Chinese Yellow Dust and Korean Infant Health

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Abstract

Naturally-occurring yellow sand outbreaks, which are produced by winds flowing to Korea from China and Mongolia, create air pollution. Although there is seasonal pattern of this phenomenon, there exists substantial variation in its timing, strength and location from year to year. Thus, exposure to the intensity of air pollution exhibits significant randomness and unpredictability. To warn residents about air pollution in general, and about these dust storms in particular, Korean authorities issue different types of public alerts. Using birth certificate data on more than 1.5 million babies born between 2003 and 2011, we investigate the impact of air pollution, and the avoidance behavior triggered by pollution alerts on various birth outcomes. We find that exposure to air pollution during pregnancy has a significant negative impact on birth weight, the gestation weeks of the baby, and the propensity of the baby being low weight. Public alerts about air quality during pregnancy have a separate positive effect on fetal health. We show that Korean women do not time their pregnancy according to expected yellow dust exposure, and that educated women's pregnancy timing is not different from those who are less-educated. The results provide evidence for the effectiveness of pollution alert systems in promoting public health. They also underline the importance of taking into account individuals' avoidance behavior when estimating the impact of air quality on birth outcomes. Specifically, we show that the estimated impact of air pollution on infant health is reduced by half when the preventive effect of public health warnings is not accounted for.

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I. Introduction

It has been documented that health at birth has long term effects on adult health, human capital accumulation and economic well-being. One of the most commonly-used indicators of health at birth is the weight of the infant when she was born. As summarized by Currie (2011) and Almond and Currie (2011), infants who are heavier at birth end up being different in adulthood from those who have lighter birth weights. For example, they are taller adults, have greater IQ scores, attain higher levels of education and earn more when they are adults. Consequently, a sizable literature has investigated the impact on birth weight of its various determinants, ranging from smoking (Lien and Evans 2005, Grossman and Joyce 1990) to prenatal care consumption (Mocan, Raschke and Unel forthcoming; Dehejia and Lleras-Muney 2004), to nutritional assistance for low-income families (Almond, Hoynes and Schanzenbach 2011).

An important component of this investigation is the extent to which in utero exposure to pollution impacts birth weight.[1] While the literature on the effect of air pollution on infant mortality is extensive[2], there are relatively few studies examining the biological effect of pollution on birth weight. Examples of this limited area of inquiry include Currie, Neidell and Schimeider (2009), who show that mother's exposure to carbon monoxide in her last trimester of pregnancy in New Jersey increases the risk of low birth weight. Coneus and Spiess (2012) find a similar effect of air pollution on birth weight using German data. Currie et al. (2015) report that

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[1] A related research has shown the impact on adult outcomes of in utero exposure to disease and pollution (Black et al. 2013, Sanders 2012, Almond 2006)

[2] Examples include Greenstone and Hanna (2014), Luechinger (2014), Agarwal, Banternghansa and Bui (2010), Jayachandran, (2009), Currie and Neidell (2005), Chay and Greenstone (2003).

toxic plant openings increase the incidence of low birth weight through their detrimental effect on air pollution within one mile radius. Currie and Walker (2012) demonstrate that the introduction of electronic toll collection on the highways of New Jersey and Pennsylvania reduced automobile emissions, resulting in fewer infants with low birth weight.

In this paper we investigate the impact of air pollution on infant health, measured by birth weight and gestational age of newborns. In contrast to the existing body of work that employed data from the U.S. or some European countries, we focus on a new setting, the Republic of Korea. We utilize the universe of birth certificates between 2003 and 2011, which allow us to analyze more than 1.5 million live births. We exploit the exogenous variation in air pollution, created by a natural phenomenon in South Korea: The Yellow Dust (Hwang-sa in Korean). This is a weather event, originated in the arid lands of Northern China and in the desert regions of Mongolia plateau "under the conditions of high temperature, low humidity, and high wind velocity" (Chun et al. 2001). Winds with abnormally high speed, particularly the Westerlies,[3] pick up dust and sand particles and carry them to the Korean peninsula. Although there is a seasonal pattern of this phenomenon, there exists substantial variation in its strength and location from year to year. In other words, while the intensity of air pollution due to yellow dust exhibits a seasonal cycle, the amplitude of the cycle varies significantly between the years, along with the timing of the up-and-down swings. For example, Figure 1 displays the average concentration of PM10 (particles with a diameter of 10 micrometers or less) levels by month between 2003 and 2006.[4] The values reported in Figure 1 are average PM10 levels, aggregated over hourly readings in about 130 weather stations across Korea. While pollution generally rises in the

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[3] The Westerlies are winds blowing from West to East, and occur in temperate zones -- in the middle latitudes between 30 and 60 degrees latitude.

[4] Particulate matter intensity is directly linked to negative health consequences such as lung and heart disease and reduced immune system function (http://www.epa.gov/pm/health.html). When inhaled by the pregnant mother, these particles get into pregnant mother's lungs and into the blood stream, and they may be transferred to the infant.

Spring and declines during Summer, the pattern is not systematic, and it exhibits substantial noise from year to year. The same irregularity is observed within a given city as well. We demonstrate, in different ways, that women do not time their pregnancy according to expected Yellow Dust exposure, and that educated women's pregnancy timing is not different from those who are less-educated. Therefore, exposure to the intensity of air pollution exhibits substantial randomness and unpredictability.

An important contribution of the paper is the ability to account for avoidance behavior, and to obtain estimates of the impact of pollution avoidance on birth outcomes. Individuals may take precautionary measures in reaction to temporary increases in pollution by such actions as wearing masks or staying indoors. The biological impact of air pollution on health is underestimated if reductions in the exposure to pollution due to avoidance are not accounted for. The paucity of data prevented most of the existing research from controlling for the avoidance behavior, although there are notable exceptions (e.g. Janke 2014; Moretti and Neidell 2011; Neidell 2009). As summarized by Zivin, Neidell and Schlenker (2011), the provision of public notifications and alerts on environmental hazards is being used increasingly as a tool to generate behavioral responses to mitigate the detrimental effects of exposure.

We utilize various pollution alerts at the local level, issued by Korean authorities, to obtain unbiased estimates of the biological impact of pollution on infant health, as well as to estimate the improvement of infant health generated by pollution avoidance.[5] Our paper is the first one to investigate the effectiveness of public air quality alerts on *birth outcomes*.[6]

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[5] Neidell (2009), Moretti and Neidell (2011) implement a similar approach when analyzing the impact of ozone on respiratory-related hospitalizations, and asthma.

[6] Janke (2014), Moretti and Neidell (2011), Neidell (2009) and Neidell (2004) also consider public warnings, but these papers focus on the effects of smog and ozone alerts on respiratory illnesses such as the asthma in the general population, rather than birth outcomes.

In a concurrent paper, using the incidence of yellow dust events in Korea, Jia and Ku (2015) investigate the effect of pollution on mortality. The authors show that during the months in which Chinese pollution is high, an increase in the number of yellow dust events triggers a rise in deaths due to respiratory and cardiovascular causes, especially in the elderly population in Korean districts. Our paper is different from Jia and Ku (2015) in a number of ways. First, we focus on infant birth outcomes, rather than aggregate mortality. Second, we employ micro data, as opposed to district-level data. Finally, Jia and Ku (2015) consider neither the avoidance behavior of Koreans nor the public alerts against poor air quality.

We find that, controlling for temperature and precipitation, exposure to air pollution during pregnancy has a significant negative impact on birth weight, gestation weeks of the baby, and the propensity of the baby being low weight (less than 2,500 gr). Public notifications about air quality have a separate statistically significant and positive effect on fetal health. We show that mothers do not time their pregnancy around expected yellow dust exposure, and that educated women's pregnancy timing is not different from those who are less-educated. We also show that white collar families and more educated and older mothers are more likely to give birth in high-pollution cities. These family attributes and the housing price index of the city in which the birth took place are correlated with birth outcomes, but adjusting for these factors does not impact the results appreciably.

Our results provide evidence for the effectiveness of pollution alert systems in promoting public health. They also underline the importance of taking into account individuals' avoidance behavior when estimating the impact of air quality on birth outcomes. Specifically, we show that the estimated impact of air pollution on infant health is reduced by half when the preventive effect of public health warnings is not accounted for. Using the regression results, and following

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the framework of Moretti and Neidell (2011), we obtain estimates of the willingness to pay to reduce air pollution and the cost of the avoidance behavior.

