing the effects of the AQI and temperature on date flags between women who live in rural areas and urban areas. In Table 3a, panel A estimate the effects of the AQI and temperature on women living in rural areas. We do not see any significant effects of the AQI. However, the temperature shows the significant positive effect on children's birthday flags of women in rural area. It is consistent with the result in the first model. In contrast, panel B presents the results of the AQI and temperature on women living in urban areas, and reveals very strong signals of the AQI increase in the aggregate date flags. Column (1) indicates that a one-standard deviation increase in the AQI increases the probability of not recalling any of these three dates by 0.81 percentage point, and Column (2) reports a one-standard deviation increase in the AQI raising the total amount of date flags by 0.0051. These two coefficients are significant at 1% level. We also see significantly weak positive effects of the AQI on the birthday flag and children's birthday flag. The positive effects of temperature on children's birthday flag is still significant in panel B, but the effect is smaller than it is in panel A (0.21 percentage point increase on children's birthday flag for women living in rural areas and 0.16 percentage point increase on children's birthday flag for women in urban areas).

We consider that the major reason that the AQI has a strong effect on women's date flag only for those in urban areas is that our pollution data fail to take into account the industrial air pollution. However, industrial air pollution is the major source of global air pollution, and urban areas are most likely to be affected by industrial air pollution. Therefore, we expect the baseline air pollution in urban areas should be higher than it is in rural areas. Women in urban areas may be exposed to higher levels of air pollution in the long term and short term than those living in rural areas. Our results in Table 3a suggest that high pollution levels in urban area cause more severe damages to women's health than those living in rural areas, so that air pollution significantly decreases women's cognitive performance in urban areas. On the other hand, we observe that high temperatures have more of an effect on women in rural areas than their urban counterparts. One explanation is that women are more likely to work outdoors in rural areas and indoor in urban ones, which makes the temperature have stronger long-term effects on rural women. In addition, since urban areas are more developed than rural areas, the interview locations in urban areas are more likely to be indoors and temperature controlled.

In Table 3b, we examine heterogeneity in these date flags by women's education. We expect higher effects of air pollution and temperature on uneducated women, since low human capital is associated with low cognitive performance. Based on panel A, there is no significant signal of the AQI on women's date flag in the uneducated sub-sample. In contrast, panel B presents the weak effects of the AQI on two aggregate date flag measurements. These results are not consistent with what we expect. However, one explanation could be that most educated women live in urban areas. As we mentioned before, industrial air pollution dominates global air pollution, and urban areas are mostly polluted by industrial air pollution. Figure 4 shows the total number of women with different education levels between rural and urban areas. It is clear to see most uneducated women live in rural areas, and the density of educated women in urban areas is higher than it is in rural areas. If we take into account the industrial air pollution, the AQI is not high enough to affect women's cognitive performance in rural areas. In addition, the dominant education level in urban areas is secondary school, which we consider not to be a high education level. What Figure 4 presents supports the results of the AQI in Table 3b. On the other hand, temperature show very strong effects on almost all date flags in rural areas, but no significant effects on urban areas. Specifically, in the second row of panel A, each degree day above 30°C increases the probability of women failing to recall any of these three dates by 0.7 percentage point, and cause an increase of 0.0127 amount of total flags. Moreover, each degree day above 30°C also leads to an increase of women not recalling marriage dates and children's birthday by 0.89 and 0.41 percentage point, respectively. These two coefficients are significant at 1% level. The results of temperature confirm our suspicion that women in rural areas are more likely to work outdoors, and women in urban areas have a higher likelihood of working indoors, which makes the temperature less influential.

Table 4 presents the nonlinear estimation of the AQI criteria on date flags. In Column (1), we find that the AQI between 51 to 150 increase the probability of failing to recall dates by 0.2 percentage point, though this effect is not significant at a conventional level. When the AQI reaches 151 – 200 (Unhealthy), the effect increases to 0.7 percentage point, but it is still not significant. As the AQI increases to 201 – 300 (Very Unhealthy), the effect increases to 1.5 percentage point and is significant at 5% level. The effect further increases to 3 percentage point when the AQI exceeds 300 (Hazardous) and significant at 1% level. Note that the average of any flag is 0.347. The effect of Hazardous implies that one out of three interviewers will fail to recall any of those three dates conditional on a Hazardous day. We also observed similar patterns of the AQI criteria on total flags, marriage date flag and birthday flag. These results provide clear evidence of a nonlinear relationship between the AQI and date flags. To further illustrate this, Figure 5a plots the nonlinear coefficients. These coefficients suggest a possible threshold of around 101 – 150 (Unhealthy to Sensitive Group) for most date flags. To make it clear, Figure 5b only indicates the nonlinear estimation of any flag. Based on Figure 5b, it is clear that the nonlinear effect occurs as the AQI exceed 150. While we cannot be certain of a threshold at this point, we note that this pattern is consistent with what the AQI suggest, which implies that as the AQI reaches Unhealthy (over 150), "everyone may begin to experience some adverse health effects, and members of the sensitive groups may experience more serious effects (AQI)."

6.2 Robustness Checks

Our results indicate that air pollution has a higher effect on women's cognitive performance in urban areas than those in rural areas. As explained earlier, it could be the case that industrial air pollution dominates the urban area air pollution, so this affects women's cognitive performance. Since we do not have the industrial air pollution data, we cannot examine this suspicion directly. What's more, in Table 3b, we find the AQI only has significant effects on educated women, and Figure 4 shows that the proportion of educated women in urban areas are far more than it is in rural areas. In order to investigate this suspicion, we tested the effect of the AQI on women who live in urban areas by their education level, because we believe women with low human capital would be affected more by air pollution. In Table 5, panel A indicates the effect on uneducated women in urban areas. Compare with the results of the whole, we lost the significance of two aggregate dates flags. The major problem here is I lost nearly 85% sample size when decompose the sample to women who are uneducated and in urban areas. However, the significance appears on children's birthday flag, which reports that a one-standard deviation increase in the AQI is associated with 0.48 percentage point increase in children's birthday flag. We also observe significant results of temperature on aggregate date flags and children birthday flag. Columns (1) and (2) report that each degree day above 30°C increases any flag by 0.76 percentage point and raise the total amount of date flags by 0.014. In Column (5), the coefficient 0.005 implies that an additional degree day above 30°C increases the probability of not recalling children's birthday by 0.5 percentage point. On the other hand, we do not see any significant results of both the AQI and temperature on educated women in panel B. Under the appropriate controls and fixed effects, these results imply that industrial air pollution should somehow respond to the effect on urban sub-sample. In addition, both air pollution and high temperatures are more likely to affect poor human capital women.