The rest of the paper is organized as follows. In section II we provide a detailed description of the public alert system that is designed to inform people about the yellow dust activity. Section III presents the empirical specification. Section IV describes the conceptual framework on cost of pollution avoidance and willingness to pay. Section V presents the data. Section VI contains the results, robustness analyses and extensions. Section VII discusses the estimates of the cost of avoidance and Section VII concludes.

II. Yellow Dust, Air Pollution, and Pollution Alerts

Yellow Dust is a weather phenomenon originated in Northern China and in the deserts of the Mongolia plateau. High winds pick up particles of dust and sand and carry them towards the Korean peninsula. These particles of dust and sand settle in Korea and they elevate the ambient air pollution, measured by PM10 concentration. This phenomenon generally occurs from March to May, but also irregularly during the winter months. These dust and sand particles are detrimental to human health and they have adverse respiratory health effects, particularly in children and the elderly (Ministry of Environment of Korea, 2002).[7]

To reduce the risk of the yellow dust exposure, the Korean government has developed a warning system with behavioral guidelines. Since 2002, Korean Meteorological Administration (KMA) has been releasing notifications to the public based on the measured PM10 levels. Between mid-2002 and 2007, KMA issued an *Advisory* in a city when the PM10 level was

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[7] Epidemiological literature has identified negative health consequences of yellow sand (Park et al. 2005; Lee, Son, and Cho 2007).

predicted to rise above 500 and 1000 μm/m^3 for over 2 hours in a day. A *Warning* was issued

when the PM10 level was predicted to rise above 1000 μm/m^3 for over 2 hours. In February

2007, these thresholds were reduced to 400 and 800 μm/m^3, respectively. These public

notifications advise individuals, especially children, the elderly, and people with respiratory

illnesses to limit outdoor activities, and staying indoors is recommended. Pregnant women are

suggested to refrain from outdoor activities and to wear protective masks if necessary.

In addition to *Warnings* and *Advisories*, officials may declare a *Yellow Dust Event* (*YDE*)

in the city if ambient yellow dust is noticeable in the air at least once at any time during a day.

This is produced daily by specially trained observers in monitoring stations who take into

account conditions such as visibility distance, atmospheric turbidity, dust stacks, and odor of the

air. Although YDEs are correlated with PM10 concentrations, they are monitored separately

from PM10 levels. Because of the health hazards associated with YDEs, YDEs are routinely

forecasted by the KMA. These forecasts, similar to weather forecasts, are announced to the

public.

Anecdotal evidence suggests that individuals tend to consider seriously the information

provided by these alerts. For example, as documented by international media, during a Yellow

Dust Event, Koreans respond by wearing preventive masks and staying indoors.[8] For example,

in 2002, in response to a particularly high-density yellow dust event elementary schools were

closed and plants in some industries, such as semiconductor manufacturing, were temporarily

shut down.[9] Later in the paper we provide evidence that people avoid outdoor activities in

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[8] The influence of Chinese Yellow Dust on Korea is frequently covered by the media. An example is a piece in New York Times on April 12th, 2002, p.3. "China's Growing Deserts Are Suffocating Korea" <http://events.nytimes.com/2002/04/14/international/asia/14KORE.html?pagewanted=print&position=top&_r=0>. CNN also covered the issue on February 23rd, 2015 "Yellow dust blankets Seoul" <http://www.cnn.com/videos/world/2015/02/23/lok-hancocks-south-korea-yellow-dust.cnn>.
[9] http://web.kma.go.kr/aboutkma/biz/asiandust02.jsp

response to *Advisories, Warnings* and *YDEs*, by demonstrating that attendance to professional

soccer games is substantially impacted by these alerts.

III. Empirical Specification

To investigate the impact of air pollution and the role of the public alerts on infant health

outcomes, we estimate the equation depicted below:

$$(1)\ Health_{ict} = \beta_1 PM10_{ict} + \boldsymbol{Alerts_{ict}\beta_2} + \beta_3 YDE_{ct} + \boldsymbol{X_{ict}\beta_4} + \boldsymbol{W_{ict}\beta_5} + \mu_c + \theta_t + \epsilon_{ict}$$

where $Health_{ict}$ indicates a particular birth outcome of infant i born to a mother residing in city

c on day t. We consider five outcome variables: birth weight in grams, a binary indicator of low

birth weight (equals to one if the infant's birth weight is less than 2,500 grams), gestation weeks,

an indicator for premature birth (whether infant's gestational age is fewer than 37 weeks), and

fetal growth (birth weight per gestation week).[10] The Korean birth certificate data released to us

do not include the exact birthday, but they have information on birth month. We assign the 15th

day of the month as the birthday to each child. Because the birth certificate data include

information on gestation in weeks, the day of conception can be determined. Using this

information, and assuming that the mother spent her pregnancy in the same city as the one in

which she gave birth, her exposure to air pollution *during each day of her pregnancy* can be

determined. We measure air pollution by calculating the PM10 level in each city using hourly

readings of all monitoring stations in that city, and by creating a *daily* average PM10 level for

each city. In Equation (1), $PM10_{ict}$ is the average hourly exposure to air pollution of infant i's

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[10] Studies, such as Coneus and Spiess (2012), also used fetal growth as a birth outcome measure.

mother throughout the duration of her pregnancy that ended with the birth of the child on day *t* in city *c*.

The vector $Alerts_{ict}$ represents the two variables that measure the total number of days in which a public notification is issued in mother's city of residence during her pregnancy that ended at time *t*. There are two types of public alerts: A*dvisories* (issued when PM10 level is anticipated to increase above 500 $\mu m/m^3$ [400 since 2007]) and *Warnings* (issued when PM10 level is anticipated to increase above 1,000 $\mu m/m^3$ [800 since 2007]). We also include in the regressions the number of days a yellow dust event is observed in mother's city during her pregnancy. This is denoted by YDE_{ict} in equation (1).

To investigate potentially differential effects of pollution and that of avoidance behavior on birth outcomes during different developmental stages of the fetus, in some specifications we examine the effect of PM10 and pollution alerts by trimester of pregnancy.

The vector X stands for control variables that include parental characteristics such as the age, education, marital status and employment status of both mother and the father. These attributes are important to control for because they may impact health outcomes. For example, more educated mothers are better producers of infant health (Chou et al. 2010, McCrary and Royer 2011) and these attributes may also be correlated with exposure to pollution (e.g. more educated mothers may be more effective in avoiding pollution, or in timing their pregnancy). While we have no income information on birth certificates, parental education is expected to be correlated with family income.

Vector X also contains other variables that impact infant's birth weight (Currie 2011), including infant's gender, an indicator of whether the infant was part of a multiple birth, and

birth parity. W is a vector of weather controls such as the average precipitation and temperature during the mother's pregnancy. All regressions include indicators for the city of residence, μ_c to account for unobserved (to us) time-invariant characteristics of cities such as the extent of economic development, urbanization and access to health care. Equation (1) also contains a vector of year-of-conception and month-of-conception dummies, represented by θ_t. Standard errors are clustered at the city level.

Anecdotal evidence suggests that Koreans try and reduce/avoid outdoor activities during a yellow dust event (YDE). In order to investigate this point more rigorously, we estimate the effect of YDEs and public alerts on an outdoor activity: attendance to professional soccer games. Soccer games are played in open air stadiums, and if Koreans attempt to avoid pollution when a public alert is issued, then we expect the attendance to a soccer game to decline when a pollution alert is released on the game day. To test this hypothesis, we estimate an equation similar to Zivin and Neidell (2009)

(2) $Attendance_{gct} = \alpha_1 PM10_{ct} + \boldsymbol{Alerts_{ct}}\boldsymbol{\alpha_2} + \alpha_3 YDE_{ct} + \boldsymbol{X_{gct}}\boldsymbol{\beta_4} + \mu_c + \theta_t + \epsilon_{gct}$

where $Attendance_{gct}$ is the number of fans (or the logarithm of fans) who attended a particular soccer game g that took place in city c on day t. $PM10_{ct}$ is the average PM10 level in city c that same day. $\boldsymbol{Alerts_{ct}}$ is the same vector of indicators that take the value of one if an advisory or a warning is issued on the day of the game, as explained above. Similarly, YDE_{ct} is a dummy variable that is equal to one if a yellow dust event is observed. In vector $\boldsymbol{X_{gct}}$ we include variables that are likely related to soccer game attendance. For example, games in which high quality teams are playing may attract greater attendance. To control for the quality of the teams, we employ teams' rankings in the league as of the game day. In addition, we control for the

round of the game in the tournament. μ_c and θ_t are city fixed effects and time dummies (month-year).

IV. Cost of Avoidance and Willingness to Pay

Exposure to air pollution, measured by PM10, has a direct biological impact on birth weight. Public alerts, triggered by air pollution, are expected to generate avoidance; and avoidance impacts birth weight positively. Therefore, an increase in PM10 affects birth weight both directly and indirectly. Thus, holding constant other determinants of birth weight (BW), the total derivative of BW with respect to $PM10$ is given by equation (3):

(3) $\qquad \dfrac{dBW}{dPM10} = \dfrac{\partial BW}{\partial PM10} + \dfrac{\partial BW}{\partial Avoid}\dfrac{\partial Avoid}{\partial Alert}\dfrac{\partial Alert}{\partial PM10}$

The first term on the right hand side of Equation (3) represents the biological health effect of PM10. The second term is the effect on birth weight of PM10 through alerts and avoidance behavior. Following Moretti and Neidell (2011) and the literature they cite, the willingness to pay (WTP) for a reduction in pollution can be expressed as

(4) $\qquad WTP = \dfrac{\partial BW}{\partial PM10} \times B$

where B is the economic benefit associated with a one-gram increase in birth weight. Following Currie, Neidell and Schimeider (2009), we use the estimate provided by Black, Devereux and Salvanes (2007) in approximating B. Specifically, we consider the increase in lifetime earnings due to the increase in birth weight as an estimate of B. The term $(\dfrac{\partial BW}{\partial PM10})$ in equation (4) is the direct biological effect of pollution on birth weight. The coefficient β_1 in Equation (1) is an estimate of $\dfrac{\partial BW}{\partial PM10}$ because the regression in Equation (1) controls for the impact of avoidance

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(*Advisories, Warnings* and *Yellow Dust Events*). Thus, the estimate of the WTP in Equation (4)

provides the loss associated with the decline in infant health due to an increase in PM10.

Re-writing equation (3) and multiplying both sides with B yields Equation (5):

(5) $$\frac{\partial BW}{\partial PM10} \times B = WTP = \left(\frac{dBW}{dPM10} \times B\right) - \left(\frac{\partial BW}{\partial Avoid}\frac{\partial Avoid}{\partial Alert}\frac{\partial Alert}{\partial PM10} \times B\right)$$

Equation (5) decomposes the willingness to pay (WTP) into two components. The first

component includes the term $\frac{dBW}{dPM10}$ which is the total derivate of birth weight with respect to

PM10. This term can be estimated by the coefficient of PM10 using the regression Equation (1),

if the regression *does not control for* variables that are related to avoidance behavior. That is, to

the extent that pollution alerts and notifications in Equation (1) capture the factors that influence

the demand for avoidance, omitting these variables from equation (1) allows the coefficient of

PM10 to represent the total effect of PM10 on birth weight, $\left(\frac{dBW}{dPM10}\right)$.

Given that one can calculate WTP, as well as the first component of WTP on the right-

hand side of Equation (5), the second term of WTP $\left(\frac{\partial BW}{\partial Avoid}\frac{\partial Avoid}{\partial Alert}\frac{\partial Alert}{\partial PM10} \times B\right)$ can be recovered.

This last term represents the cost of pollution avoidance (Moretti and Neidell 2011). As

discussed by Neidell (2009), providing estimates on the cost of pollution avoidance is critical in

the assessment of full cost environmental pollution and the design of policy.

V. Data

Our data set is compiled from multiple sources. We have information on all births in

Korea between 2003 and 2011, obtained from Vital Statistics-Natality Files provided by

Statistics Korea Micro Data Service System. Birth certificates provide information about the

infant (such as gender, birth weight, gestational length, whether the infant was singleton, and the birth order) and about the parents (such as their age, education level, employment status, and marital status). In addition, the month, year and the city of the birth are reported. Following Knittel, Miller, and Sanders (2011), we restrict our sample to infants whose gestational age is between 27 and 42 weeks in order to accurately determine the three trimesters of the pregnancy. In our regressions, we only consider the singleton births, since birth weight differences in twins are largely attributable to biological factors attributable to the mother (Almond, Chay and Lee 2005).

We augment the birth certificate data with data on city air quality, yellow dust events and public notifications. To proxy for air quality, we use PM10 concentration which is measured hourly by the monitoring stations in cities.[11] These PM10 data are obtained from National Institute of Environmental Research (NIER) in Korea. The variable *PM10* is the average hourly PM10 concentration in the city of residence of the mother during her pregnancy.[12] Figure 2 shows the average daily PM10 concentrations in each region across Korea between years 2003 and 2011 in our sample.[13] PM10 concentration is relatively higher in the North, in cities close to Northern China and the Mongolia plateau. For example, average PM10 was 58.6 $\mu m/m^3$ in Seoul between 2003 and 2011, whereas Geoje-si, the most-Southeastern region used in our sample, had 36.3 Geoje-si $\mu m/m^3$. We show later in the paper that the results do not change when we estimate models by geographical location. An important issue is the timing of the pregnancy around the yellow dust season. We show that mothers do not time their pregnancy

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[11] PM10 stands for particulate matter 10. These are tiny objects in the air that are less than or equal to 10 micrometers in size.

[12] The birth certificates data set only includes month and year of birth, but not day of birth. In our analysis, we assumed that infants are born on the 15th day of the month reported in the certificate.

[13] Although PM10 concentrations are available at the weather station level in a region, for eight regions (Seoul, Busan, Daegu, Incheon, Gwangju, Daejeon, Ulsan, and Gyeonggi-do) we report the average PM10 levels in a region in this map due to the lack of space.

around yellow dust, arguably because there is substantial uncertainty in the intensity of yellow dust phenomenon from year to year.

Although there are about 4 million births between 2003 and 2011, our estimation sample contains over 1.5 million of these births because births in most locations cannot be matched reliably with air pollution measures because air quality is not measured or not measured consistently in these locations. In addition, some regions such as Jeong-eup in North-Jeolla Province are excluded at the advice of the Korean Meteorological Administration because of the inaccuracy of the yellow dust outbreak indicators in those areas.

The descriptions and the summary statistics of the variables are presented in Table 1.[14] The average Korean infant was born just above 3,200 grams with gestational age of 39 weeks.[15] Approximately, three and a half percent of Korean infants are classified as low birth weight (<2,500 grams at birth), and four percent of the infants were born premature (gestational age<37 weeks). Thirty percent of Korean mothers and 95 percent of fathers are employed. Sixty-six percent of mothers and 70 percent of fathers have a college education or higher.

Average hourly PM10 exposure of a mother during pregnancy is about 54 $\mu m/m^3$. Due to yellow dust breaks, mothers experienced about 1.7 *Advisories* and 0.5 *Warnings* during pregnancy. The average Korean mother experienced 7 *Yellow Dust Events*.

To investigate whether Koreans respond to public notifications of yellow dust events and poor air quality by avoiding outdoors activities, we estimate these notifications' effect on attendance to soccer games played in Korean premier soccer league: K League. These data are

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[14] Our sample period starts in 2003 since dust alert systems have been established during the middle of the year 2002. In the data set we obtained from the Statistics Korea, there are about 4 million birth certificates between 2003 and 2011. However, we lose observations since the PM10 data is not available for some Korean cities. The birth outcomes and parent characteristics of infants that are out of sample are similar to those that enter into our regressions (Appendix Table 1).

[15] In comparison, the average birth weight of U.S. born babies is 3320 gr. (Mocan et al. 2013)

obtained from the English version of the official website of the K League.[16] From this website, we scraped information about the number of people who attended a particular game, the final score, and the teams' performance in the league (standings table). The attendance data span the period between 2004 and 2011. The average attendance to a game during this time period is about 12,500.

VI. Results

The Effect of Air Quality, Pollution Alerts and Yellow Dust Events on Birth Outcomes

The results obtained from estimating Equation (1) are presented in Table 2. In addition to the variables listed, all regressions include city fixed effects and year-of-conception and month-of-conception fixed effects. Outcome variables are the birth weight in grams (column 1), an indicator for whether the birth weight is less than 2,500 grams (column 2), gestational age in weeks (column 3), an indicator for whether infant's gestational age is less than 37 weeks (column 4), and ratio of birth weight to gestational age (column 5). Standard errors, reported in parentheses, are clustered at the city level.