Since our air pollution data are primarily estimated according to the global fire activities, one concern is that the temperature may correlate with our pollution, which makes our estimation biased. For example, high degree days have higher probability to cause fire activities (e.g., forest fires). In order to test this concern, we exclude the temperature and precipitation variables from our main specification, and check the effects of the AQI only. Table 6 presents the results that exclude the temperature measurement. The results are very similar to Table 2, which rules out any concern about correlation between temperature and air pollution.

Finally, we explore heterogeneity in the effects of each pollutant. We decompose the AQI to PM2.5, PM10 and CO, and run the same regressions of Table 2 to test the whole sample's effects. Table 7 indicates that the significance is only revealed on any flag, and driven by PM2.5 and PM10. It is consistent with the results in Table 2, because the AQI in our sample is also mainly driven by PM2.5 and PM10.

7. Conclusion

In this paper, we estimate the causal effects of ambient air pollution and temperature on women's cognitive performance. Using the date flag variables (a measurement of women's ability to recall dates, which test women attention and short-term memory) from the Demographic and Health Surveys as the measurement of cognitive performance and daily information of air pollution and monthly temperature on a 55 km by 55 km grid, we exploit exogenous variation in respondents' exposure to air pollution and temperature due to the natural air pollution source and fixed interview dates and locations.

Our results indicate that air pollution and temperature have negative effects on women's ability to recall dates in the short run, and these effects particularly affect uneducated women. These linear effects are statistically significant and robust. In addition, when allowing for a nonlinear dose-response relationship, substantial positive effects of air pollution on date flags are found: any date flag increases dramatically as the AQI reaches 150 (Unhealthy to Sensitive Group), and keeps increasing when the AQI exceeds 200 (Unhealthy), and becoming significant. These nonlinear effects suggest a threshold of 150 of the AQI.

Although the interviewers and interviewees have been randomly assigned, our cross-sectional data do not allow us to identify each individual and apply an individual fixed effects to control all individuals' characteristics. While we suspect there is a negative effect of industrial air pollution on cognitive performance, our results could be underestimated without taking into account industrial air pollution. Since our temperature measurement is at monthly, our results of monthly GDD-30 on date flags could be noisy. Future research on adults' cognitive performance should further examine the effect of daily air pollution with taking into account industrial air pollution. Furthermore, future research should test the short-term effects of daily temperatures instead of monthly temperatures. Moreover, a perfect panel data could be applied in future research to re-examine the short-term effects of air pollution and temperatures on adults' cognitive performance.

Our analyses highlight that air pollution and temperature are not limited to adverse impacts on population health. Even moderate concentrations of air pollution that is generated by natural sources can negatively affect women's cognitive performance. Our findings complement previous studies of air pollution and high temperatures negative effects on cognitive performance in the short term (e.g. Graff Zivin et al., 2015; Froom et al., 1993; Lavy et al., 2014; Chang et al., 2014; Li et al., 2015; Pestel 2015), and add new evidence that both air pollution and temperature affect adult women's cognitive performance, particularly that of low-educated women. The results presented here suggest that the benefits from regulating air pollution and greenhouse gases emission may be underestimated by a narrow focus on health impacts. As air pollution and high temperatures may have decreased cognitive performance, the consequences of air pollution and climate change may be relevant to everyday activities which require concentration and working memory. Low schooling performance and reduced worker productivity could be the byproducts of decreased cognitive performance. Furthermore, the results suggest that air pollution and extreme temperatures may also reduce the accuracy of large surveys' outcomes. Therefore, an optimal design of climate change and air pollution regulating policies may yield tremendous benefits to the welfare of population.

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Figure 1: Daily Average PM2.5 (ug/m^3) from 1997 to 2008