Column 1 of Table 2 shows that infants born to mothers who were exposed to greater daily PM10 levels (worse air quality) during their pregnancy are born with lower weights. Specifically, a one $\mu m/m^3$ increase in average exposure to PM10 during pregnancy leads to about 0.8 gram reduction in newborn's birth weight. This indicates that a 10 percent increase in

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[16] http://www.kleague.com/eng

the average hourly PM10 exposure reduces birth weight by about 0.13% (from the baseline of 3,256 grams), which implies an elasticity of birth weight with respect to PM10 of about 0.013.[17]

The results of column (1) in Table 2 also indicate that each additional pollution *Advisory* and *Warning* that a mother experiences during her pregnancy *improves* infant's birth weight by 4.4 and 13.6 grams, respectively. A warning's effect is larger than an advisory's effect (p-value < 0.01). This could be because a *Warning* provides a stronger signal about the dust level than an *Advisory*, and therefore a warning is associated with stronger health risk and may prompt a stronger avoidance response. The coefficient of *Yellow Dust Events* in column 1 indicates that each additional day a yellow dust event is issued during pregnancy increases birth weight of the infant by about 8.6 grams. These positive estimates are consistent with the hypothesis that Korean mothers avoid/reduce outside activities when an air quality alert is issued or when there is a yellow dust event in the city of residence of the expecting mother.

Similar to those in column (1), the results presented in columns (2)-(4) in Table 2 provide evidence for the detrimental effect of PM10 exposure and the beneficial effect of pollution alerts and yellow dust events on birth outcomes. Each *Advisory, Warning* and *Yellow Dust Event* reduces the probability of low birth weight by 0.2, 0.5 and 0.3 percentage points (from the sample mean of 3.4 percentage points), respectively. Similarly, advisories, warnings and yellow dust events increase the gestational age of the infant, probability of premature birth and its average fetal growth, while a rise in PM10 exposure reduces them.

The signs of the control variables in Table 2 are consistent with expectations. Girls and babies born to mothers who have not previously given birth weigh less at birth compared to boys

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[17] The elasticity is calculated as $\frac{\partial BW}{\partial PM10} \div \frac{\overline{BW}}{\overline{PM10}} = 0.8 \times \frac{54.27}{3256} = 0.013.$

and babies born to mothers who have given birth to at least one baby, respectively. Infants whose parents are employed and have attained higher education levels are born healthier.

Previous papers provide evidence for differential effect on birth outcomes of external factors in different developmental stages of the fetus (Currie 2011). To investigate this possibility, we include in the regressions the exposure to PM10 and the number of alerts against poor air quality during the first, second and third trimesters of pregnancy (instead of the overall exposure during the whole pregnancy). For example, instead of the variable *Advisories*, we include *Advisories – trimester 1*, *Advisories – trimester 2* and *Advisories – trimester 3* that decompose the number of advisories a pregnant woman has experienced during her pregnancy into its first, second and third trimester components. The results, presented in Table 3, are similar to those in Table 2. The number of *Advisories, Warnings* and *Yellow Dust Events* experienced in any trimester has a positive and significant impact on birth weight. These effects are not statistically different from each other. An increase in PM10 exposure in the third trimester worsens birth outcomes. Average PM10 exposure in late stages of pregnancy (third trimester) has a larger negative impact on the birth outcomes compared to its effect in the first- or second-trimesters. This finding is consistent with that of Currie, Neidell and Schmieder (2009) who report that exposure to pollution during the third trimester has a more significant impact than exposure during the two earlier trimesters.

The Estimates of Pollution on Birth Outcomes When Avoidance is Omitted

The results in Tables 2 and 3 indicate that mothers' exposure to PM10 is detrimental to the infants' health, while air quality alerts and yellow dust events are beneficial as they allow the pregnant women to avoid pollution. That is, advisories and warnings help pregnant women avoid

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harmful effects of pollution. Pollution advisories and warnings are issued based on anticipated

PM10 concentrations, and elevated PM10 level triggers these notifications. Similarly, *Yellow*

Dust Events cause an increase in ambient PM10 levels. In other words, PM10 levels are

positively correlated with the intensity of pollution alerts issued by the government. Given that

people take precautions when these warnings are issued, the failure to control for pollution

warnings and advisories would bias downwards the estimated biological impact of air pollution.

In Table 4 we report the results of the models that exclude pollution alert indicators.

These are the same models as shown in Equation (1), but the variables *Advisories*, *Warnings* and

Yellow Dust Events are omitted. Put differently, Table 4 is similar to Table 2, except for the

pollution alert variables. The coefficients of *PM10* in columns (1)-(4) of Table 4 indicate that

PM10 is harmful for infants' birth outcomes as shown earlier. However, the magnitude of the

impact is much smaller in absolute value when compared to those in Table 2. For example,

according to the results in column 1 of Table 4 (where public notifications and yellow dust

events are omitted), a one $\mu m/m^3$ increase in the average exposure to PM10 during pregnancy

leads to about 0.2 gram reduction in the newborn's birth weight. This same effect is estimated to

be 0.8 grams when the full set of control variables is included in the regressions (Column 1 in

Table 2). Thus, a comparison of PM10 coefficients between Tables 2 and 4 reveals that the

inability to account for the beneficial effect of pollution warnings on health generates a

substantial underestimation of the negative impact of pollution on health.

The Impact of Air Quality, Pollution Notifications and Yellow Dust Events on Attendance to
Soccer Games

Our results show that air pollution alerts in terms of *Advisories*, *Warnings* and *Yellow Dust Event* notifications are beneficial to birth weight and gestational age. These findings are consistent with the hypothesis that mothers avoid/reduce outdoors activities when a public air quality alert is issued or when a yellow dust event is observed. Ideally, we would like to test this hypothesis using data on the amount of time pregnant mothers spend outside. No such data, however, are available. Instead, we use data on another outdoors activity: attendance to professional soccer games. Soccer games are played in open air stadiums, and the attendees are exposed to air pollution. If Koreans try to avoid pollution when an air pollution notification is announced, then the number of fans who attend a soccer game should decrease when a pollution alert is issued on the game day. To estimate the effect of YDEs and alerts on attendance to the soccer games, we run the regression depicted by equation (2).

Table 5 presents the results obtained from equation (2) where the unit of observation is a soccer game played between two teams of the Korean premier league, K League. The outcome variable is the number of individuals who attended the game. We control for various attributes of the games, including the strength of both teams (approximated by their rank that week), the number of goals scored that far during the season, the week of the season, and whether the game is played during the day or at night and in weekdays or at the weekend. We also add stadium fixed-effects, time dummies (month and year), and indicators for the team match-ups. Standard errors are clustered at the stadium level.

In Table 5, the coefficients of *Yellow Dust Events* and *Warnings* are negative and significant, lending support to the hypothesis that individuals avoid spending time outside during

days of pollution warnings and yellow dust events. Specifically, if a yellow dust event occurs on game day, about 3,400 fewer individuals attend that particular game. This corresponds to about 26 percent decline (from the baseline of 12,500 spectators). Similarly, a *Warning* on the game day reduces the game attendance by about 7,000.

A Falsification Test

Neither exposure to pollution, nor avoidance of pollution should impact birth outcomes if pollution is measured *after the birth of the infant.* To operationalize this idea as a falsification test, we estimated equation (1) using *future values* of PM10, air quality alerts, and yellow dust events as explanatory variables. Specifically, we ran the regression below:

(6) $Health_{ict} = \beta_1 PM10_{ict+k} + \boldsymbol{Alerts_{ict+k}\beta_2} + \beta_3 YDE_{ict+k} + \boldsymbol{X_{ict}\beta_4} + \mu_c + \theta_t + \epsilon_{ict}$

where subscript $t + k$ indicates k days after the delivery of the baby at time t.

The results obtained from estimating equation (6) are presented in Table 6 where the outcome variable is infant's birth weight.[18] Columns (1) to (4) pertain to k=30, 60, 90 and 120 days. For example, in column (1) of Table 6, the rows *PM10*, *Advisories*, *Warnings*, and *Yellow Dust Events* stand for the corresponding variables measured during the 30 days subsequent to the delivery of the baby. In column 2, these rows indicate the air quality and notification during 60 days following the baby's birth. The full set of control variables, as in Table 2, is included in all regressions. As expected, results show that mother's exposure to poor air quality or her avoidance behavior due to notifications after she delivered the baby does not have any influence of the baby's birth weight.

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[18] Similar results are obtained when other outcome variables are used in the regressions.

Other Robustness Checks

As an extension, to investigate whether air quality and pollution notifications have differential impacts on birth weight, we estimated equation (1) over a number of subsamples. The results are presented in Table 7, where the outcome variable is infant's weight at birth. First, we split the sample into two groups by geographical location. Mothers who live in the North and Northwest Korea could be more responsive to pollution and notifications. The Northern part of Korea is closer to China and it is exposed to more frequent yellow dust events. As a result, individuals could be more aware of adverse effects of yellow dust and poor air quality, and they may respond more intensely. However, the results in columns 1 and 2 of Table 7 suggest the effects of PM10, air quality notifications and yellow dust events on birth weight are similar in both samples. Similarly, there is no difference between mothers who live in cities with poor versus high air quality (PM10 greater or smaller than the median) regarding the effect of air quality and notifications on birth weight (columns 3 and 4).

A potential concern is selection due to unobservables related to mother's health knowledge. For example, pregnant mothers who are more knowledgeable about the detrimental impact of poor air quality may take better preventive action against pollution. They may move away from cities of low air quality, or they may time the birth to avoid exposure to high levels of PM10. Alternatively, they may be better at following the advisories and warnings. In that case, our baseline results in Table 2 may be overestimates of the true effect of pollution.

To investigate this possibility, we first estimated equation (1) in subsamples that are separated by mother attributes: mother's education, work experience, and pregnancy experience. Mothers with more education or more experience in the labor market are likely to command more know-how about reducing/eliminating harmful effects of air pollution. Similarly, a mother

who has given birth before could be more knowledgeable compared to her counterparts who are expecting their first babies. The results, presented in columns (5) to (10) of Table 7, suggest that our baseline findings are not driven by certain types of mothers. For example, advisories, warnings and yellow dust events improve birth weights of infants born to high-educated or experienced mothers as much as they improve birth weights of low-educated or inexperienced mothers' babies. Similarly, exposure to PM10 is detrimental to infants of high-educated or experienced mothers as much as it is damaging to the health of babies born to low-educated or inexperienced mothers.

As another robustness check, we investigated whether high-educated parents alter the timing of their pregnancies in order to select themselves out of poor air quality seasons. First, using each birth as the unit of observation, we regressed total exposure to pollution during the pregnancy of the mother (measured by PM10) on monthly dummies for the month of conception (n=1,549,376). This regression showed that PM10 exposure during pregnancy is lower if conception is between the months of March and June. We then created a dummy variable for each mother to indicate if her conception of pregnancy was during this more favorable period (March to June). We ran this *Conception Timing* dummy on mother's and father's education (dummy indicators of having high school education, and having college education as used in all regressions). The results showed that neither mother's nor father's education had any impact on the timing of pregnancy.[19] Thus, we could not find support for the hypothesis that educated parents adjust the time of their pregnancies to avoid poor air quality.

To investigate any overall seasonal pattern in conceptions, we calculated the total number of conceptions by month in the country and regressed them on 11 monthly dummies to analyze

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[19] The point estimates ranged from -0.005 to 0.0007 with p-values ranging from 0.15 to 0.81.

whether the number of conceptions rises or declines in certain months of the year (possibly to avoid pollution). The estimated monthly coefficients and the corresponding confidence intervals are reported in Figure 3. In no case the coefficients are different from zero, signifying that the number of conceptions does not exhibit any seasonal pattern.

Residential Location Decision

A possible bias in our estimates could emerge due to the geographical selection of parents. For example, if families with more income and higher education reside in bigger cities with worse ambient air quality, and if such families have high productive and/or allocative efficiency in infant health production (Grossman 2008, 1972; Rosenzweig and Schultz 1982, Kenkel 1991, Altindag, Cannonier and Mocan 2011), then the negative impact of pollution on birth outcomes is underestimated.

To investigate the correlation between city-level air pollution and parent attributes, we estimated a regression where the outcome variable is an indicator that takes the value of one if the infant is born in a city where average PM10 level is above the national median.[20] The explanatory variables included parent characteristics and month- and year-of conception dummies. In addition, the variable *White Collar Family* took the value of one if both mother and father have white collar jobs such as managers, engineers and office workers. Families for which *White Collar Family* is zero include at least one parent with a blue collar job (such as laborer, technician) or an agricultural job. The results presented in column (1) of Table 8 indicate that mothers who delivered their baby in high pollution cities are more likely to be working, older, married and slightly more educated. Also, those mothers are delivering their first

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[20] This is the variable that we use to divide the sample into two (columns 3 and 4) in Table 7.

infant. Father characteristics are unrelated to the probability of the child being born in a high

pollution city. In column (2) of Table 8, the coefficient of *White Collar Family* is positive

indicating that infants whose parents have white collar jobs are more likely to be born in more

polluted cities. Thus, the results of Table 8 support the hypothesis that parents with potentially

higher incomes select into more polluted cities. To the extent that such families are more

efficient in the production of infant health, the negative impact of pollution on infant health

could be underestimated.   In this case, our baseline result presented in Tables 2-4 represent an

underestimate of the effect of PM10 on infant health.

To investigate this issue, we augmented the regression depicted in equation (1) with two

variables that are shown to be related to air pollution in the city at the time of the birth (Table 8)

as well as potentially correlated with productive/allocative efficiency of the family. The first

variable is *White Collar Family* as described earlier.   We also added the housing price index of

the city (*Housing Price Index*) in which the family resides. Higher housing prices may reflect

more favorable city characteristics including better health care services.[21] The results are

reported in Panel A of Table 9.[22] As expected, *Housing Price Index* is positively correlated with

infant health. Similarly infants born to white collar families have better health at birth.   The

coefficients of PM10, Advisories, Warnings and Yellow Dust Events do not change in any

significant way when *White Collar Family* and *Housing Price Index* are not controlled for in the

regressions (Panel B of Table 9).

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[21] We include 9 month lagged Housing Price Index (HPI) to capture city amenities at the time of conception. Using contemporaneous HPI does not change the results.
[22] Sample size is smaller in these regressions since we lose observations due to lack of HPI data in some cities.

VII. The Willingness to Pay and the Cost of Avoidance Behavior

Conditional on avoidance, the impact of a 10% increase in PM10 on birth weight ($\frac{\partial BW}{\partial PM10}$)

is 4.3 grams (using the coefficient of -0.8 in column 1 of Table 2). This represents a 0.13%

decrease from the baseline average of 3,256 gr. Black, Devereux and Salvanes (2007) report that

a one-percent increase in an infant's birth weight generates an increase in future earnings by

about 0.13%. An average full time Korean worker's annual earning was about $28,000 in

2010.[23] Assuming the average newborn will earn as much as the average worker, and considering

that a typical Korean starts working at age 25 and retires at age 60 (the official retirement age in

Korea), and using a discount rate of six percent, the present value of the benefit generated by a

10% decline in PM10 is about $20. This is the estimated value of the Willingness to Pay (WTP),

which is depicted by equation (4). In 2010, 470,000 babies were born in Korea. Thus, the full

cost of a 10% increase in PM10 for one cohort of Koreans is $9.5 million.

The estimated coefficient of PM10 reported in column (1) of Table 4 corresponds to

($\frac{dBW}{dPM10}$). This is because the models reported in Table 4 do not control for pollution alerts which

shift the demand for avoidance. In this specification, a 10% increase in PM10 generates a

reduction in birth weight by 0.03%; and using the same B as above, this produces a cost of $2

million for one cohort of Korean babies. Using Equation (5), this implies that the cost of

avoidance is $7.5 million (in 2010 dollars). We should note that the benefit value used in this

exercise pertains to increased future earnings of the infant, and it does not include any other

elements such as health-related expenditures. For example, to the extent that poor health at birth

has an impact on chronic health conditions in adulthood, the benefits should be adjusted

upwards. Thus, the magnitudes we report should be considered as lower bounds.

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[23] Source: OECD Statistics. http://stats.oecd.org/.