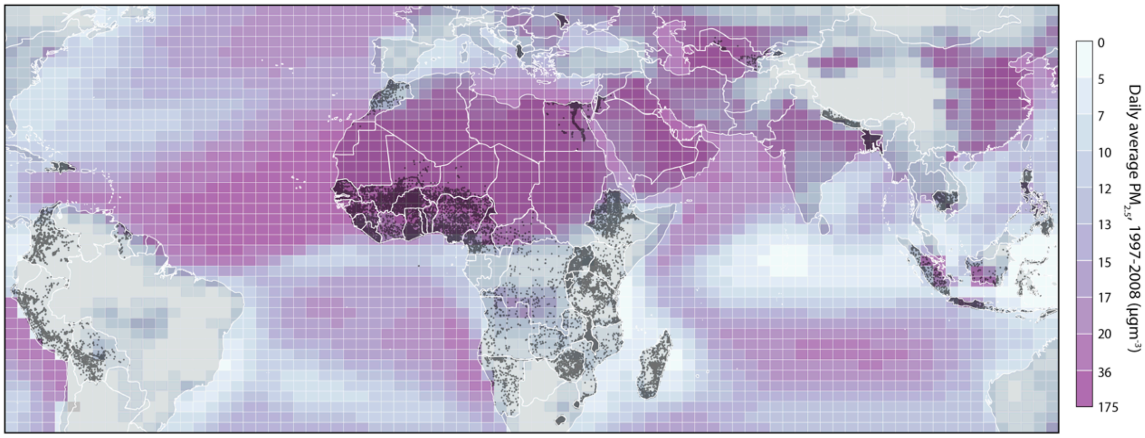


Figure 2: Accumulated Daily Exceedances Over AQI Criteria

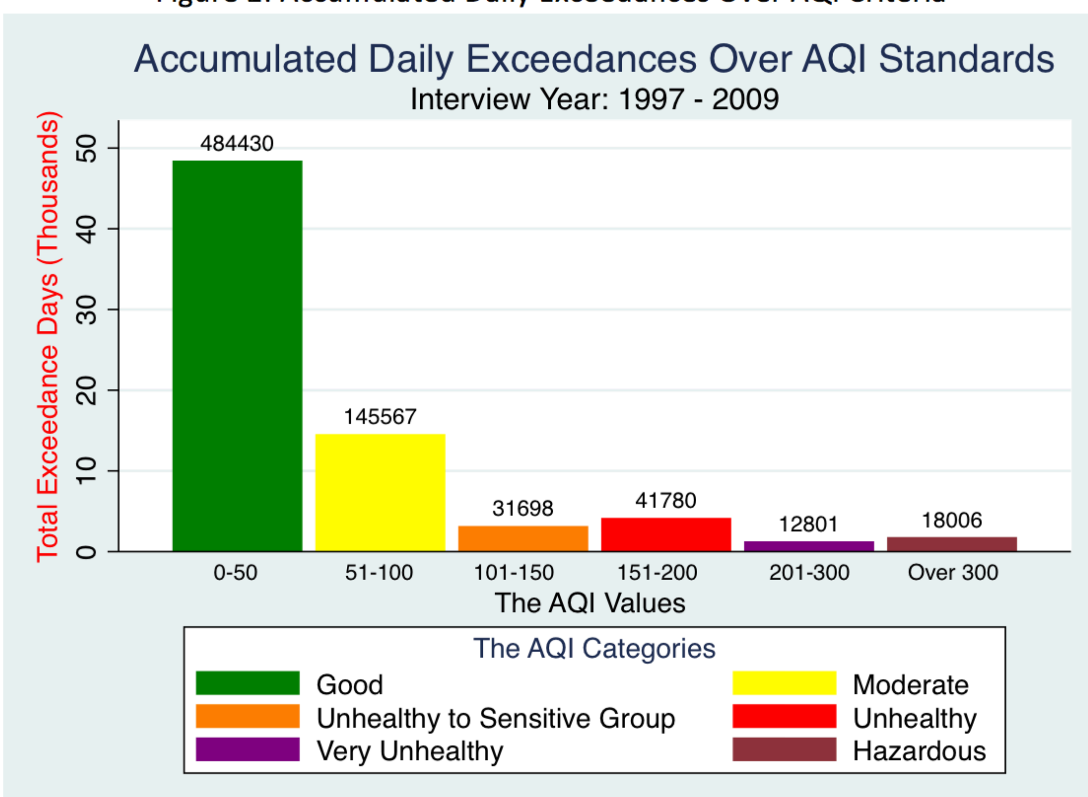


Figure 3: DHS Countries and Observations

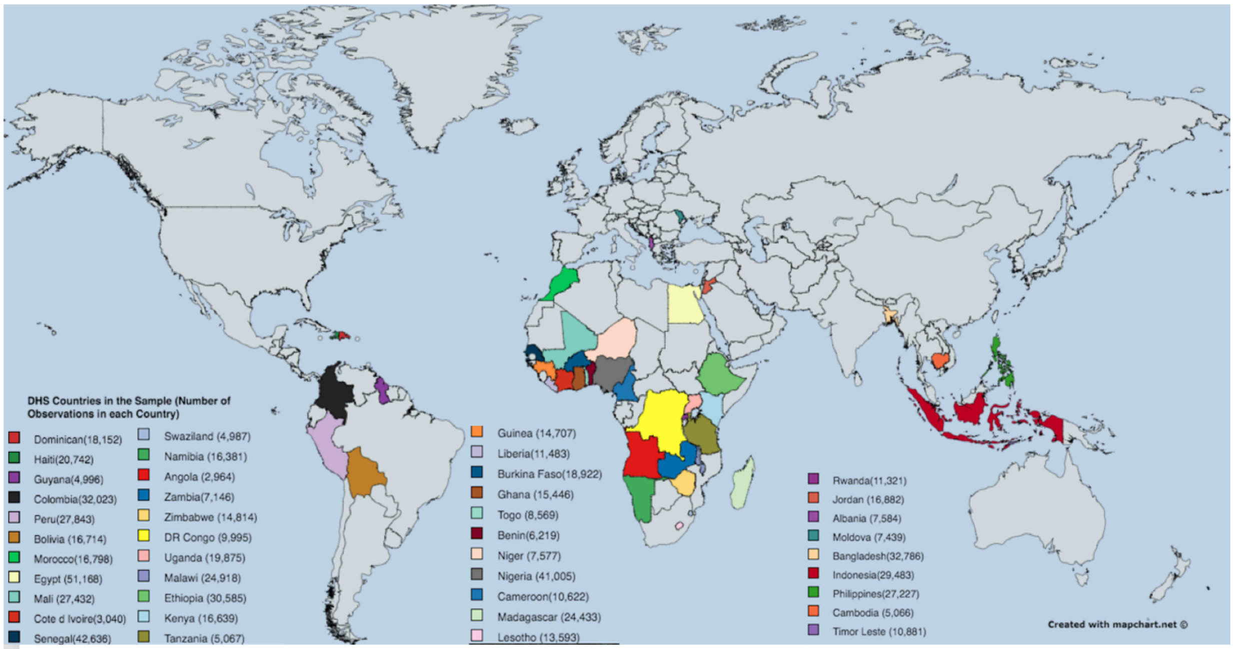


Figure 4: Total Number of Women in Different Education Levels (Rural vs. Urban)

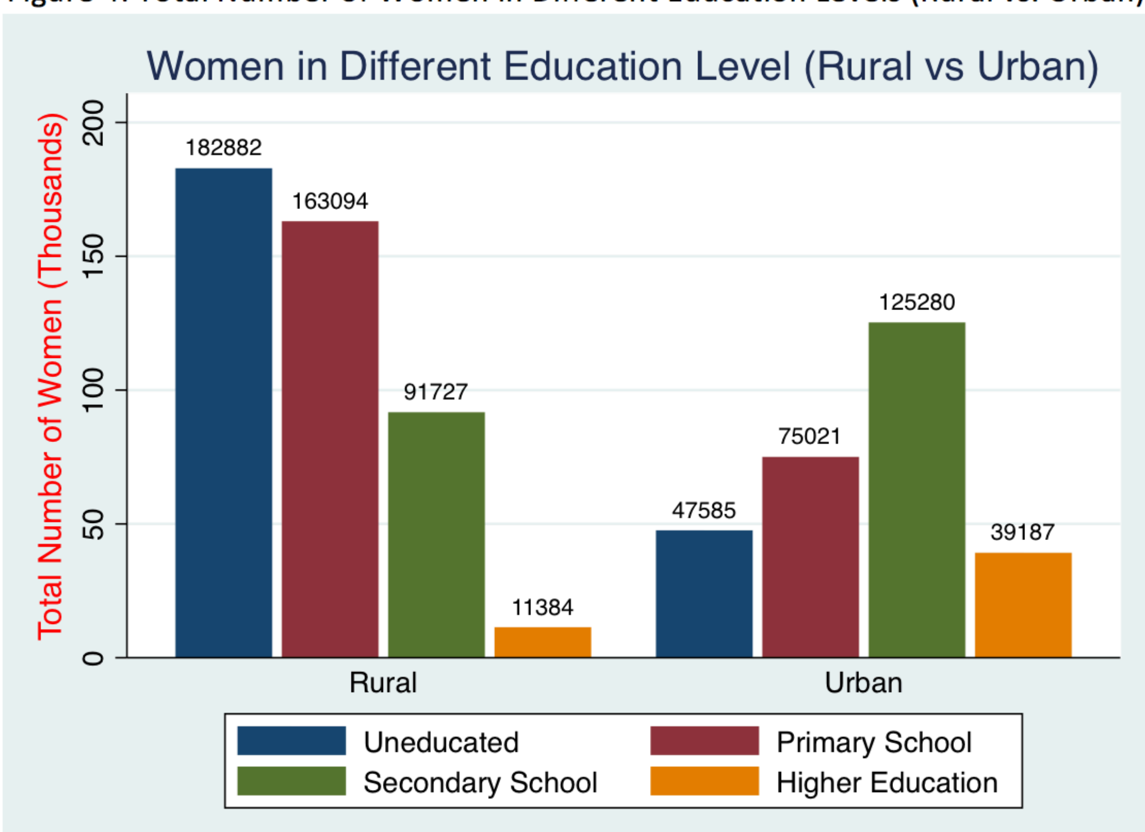


Figure 5a

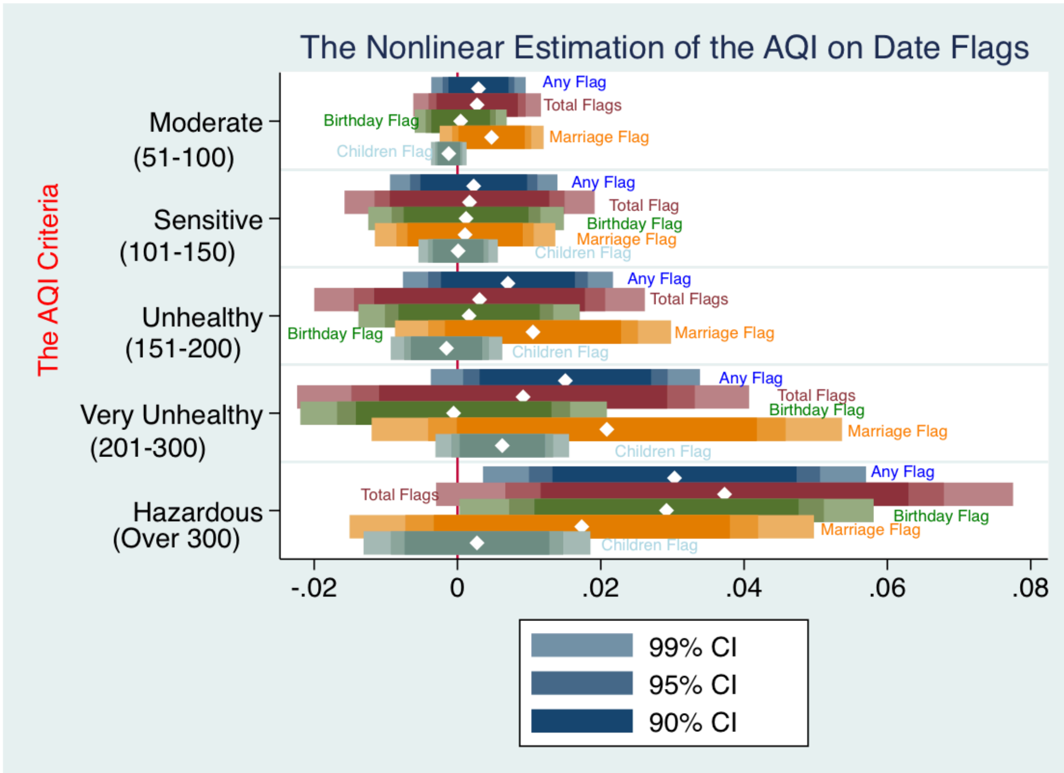


Figure 5b

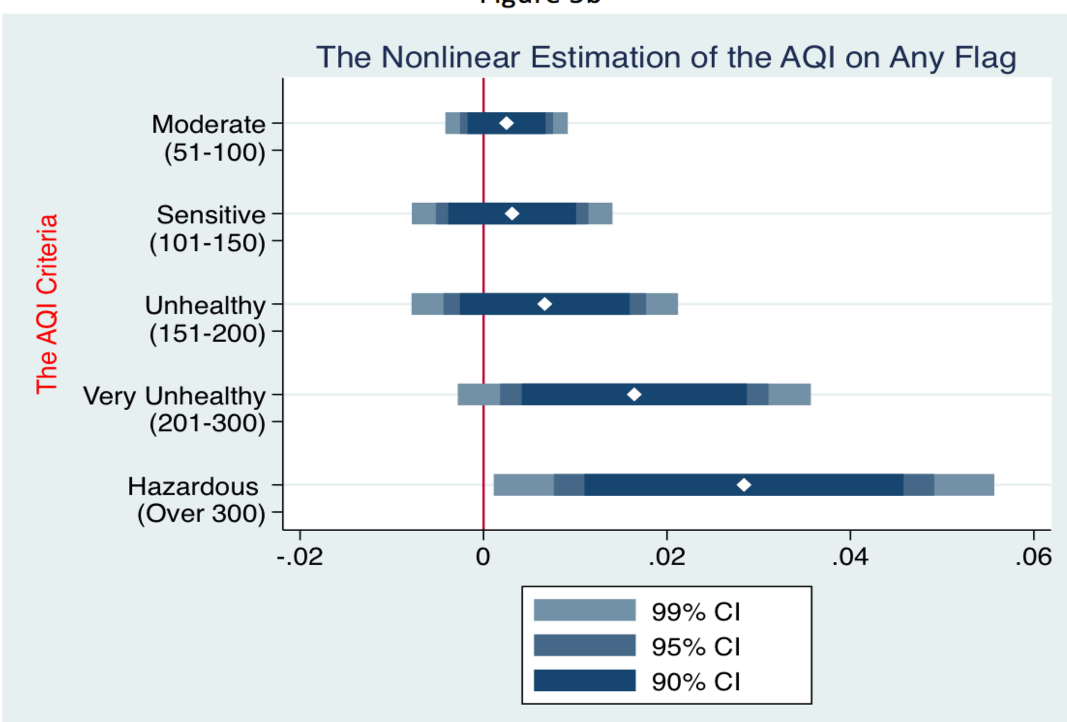


Table 1: Summary Statistics

Panel A: Sample Means of Date Flags By Women's Categories								
	Total Flags			*Any Flag*	*Birthday Flag*	*Marriage Date Flag*	*Children's Birthday*	
	Mean	Max	Min	Mean	Mean	Mean	Mean	
	1	2	3	4	5	6	7	8
Overall	0.471	3	0	0.347	0.308	0.242	0.04	
None Educated	0.99	3	0	0.687	0.624	0.512	0.085	
Educated	0.234	3	0	0.192	0.163	0.108	0.015	
Rural	0.592	3	0	0.429	0.387	0.296	0.048	
Urban	0.282	3	0	0.219	0.184	0.147	0.026	

Panel B: Average and Total of GDD and AQI By Area								
	AQI (Daily)							GDD (Monthly)
	Overall		Moderate	Unhealthy to Sensitive Group	Unhealthy	Very Unhealthy	Hazardous	
	Mean	SD	Total Days	Total Days	Total Days	Total Days	Total Days	Mean
Overall	61.72	114.9	145,567	31,698	41,780	12,801	18,006	5.25
Rural	63.44	123.9	88,661	20,299	25,383	7,621	11,977	5.5
Urban	59.03	99.13	56,906	11,399	16,397	5,180	6,029	4.85

Note: Panel A presents summary statistics of five dependent variables for the overall sample and by each women's category. Column 5 is the average of respondent's birthday flag. Column 6 is the mean of marriage date flag, which only include women who have married. Column 7 is the average of children's birthday flag, which excluding women who do not have children. Column 4 is the mean of any flag, which is a dummy and turns to 1 if any of these three date flags pop up. Column 1 to 3 is the summary statistics of total flags, which is the sum of these three date flags with the maximum value of 3. Panel B reports the summary statistics of the major treatment variables for over and by living area. Column 1 is the average of daily AQI. Column is the standard deviation of the AQI.Column 3 to 7 report the total exceedance days of each AQI categories. Column 8 is the monthly mean of GDD-30, which indicates the average days exceed 30C.