VIII. Summary and Conclusion

Previous research has shown that infant health, particularly weight at birth, is an important predictor of future well-being of individuals, including earnings. An important determinant of birth weight is prenatal exposure to pollution. A complicating issue in the investigation of the impact of environmental pollution to infant health is the difficulty in finding exogenous exposure to pollution. Individuals and families who are likely to live in less polluted areas may have better health outcomes because of particular attributes of these families, unrelated to pollution. Such endogenous geographical selection, or endogenous timing of a pregnancy would confound the estimated impact of pollution on infant health. Second, as policy makers increasingly emphasize the relevance of pollution warnings and air quality alerts as a potential tool to modify exposure of individuals through avoidance behavior, it is essential to determine the effectiveness of such alerts. This is important not only because the failure to account for avoidance behavior would provide an underestimate of the biological impact of pollution on health, but also because of the significance of the welfare loss associated with such avoidance behavior.

In this paper we investigate the impact of air pollution on infant health using information on more than one and a half million live births in the Republic of Korea. The novelty of our identification strategy is the ability to measure the exposure of pregnant women to pollution generated by a natural phenomenon: the yellow dust. Winds carry particles of dust and sand from the arid lands of Northern China and the deserts of Mongolia to the Korean peninsula. These particles of dust and sand settle in Korea and they elevate the ambient air pollution, measured by PM10 concentration. Although there is a seasonal pattern of this phenomenon,

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there is significant variation in its timing, strength and location from year to year. Thus, exposure to the intensity of air pollution exhibits substantial randomness and unpredictability. We also show that Korean women do not time their pregnancy according to expected yellow dust exposure, and that educated women's pregnancy timing is not different than those who are less-educated.

We measure air pollution in each city by calculating the PM10 level, using hourly readings of all monitoring stations in that city, and creating a city-level daily average PM10. Using these daily air pollution data and making use of the gestation weeks reported on birth certificates, we measure the extent of exposure to pollution of each pregnancy.

An important contribution of the paper is the ability to account for avoidance behavior. We utilize pollution advisories, pollution warnings as well as alerts on yellow dust events that are issued by Korean authorities at the local level. We obtain estimates of the biological impact of pollution on infant health, and the improvement in infant health generated by pollution avoidance. Our paper is the first one to investigate the effectiveness of pollution alerts on birth outcomes.

The results show that exposure to air pollution during pregnancy has a significant negative impact on birth weight, gestation weeks of the baby, and the propensity of the baby being low weight. Public notifications about air quality have a separate statistically significant and positive effect on infant health. In complementary analysis we show that the same public notifications significantly reduce attendance to professional soccer games, supporting the premise that individuals avoid being outdoors when pollution alerts are issued.

We find white collar families and more educated and older mothers are more likely to give birth in high-pollution cities. These family attributes and the housing price index of the city

in which the birth took place are correlated with birth outcomes.   Adjusting for these factors,
however, does not impact the results.

Our results provide evidence for the effectiveness of pollution alert systems in promoting
public health. They also underline the importance of taking into account individuals' avoidance
behavior when estimating the impact of air quality on birth outcomes. We show that the
estimated impact of air pollution on infant health is reduced by half when the preventive effect of
public health warnings is not accounted for. Using future earnings as the only component of the
benefit of pollution reduction, our estimates imply that willingness to pay, associated with a 10%
decline in the level of PM10, is $9.5 million (in 2010 dollars) for one cohort of babies, and the
corresponding cost of avoidance is $7.5 million. To the extent that poor health at birth has an
impact on health conditions later in life, the magnitudes we report should be considered as lower
bounds.

Table 1: Summary Statistics

Variable	Description	Mean	Std. Dev.
Birth weight	Baby's weight at birth (grams)	3257	430
Low birth weight	=1 if birth weight is less than 2,500 grams.	0.034	0.181
Gestation	Gestational age in weeks	38.94	1.48
Premature	=1 if gestation <37 weeks	0.042	0.200
Fetal growth	Birth weight/Gestation	83.54	10.20
Advisories	Number of advisories issued during pregnancy	1.72	1.36
Warnings	Number of warnings issued during pregnancy	0.51	0.59
Yellow dust events	Number of observed yellow dust outbreaks.	6.77	3.80
PM10	Average daily PM10 during pregnancy	54.27	8.79
Temperature	Average temperature during pregnancy (°C)	13.43	3.00
Precipitation	Average precipitation during pregnancy (mm.)	125.26	46.77
Girl	=1 if the baby is a girl	0.484	0.500
Second baby	=1 if the baby is mother's second child	0.376	0.484
Third baby	=1 if the baby is mother's third, fourth,…etc.	0.085	0.278
Married	=1 if baby is born within a marriage	0.991	0.096
Mother working	=1 if mother is working	0.288	0.453
Mother's age 20-30	=1 if mother's age is between 20 and 30	0.408	0.491
Mother's age 30-40	=1 if mother's age is between 30 and 40	0.573	0.495
Mother's age 40+	=1 if mother is older than 40	0.015	0.122
Mother high school grad.	=1 if mother has completed high school	0.323	0.468
Mother college grad.	=1 if mother has completed college or more	0.659	0.474
Father working	=1 if father is working	0.954	0.210
Father's age 20-30	=1 if father's age is between 20 and 30	0.181	0.385
Father's age 30-40	=1 if father's age is between 30 and 40	0.749	0.433
Father's age 40+	=1 if father is older than 40	0.069	0.253
Father high school grad.	=1 if father has completed high school	0.291	0.454
Father college grad.	=1 if father has completed college or more	0.689	0.463

Notes: Sample consists of 1,549,376 observations. Unit of observation is newborn baby.

Table 2: The Effect of Alerts and Air Pollution on Birth Outcomes

	(1)	(2)	(3)	(4)	(5)
	Birth Weight	Low Birth Weight	Gestation	Premature Birth	Fetal Growth
PM10	-0.798***	0.0003***	-0.004***	0.001***	-0.012***
	(0.150)	(0.0001)	(0.001)	(0.000)	(0.003)
Advisories	4.360***	-0.002***	0.037***	-0.004***	0.043**
	(1.007)	(0.000)	(0.006)	(0.001)	(0.018)
Warnings	13.565***	-0.005***	0.086***	-0.007***	0.186***
	(1.488)	(0.001)	(0.009)	(0.001)	(0.028)
Yellow dust events	8.578***	-0.003***	0.057***	-0.006***	0.113***
	(0.403)	(0.000)	(0.002)	(0.000)	(0.007)
Temperature	-18.634***	0.005***	-0.148***	0.003***	-0.180***
	(1.587)	(0.001)	(0.009)	(0.001)	(0.031)
Precipitation	-0.160***	0.0000***	-0.001***	0.0001***	-0.002***
	(0.023)	(0.0000)	(0.000)	(0.0000)	(0.000)
Girl	-97.816***	0.007***	0.134***	-0.008***	-2.789***
	(0.723)	(0.000)	(0.003)	(0.000)	(0.016)
Second baby	30.726***	-0.011***	-0.403***	0.0002	1.677***
	(1.331)	(0.000)	(0.005)	(0.0004)	(0.031)
Third baby	60.913***	-0.010***	-0.406***	0.006***	2.452***
	(2.029)	(0.001)	(0.006)	(0.001)	(0.050)
Married	32.039***	-0.012***	0.111***	-0.012***	0.609***
	(4.006)	(0.002)	(0.012)	(0.002)	(0.099)
Mother working	5.525***	-0.0005	-0.002	0.0003	0.144***
	(0.944)	(0.0003)	(0.003)	(0.0003)	(0.022)
Mother's age 20-30	66.926***	-0.005	0.048**	-0.007*	1.610***
	(6.820)	(0.003)	(0.023)	(0.004)	(0.165)
Mother's age 30-40	63.824***	0.002	-0.029	-0.0001	1.670***
	(6.871)	(0.003)	(0.023)	(0.0039)	(0.167)
Mother's age 40+	19.946***	0.021***	-0.294***	0.023***	1.064***
	(7.198)	(0.004)	(0.027)	(0.004)	(0.177)
Mother high sch. grad.	43.048***	-0.011***	0.053***	-0.006***	1.006***
	(3.311)	(0.002)	(0.012)	(0.002)	(0.077)
Mother college grad.	49.751***	-0.016***	0.115***	-0.012***	1.056***
	(3.499)	(0.002)	(0.012)	(0.002)	(0.082)
Father working	8.173***	-0.003***	-0.004	-0.003***	0.235***
	(1.598)	(0.001)	(0.006)	(0.001)	(0.037)
Father's age 20-30	35.193***	-0.019**	0.047	-0.019***	0.838***
	(11.528)	(0.008)	(0.044)	(0.007)	(0.267)
Father's age 30-40	36.428***	-0.019**	0.052	-0.019***	0.859***
	(11.464)	(0.008)	(0.044)	(0.007)	(0.268)
Father's age 40+	27.342**	-0.012	-0.027	-0.011	0.776***
	(11.136)	(0.008)	(0.045)	(0.007)	(0.256)
Father high sch. grad.	22.819***	-0.005***	0.020**	-0.004***	0.541***
	(3.012)	(0.001)	(0.009)	(0.001)	(0.072)
Father college grad.	28.774***	-0.010***	0.069***	-0.008***	0.602***
	(3.237)	(0.001)	(0.010)	(0.001)	(0.078)
N	1,549,376	1,549,376	1,549,376	1,549,376	1,549,376

Notes: Outcome variables are baby's weight at birth in grams, an indicator for whether baby's birth weight is less than 2,500 grams, gestation weeks, an indicator for whether infant is born with gestational age less than 37 weeks, and the ratio of birth weight to gestation weeks in columns 1 to 5, respectively. Regressions include city fixed effects, and time dummies for conception year and month. Standard errors clustered at the city level are presented in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 3: The Effect of Alerts and Air Pollution on Birth Outcomes (Trimesters)

	(1) Birth Weight	(2) Low Birth Weight	(3) Gestation	(4) Premature Birth	(5) Fetal Growth
PM10					
in trimester 1	-0.110	0.0001*	-0.0002	-0.0000	-0.002
	(0.090)	(0.0000)	(0.0007)	(0.0001)	(0.002)
in trimester 2	-0.049	0.0001	0.0000	0.0001***	-0.002
	(0.092)	(0.0000)	(0.0006)	(0.0000)	(0.002)
in trimester 3	-0.799***	0.0002***	-0.006***	0.0003***	-0.009***
	(0.110)	(0.0000)	(0.001)	(0.0001)	(0.002)
Advisories					
in trimester 1	4.647***	-0.002***	0.042***	-0.003***	0.037
	(1.455)	(0.001)	(0.009)	(0.001)	(0.026)
in trimester 2	12.571***	-0.006***	0.084***	-0.009***	0.167***
	(1.170)	(0.000)	(0.007)	(0.001)	(0.020)
in trimester 3	6.427***	-0.003***	0.055***	-0.006***	0.060**
	(1.305)	(0.001)	(0.008)	(0.001)	(0.023)
Warnings					
in trimester 1	13.515***	-0.004***	0.093***	-0.005***	0.167***
	(2.185)	(0.001)	(0.016)	(0.001)	(0.037)
in trimester 2	7.848***	-0.004***	0.034***	-0.010***	0.150***
	(1.896)	(0.001)	(0.012)	(0.001)	(0.035)
in trimester 3	14.982***	-0.005***	0.097***	-0.006***	0.197***
	(1.991)	(0.001)	(0.011)	(0.001)	(0.037)
Yellow dust events					
in trimester 1	8.597***	-0.004***	0.054***	-0.006***	0.121***
	(0.459)	(0.000)	(0.003)	(0.000)	(0.009)
in trimester 2	10.935***	-0.004***	0.074***	-0.007***	0.140***
	(0.498)	(0.000)	(0.003)	(0.000)	(0.008)
in trimester 3	11.778***	-0.004***	0.083***	-0.006***	0.142***
	(0.570)	(0.000)	(0.003)	(0.000)	(0.010)
Temperature					
in trimester 1	6.851***	0.0000	0.060***	0.005***	0.041**
	(0.968)	(0.0005)	(0.006)	(0.001)	(0.018)
in trimester 2	-3.228***	-0.0004	-0.035***	-0.004***	-0.002
	(0.519)	(0.0003)	(0.003)	(0.000)	(0.010)
in trimester 3	-8.913***	0.004***	-0.056***	0.007***	-0.128***
	(0.843)	(0.000)	(0.005)	(0.001)	(0.016)
Precipitation					
in trimester 1	-0.004	0.0000	0.0002**	0.0000***	-0.0005**
	(0.009)	(0.0000)	(0.0001)	(0.0000)	(0.0002)
in trimester 2	-0.096***	0.0000***	-0.001***	0.0000***	-0.001***
	(0.009)	(0.0000)	(0.000)	(0.0000)	(0.000)
in trimester 3	0.006	0.0000**	0.0002*	0.0001***	-0.0003
	(0.017)	(0.0000)	(0.0001)	(0.0000)	(0.0003)
Girl	-97.967***	0.007***	0.133***	-0.008***	-2.790***
	(0.717)	(0.000)	(0.003)	(0.000)	(0.016)

Table 3 (concluded)

	(1) Birth Weight	(2) Low Birth Weight	(3) Gestation	(4) Premature Birth	(5) Fetal Growth
Second baby	31.179***	-0.011***	-0.399***	0.0001	1.682***
	(1.347)	(0.000)	(0.005)	(0.0004)	(0.031)
Third baby	61.531***	-0.010***	-0.401***	0.006***	2.458***
	(2.035)	(0.001)	(0.006)	(0.001)	(0.050)
Mother's age 20-30	66.811***	-0.005	0.047**	-0.007*	1.609***
	(6.802)	(0.003)	(0.022)	(0.004)	(0.165)
Mother's age 30-40	63.816***	0.003	-0.029	-0.0001	1.670***
	(6.866)	(0.003)	(0.023)	(0.0039)	(0.167)
Mother's age 40+	20.213***	0.021***	-0.292***	0.023***	1.068***
	(7.190)	(0.004)	(0.027)	(0.004)	(0.177)
Mother high sch. grad.	43.299***	-0.011***	0.054***	-0.006***	1.008***
	(3.308)	(0.002)	(0.012)	(0.002)	(0.078)
Mother college grad.	49.954***	-0.016***	0.116***	-0.012***	1.059***
	(3.501)	(0.002)	(0.012)	(0.002)	(0.082)
Father working	8.188***	-0.003***	-0.004	-0.003***	0.236***
	(1.590)	(0.001)	(0.006)	(0.001)	(0.037)
Father's age 20-30	34.563***	-0.019**	0.043	-0.019***	0.830***
	(11.611)	(0.008)	(0.045)	(0.007)	(0.268)
Father's age 30-40	35.772***	-0.019**	0.048	-0.019***	0.850***
	(11.567)	(0.008)	(0.044)	(0.007)	(0.269)
Father's age 40+	26.831**	-0.012	-0.030	-0.011	0.770***
	(11.217)	(0.008)	(0.045)	(0.007)	(0.258)
Father high sch. grad.	22.922***	-0.005***	0.021**	-0.004***	0.542***
	(3.010)	(0.001)	(0.009)	(0.001)	(0.072)
Father college grad.	28.771***	-0.010***	0.069***	-0.008***	0.601***
	(3.235)	(0.001)	(0.009)	(0.001)	(0.078)
N	1,549,376	1,549,376	1,549,376	1,549,376	1,549,376

Notes: Outcome variables are baby's weight at birth in grams, an indicator for whether baby's birth weight is less than 2,500 grams, gestation weeks, an indicator for whether infant was born with gestational age less than 37 weeks, and the ratio of birth weight to gestation weeks in columns 1 to 5, respectively. Regressions include number of advisories, warnings, yellow dust events, average PM10, temperature and precipitation in each trimester instead of the whole pregnancy. Regressions also include city fixed effects, and time dummies for conception year and month. Standard errors clustered at the city level are presented in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 4: The Effect of Air Pollution on
Birth Outcomes without Controlling for Pollution Alerts