Table 2: Whole Sample Cognitive Performance
Dependent Variable: 1 = The Correspondent Dates are not Complete
OLS on Cross-Sectional Data, Cluster Standard Errors at Region Level

Variable	(1) Any Flag	(2) Total Flag	(3) Birthday Flag	(4) Marriage Date Flag	(5) Children's Birthday Flag
AQI (Z-Score)	0.0044**	0.007**	0.0048**	0.0030	0.0009
	(0.00213)	(0.00330)	(0.00238)	(0.00250)	(0.00118)
Temperature (GDD-30)	0.0007	0.0035	0.0009	0.0015	0.0017***
	(0.00224)	(0.00306)	(0.00215)	(0.00199)	(0.000494)
Age	0.0024***	0.0119***	0.0010	0.024***	0.0027***
	(0.000787)	(0.00178)	(0.000716)	(0.00264)	(0.000682)
Age Square	3.07e-06	-9.58e-05***	6.12e-06	-0.000281***	-1.36e-05
	(1.20e-05)	(2.61e-05)	(1.05e-05)	(3.69e-05)	(8.67e-06)
Fertility	0.0125***	0.0204***	0.00646***	0.00815***	0.00301***
	(0.000572)	(0.00114)	(0.000431)	(0.000823)	(0.000276)
Precipitation (mm)	2.64e-06	2.93e-06	-5.33e-07	2.04e-06	-1.90e-07
	(4.29e-06)	(6.24e-06)	(4.08e-06)	(6.40e-06)	(1.30e-06)
Country by Education	Yes	Yes	Yes	Yes	Yes
Country by Rural	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes
Country by Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Constant	0.605***	0.603***	0.549***	0.0225	-0.00747
	(0.0191)	(0.0386)	(0.0209)	(0.0555)	(0.0145)
Observations	736,160	736,160	735,937	352,054	541,727
R-squared	0.596	0.653	0.601	0.618	0.390

Notes: For marriage date flag, we only test women who have married in our regression. For children's birthday flag, we only include women who have at least one child in our regression. * p≤.1; ** p≤.05; *** p≤.01.

Table 3a: Sub-Sample Cognitive Performance (Rural vs.Urban)
Dependent Variable: 1 = The Correspondent Dates are not Complete
OLS on Cross-Sectional Data, Cluster Standard Errors at Region Level

Variable	(1) Any Flag	(2) Total Flag	(3) Birthday Flag	(4) Marriage Date Flag	(5) Children's Birthday Flag
Panel A: Rural Sub-Sample					
AQI (Z-Score)	0.0024	0.0051	0.0048	0.0025	-0.0003
	(0.00284)	(0.00486)	(0.00338)	(0.00326)	(0.00165)
Temperature (GDD-30)	0.0022	0.006	0.0027	0.0019	0.0021***
	(0.00339)	(0.00435)	(0.00328)	(0.00235)	(0.000795)
Constant	0.685***	0.686***	0.632***	0.121*	-0.0134
	(0.0291)	(0.0581)	(0.0320)	(0.0627)	(0.0201)
Observations	449,087	449,087	448,922	225,101	345,972
R-squared	0.590	0.652	0.591	0.630	0.410
Panel B: Urban Sub-Sample					
AQI (Z-Score)	0.0081***	0.011***	0.0053*	0.0037	0.0032*
	(0.00282)	(0.00384)	(0.00297)	(0.00406)	(0.00172)
Temperature (GDD-30)	0.0002	0.0026	5.63e-05	0.0004	0.0016***
	(0.00177)	(0.00271)	(0.00158)	(0.00265)	(0.000498)
Constant	0.558***	0.599***	0.488***	0.0246	0.0152
	(0.0223)	(0.0394)	(0.0248)	(0.0633)	(0.0154)
Observations	287,073	287,073	287,015	126,953	195,755
R-squared	0.552	0.601	0.565	0.544	0.322

Note: All regressions control age, age square, fertility, precipitation and country by education. All regressions also include country by year fixed effects, month fixed effects and DHS cluster fixed effects. For marriage date flag, we only test women who have married in our regression. For children's birthday flag, we only include women who have at least one child in our regression. * p≤.1; ** p≤.05; *** p≤.01.

Table 3b: Sub-Sample Cognitive Performance (Uneducated vs. Educated)
Dependent Variable: 1 = The Correspondent Dates are not Complete
OLS on Cross-Sectional Data, Cluster Standard Errors at Region Level

Variable	(1) Any Flag	(2) Total Flag	(3) Birthday Flag	(4) Marriage Date Flag	(5) Children's Birthday
Panel A: Uneducated Sub-Sample					
AQI (Z-Score)	0.0026	0.0047	0.0047	0.0012	0.0005
	(0.00324)	(0.00493)	(0.00352)	(0.00325)	(0.00152)
Temperature (GDD-30)	0.007*	0.0127**	0.0037	0.0089***	0.0041***
	(0.00411)	(0.00518)	(0.00420)	(0.00301)	(0.00127)
Constant	0.421***	-0.140	0.447***	-0.302***	-0.163***
	(0.0428)	(0.0974)	(0.0462)	(0.0742)	(0.0381)
Observations	230,467	230,467	230,331	116,804	195,837
R-squared	0.535	0.613	0.540	0.647	0.454
Panel B: Educated Sub-Sample					
AQI (Z-Score)	0.00615*	0.00798*	0.00424	0.00140	0.00148
	(0.00357)	(0.00428)	(0.00344)	(0.00443)	(0.00143)
Temperature (GDD-30)	-0.00178	-0.00132	-0.00105	-0.000899	0.000516
	(0.00225)	(0.00300)	(0.00195)	(0.00242)	(0.000318)
Constant	0.187***	0.174***	0.163***	-0.162**	-0.000434
	(0.0205)	(0.0295)	(0.0188)	(0.0699)	(0.00691)
Observations	505,693	505,693	505,606	235,250	345,890
R-squared	0.492	0.549	0.515	0.472	0.278

Note: All regressions control age, age square, fertility, precipitation and country by rural. In panel B, we control the country by education (country by primary school, country by secondary school). All regressions also include country by year fixed effects, month fixed effects and DHS cluster fixed effects. For marriage date flag, we only test women who have married in our regression. For children's birthday flag, we only include women who have at least one child in our regression. * p≤.1; ** p≤.05; *** p≤.01.

Table 4: Whole Sample Nonlinear Effects on Cognitive Performance
Dependent Variable: 1 = The Correspondent Dates are not Complete
OLS on Cross-Sectional Data, Cluster Standard Errors at Region Level

Variables	(1) Any Flag	(2) Total Flag	(3) Birthday Flag	(4) Marriage Date Flag	(5) Children's Birthday Flag
Moderate	0.0029	0.0027	0.0004	0.0048*	-0.0012
(51-100)	(0.00255)	(0.00345)	(0.00248)	(0.00281)	(0.000961)
Unhealthy to Sensitive Group	0.0022	0.0017	0.0012	0.0011	9.29e-05
(101-150)	(0.00452)	(0.00675)	(0.00528)	(0.00487)	(0.00214)
Unhealthy	0.007	0.0031	0.0016	0.0105	-0.0015
(151-200)	(0.00567)	(0.00892)	(0.00598)	(0.00745)	(0.00301)
Very Unhealthy	0.0151**	0.0092	-0.0005	0.0208	0.0063*
(201-300)	(0.00727)	(0.0122)	(0.00828)	(0.0127)	(0.00361)
Hazardous	0.0303***	0.0373**	0.0292***	0.0173	0.0027
(Over 300)	(0.0103)	(0.0156)	(0.0112)	(0.0125)	(0.00612)
Temperature (GDD-30)	0.000762	0.00357	0.0009	0.0015	0.0017***
	(0.00225)	(0.00306)	(0.00214)	(0.00199)	(0.000493)
Constant	0.603***	0.601***	0.545***	0.0202	-0.00595
	(0.0191)	(0.0386)	(0.0214)	(0.0557)	(0.0147)
Observations	736,160	736,160	735,937	352,054	541,727
R-squared	0.596	0.653	0.601	0.618	0.390

Note: All regressions control age, age square, fertility, precipitation country by education and country by rural. All regressions also include country by year fixed effects, month fixed effects and DHS cluster fixed effects. For marriage date flag, we only test women who have married in our regression. For children's birthday flag, we only include women who have at least one child in our regression. * p≤.1; ** p≤.05; *** p≤.01.

Table 5:Urban Sample Cognitive Performance (Uneducated vs Educated)
Dependent Variable: 1 = The Correspondent Dates are not Complete
OLS on Cross-Sectional Data, Cluster Standard Errors at Region Level

Variable	(1) Any Flag	(2) Total Flag	(3) Birthday Flag	(4) Marriage Date Flag	(5) Children's Birthday
Panel A: Uneducated Sub-Sample (Urban)					
AQI (Z-Score)	0.009	0.009	0.004	4.51e-08	0.0048**
	(0.00610)	(0.00744)	(0.00487)	(0.00850)	(0.00239)
Temperature (GDD-30)	0.0076*	0.014**	0.0006	0.0099	0.005**
	(0.00411)	(0.00643)	(0.00452)	(0.00677)	(0.00247)
Constant	0.534***	0.0522	0.577***	-0.330***	-0.135**
	(0.0778)	(0.163)	(0.0885)	(0.120)	(0.0550)
Observations	47,585	47,585	47,556	21,934	39,222
R-squared	0.531	0.592	0.538	0.648	0.428
Panel B: Educated Sub-Sample (Urban)					
AQI (Z-Score)	0.0052	0.006	0.0048	-0.0013	0.0013
	(0.00383)	(0.00427)	(0.00331)	(0.00574)	(0.00169)
Temperature (GDD-30)	-0.000470	0.000139	0.000114	-0.000889	0.000400
	(0.00210)	(0.00297)	(0.00166)	(0.00302)	(0.000373)
Constant	0.162***	0.130***	0.137***	-0.172**	-0.00345
	(0.0233)	(0.0317)	(0.0212)	(0.0686)	(0.00797)
Observations	239,488	239,488	239,459	105,019	156,533
R-squared	0.442	0.492	0.474	0.403	0.236

Note: All regressions control age, age square, fertility and precipitation. In panel B, we control the country by education (country by primary school, country by secondary school). All regressions also include country by year fixed effects, month fixed effects and DHS cluster fixed effects. For marriage date flag, we only test women who have married in our regression. For children's birthday flag, we only include women who have at least one child in our regression. * p≤.1; ** p≤.05; *** p≤.01.

Table 6: Whole Sample Cognitive Performance without Temperature
Dependent Variable: 1 = The Correspondent Dates are not Complete
OLS on Cross-Sectional Data, Cluster Standard Errors at Region Level

Variable	(1) Any Flag	(2) Total Flag	(3) Birthday Flag	(4) Marriage Date Flag	(5) Children's Birthday
AQI (Z-Score)	0.00439**	0.00693**	0.00482**	0.00294	0.000923
	(0.00215)	(0.00332)	(0.00239)	(0.00250)	(0.00118)
Age	0.00238***	0.0119***	0.00104	0.0240***	0.00274***
	(0.000787)	(0.00178)	(0.000716)	(0.00264)	(0.000681)
Age Square	3.08e-06	-9.58e-05***	6.12e-06	-0.000281***	-1.36e-05
	(1.20e-05)	(2.61e-05)	(1.05e-05)	(3.69e-05)	(8.67e-06)
Fertility	0.0125***	0.0204***	0.00646***	0.00815***	0.00301***
	(0.000572)	(0.00114)	(0.000431)	(0.000823)	(0.000276)
Country by Education	Yes	Yes	Yes	Yes	Yes
Country by Rural	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes
Country by Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Constant	0.611***	0.620***	0.552***	0.0293	-7.33e-05
	(0.0198)	(0.0371)	(0.0210)	(0.0540)	(0.0139)
Observations	736,160	736,160	735,937	352,054	541,727
R-squared	0.596	0.653	0.601	0.618	0.390

Notes: For marriage date flag, we only test women who have married in our regression. For children's birthday flag, we only include women who have at least one child in our regression. * p≤.1; ** p≤.05; *** p≤.01.

Table 7: Each Air Pollutants on Cognitive Performance (PM2.5, PM10 and CO)
Dependent Variable: 1 = The Correspondent Dates are not Complete
OLS on Cross-Sectional Data, Cluster Standard Errors at Region Level

	1	2	3	4	5
Variables	**Any Flag**	**Total Flag**	**Birthday Flag**	**Marriage Date Flag**	**Children's Birthday Flag**
Panel A: PM2.5					
PM2.5 (ug/m3)	7.86e-05**	9.18e-05	7.18e-05	4.92e-05	1.43e-05
	(3.67e-05)	(5.98e-05)	(4.36e-05)	(5.04e-05)	(2.06e-05)
Temperature (GDD-30)	0.000744	0.00354	0.000870	0.00153	0.00173***
	(0.00225)	(0.00306)	(0.00215)	(0.00199)	(0.000494)
Observations	736,160	736,160	735,937	352,054	541,727
R-squared	0.596	0.653	0.601	0.618	0.390
Panel B: PM10					
PM10 (ug/m3)	3.57e-05**	4.25e-05	3.16e-05	2.45e-05	7.12e-06
	(1.79e-05)	(2.91e-05)	(2.13e-05)	(2.33e-05)	(1.00e-05)
Temperature (GDD-30)	0.000742	0.00354	0.000867	0.00153	0.00173***
	(0.00225)	(0.00306)	(0.00215)	(0.00199)	(0.000494)
Observations	736,160	736,160	735,937	352,054	541,727
R-squared	0.596	0.653	0.601	0.618	0.390
Panel C: CO					
CO (ppm)	0.00878	0.0321	-0.00331	0.0347	-0.000550
	(0.0209)	(0.0290)	(0.0195)	(0.0274)	(0.0100)
Temperature (GDD-30)	0.000691	0.00346	0.000831	0.00149	0.00172***
	(0.00224)	(0.00306)	(0.00215)	(0.00199)	(0.000492)
Observations	736,160	736,160	735,937	352,054	541,727
R-squared	0.596	0.653	0.601	0.618	0.390

Note: All regressions control age, age square, fertility, precipitation country by education and country by rural. All regressions also include country by year fixed effects, month fixed effects and DHS cluster fixed effects. For marriage date flag, we only test women who have married in our regression. For children's birthday flag, we only include women who have at least one child in our regression. * p≤.1; ** p≤.05; *** p≤.01.

Appendix I: The AQI Calculation

The Air Quality Index (AQI) is calculated according to the "Guidelines for the Reporting of Daily Air Quality – the Air Quality Index (AQI)." The calculation is based on the pollutant concentration data, the following parameters table and the following equation (linear interpolation):

This Breakpoint...						...equal this AQI		...and this category
o_3 (ppm) 8-hour	O_3 (ppm) 1-hour[1]	PM_{10} ($\mu g/m^3$)	$PM_{2.5}$ ($\mu g/m^3$)	CO (ppm)	SO_2 (ppm)	NO_2 (ppm)	AQI	
0.000 - 0.064	-	0 - 54	0.0 - 15.4	0.0 - 4.4	0.000 - 0.034	([2])	0 - 50	Good
0.065 - 0.084	-	55 - 154	15.5 -40.4	4.5 - 9.4	0.035 - 0.144	([2])	51 - 100	Moderate
0.085 - 0.104	0.125 - 0.164	155 - 254	40.5 - 65.4	9.5 - 12.4	0.145 - 0.224	([2])	101 - 150	Unhealthy for Sensitive Groups
0.105 - 0.124	0.165 - 0.204	255 - 354	65.5 - 150.4	12.5 - 15.4	0.225 - 0.304	([2])	151 - 200	Unhealthy
0.125 - 0.374 (0.155 - 0.404)[4]	0.205 - 0.404	355 - 424	150.5 - 250.4	15.5 - 30.4	0.305 - 0.604	0.65 - 1.24	201 - 300	Very unhealthy
([3])	0.405 - 0.504	425 - 504	250.5 - 350.4	30.5 - 40.4	0.605 - 0.804	1.25 - 1.64	301 - 400	Hazardous
([3])	0.505 - 0.604	505 - 604	350.5 - 500.4	40.5 - 50.4	0.805 - 1.004	1.65 - 2.04	401 - 500	Hazardous

[1] Areas are required to report the AQI based on 8-hour ozone values. However, there are areas where an AQI based on 1-hour ozone values would be more protective. In these cases the index for both the 8-hour and the 1-hour ozone values may be calculated and the maximum AQI reported.

[2] NO_2 has no short-term NAAQS and can generate an AQI only above a value of 200.

[3] 8-hour O_3 values do not define higher AQI values ($\geq$ 301). AQI values of 301 or higher are calculated with 1-hour O_3 concentrations.

[4] The numbers in parentheses are associated 1-hour values to be used in this overlapping category only.

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{HI} - BP_{Lo}}(C_p - BP_{Lo}) + I_{Lo}.$$

Where I_p = the index for pollutant p

C_p = the rounded concentration of pollutant p
BP_{Hi} = the breakpoint that is greater than or equal to C_p

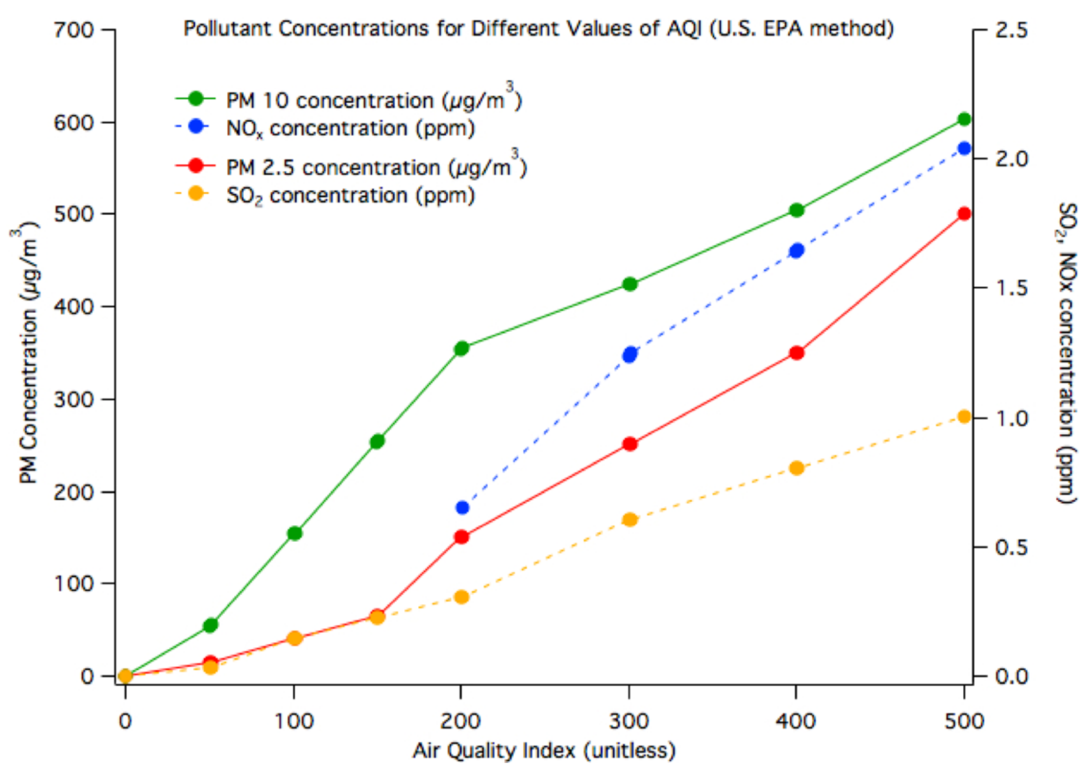
BP_{Lo} = the breakpoint that is less than or equal to C_p

BP_{Hi} = the breakpoint that is greater than or equal to C_p

I_{Hi} = the AQI value corresponding to BP_{Hi}

I_{Lo} = the AQI value corresponding to BP_{Lo}

The relationship between the AQI and each air pollutant is shown in the Figure below:



The table below indicates each AQI category and its correspond health concern:

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk.
Moderate	51 to 100	Air quality is acceptable: however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects: members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health alert: everyone may experience more serious health effects.
Hazardous	301 to 500	Health warming of emergency conditions. The entire population is more likely to be affected.