	(1)	(2)	(3)	(4)	(5)
	Birth Weight	Low Birth Weight	Gestation	Premature Birth	Fetal Growth
PM10	-0.232**	0.0001**	-0.001	0.0001***	-0.005*
	(0.101)	(0.0000)	(0.001)	(0.0000)	(0.003)
Temperature	-19.617***	0.005***	-0.158***	0.002*	-0.181***
	(1.595)	(0.001)	(0.009)	(0.001)	(0.031)
Precipitation	-0.110***	0.0000***	-0.001***	0.0000***	-0.002***
	(0.019)	(0.0000)	(0.000)	(0.0000)	(0.000)
Girl	-97.641***	0.006***	0.134***	-0.008***	-2.785***
	(0.669)	(0.000)	(0.003)	(0.000)	(0.015)
Second baby	29.671***	-0.010***	-0.405***	0.001	1.653***
	(1.308)	(0.000)	(0.005)	(0.000)	(0.029)
Third baby	61.713***	-0.010***	-0.402***	0.006***	2.464***
	(2.056)	(0.001)	(0.006)	(0.001)	(0.050)
Married	31.471***	-0.012***	0.107***	-0.011***	0.606***
	(4.064)	(0.002)	(0.012)	(0.002)	(0.100)
Mother working	5.572***	-0.001	-0.002	0.0003	0.145***
	(0.925)	(0.000)	(0.003)	(0.0003)	(0.022)
Mother's age 20-30	66.830***	-0.006**	0.066***	-0.009**	1.575***
	(7.003)	(0.003)	(0.023)	(0.004)	(0.167)
Mother's age 30-40	63.473***	0.001	-0.013	-0.002	1.634***
	(7.048)	(0.003)	(0.023)	(0.004)	(0.170)
Mother's age 40+	17.553**	0.020***	-0.281***	0.022***	0.979***
	(7.187)	(0.003)	(0.026)	(0.004)	(0.176)
Mother high sch. grad.	44.226***	-0.011***	0.055***	-0.006***	1.031***
	(3.192)	(0.001)	(0.012)	(0.002)	(0.073)
Mother college grad.	50.789***	-0.017***	0.116***	-0.012***	1.082***
	(3.400)	(0.002)	(0.012)	(0.002)	(0.079)
Father working	8.956***	-0.003***	-0.004	-0.004***	0.253***
	(1.503)	(0.001)	(0.006)	(0.001)	(0.035)
Father's age 20-30	33.031***	-0.016**	0.025	-0.015**	0.820***
	(10.875)	(0.007)	(0.043)	(0.006)	(0.250)
Father's age 30-40	34.821***	-0.016**	0.031	-0.016**	0.852***
	(10.760)	(0.007)	(0.042)	(0.006)	(0.249)
Father's age 40+	25.221**	-0.009	-0.051	-0.007	0.761***
	(10.392)	(0.007)	(0.043)	(0.007)	(0.238)
Father high sch. grad.	21.935***	-0.006***	0.015*	-0.004***	0.529***
	(2.680)	(0.001)	(0.009)	(0.001)	(0.065)
Father college grad.	27.810***	-0.010***	0.063***	-0.008***	0.590***
	(2.945)	(0.001)	(0.009)	(0.001)	(0.072)
N	1,676,096	1,676,096	1,676,096	1,676,096	1,676,096

Notes: Outcome variables are baby's weight at birth in grams, an indicator for whether baby's birth weight is less than 2,500 grams, gestation weeks, an indicator for whether infant was born with gestational age less than 37 weeks, and the ratio of birth weight to gestation weeks in columns 1 to 5, respectively. Regressions include the whole set of covariates as in Table2 except Advisories, Warnings, and Yellow Dust Events. Standard errors clustered at the city level are presented in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 5: Effect of Yellow Dust Events and
Air Quality Notifications on Soccer Attendance

	(1)	(2)
	Attendance	Log(Attendance)
PM10	8.489	0.001
	(7.277)	(0.001)
Advisory	2346.761	-0.041
	(2423.710)	(0.155)
Warning	-7051.620*	-0.564*
	(3677.459)	(0.277)
Yellow Dust Event	-3377.854**	-0.219**
	(1237.069)	(0.079)
Temperature (°C)	208.512***	0.020***
	(36.196)	(0.004)
Precipitation (mm.)	-61.354***	-0.007***
	(8.527)	(0.001)
Weekend	-868.899	0.131
	(1781.747)	(0.155)
Evening	-4470.460**	-0.292*
	(2008.817)	(0.162)
Weekend×Evening	4978.367**	0.301
	(2027.002)	(0.186)
Round in Tournament	-337.412***	-0.048***
	(105.130)	(0.011)
Home Team Goals For	203.218**	0.025***
	(78.056)	(0.005)
Away Team Goals For	13.915	0.002
	(43.662)	(0.005)
Rank of Home Team	-218.622**	-0.015*
	(78.521)	(0.007)
Rank of Away Team	-217.373***	-0.016**
	(72.318)	(0.006)
N	1,061	1,061

Notes: Outcome variable in column 1, *Attendance*, is the number of people who attended a soccer game in the Korean K-League between years 2004 and 2011. Mean *Attendance* is about 12,500. Outcome in column 2 is the natural logarithm of *Attendance*. *Yellow Dust Event*, *Advisory* and *Warning* are indicators for whether the corresponding notification is released on the game day. *PM10* is the average of hourly measure in the game day. *Temperature* is the maximum temperature in Celsius in the day. *Precipitation* is measured in millimeters. *Weekend* denotes Saturday and Sunday games. *Evening* is equal to one if the whole game is played after sunset. *Round in Tournament* is the week number in the season. *Goals For* and *Rank* measures the number of goals scored by the corresponding team in the previous rounds in the tournament and the rank of the team as of the start of the game. Regressions also include stadium and team match-up fixed effects, year and month dummies.

Table 6: Falsification Test: The Effect of Future Alerts and Air Quality on Birth Weight

	(1)	(2)	(3)	(4)
	During 30 Days following Birth	During 60 Days following Birth	During 90 Days following Birth	During 120 Days following Birth
PM10	-0.030	-0.067	-0.078	-0.113
	(0.043)	(0.056)	(0.074)	(0.082)
Advisories	-0.677	-0.171	-0.255	-0.743
	(1.029)	(0.731)	(0.679)	(0.596)
Warnings	1.217	0.118	0.239	-0.777
	(1.888)	(1.457)	(1.335)	(1.036)
Yellow dust events	0.371	0.396	0.470*	0.583**
	(0.397)	(0.297)	(0.255)	(0.251)
Temperature	0.490*	0.070	0.590**	0.350
	(0.252)	(0.240)	(0.251)	(0.293)
Precipitation	-0.011***	0.001	-0.003	-0.004
	(0.003)	(0.004)	(0.004)	(0.004)
Girl	-97.620***	-97.623***	-97.617***	-97.683***
	(0.748)	(0.755)	(0.743)	(0.725)
Second baby	29.991***	30.062***	29.985***	30.013***
	(1.326)	(1.338)	(1.364)	(1.365)
Third baby	59.912***	60.167***	60.216***	60.058***
	(2.058)	(2.067)	(2.074)	(2.089)
Married	32.933***	32.651***	31.980***	32.619***
	(3.979)	(3.993)	(4.072)	(4.250)
Mother working	5.785***	5.921***	5.930***	5.718***
	(0.958)	(0.940)	(0.936)	(0.922)
Mother's age 20-30	70.595***	70.169***	69.749***	69.243***
	(7.023)	(7.047)	(7.055)	(7.096)
Mother's age 30-40	66.975***	66.499***	65.911***	65.358***
	(7.082)	(7.124)	(7.134)	(7.173)
Mother's age 40+	21.208***	20.996***	20.509***	19.847***
	(7.385)	(7.321)	(7.208)	(7.269)
Mother high sch. grad.	44.008***	44.002***	44.347***	44.684***
	(3.342)	(3.347)	(3.352)	(3.369)
Mother college grad.	50.406***	50.293***	50.593***	51.092***
	(3.544)	(3.514)	(3.534)	(3.515)
Father working	8.356***	8.040***	8.200***	8.478***
	(1.642)	(1.641)	(1.702)	(1.738)
Father's age 20-30	32.471***	34.241***	36.141***	36.758***
	(11.761)	(11.566)	(11.910)	(12.234)
Father's age 30-40	34.017***	35.834***	37.795***	38.514***
	(11.652)	(11.473)	(11.785)	(12.124)
Father's age 40+	24.151**	25.700**	27.536**	28.145**
	(11.287)	(11.142)	(11.474)	(11.833)
Father high sch. grad.	22.267***	21.748***	22.192***	22.192***
	(3.054)	(3.116)	(3.216)	(3.185)
Father college grad.	28.361***	27.915***	28.364***	28.353***
	(3.281)	(3.324)	(3.448)	(3.443)
N	1,516,650	1,483,838	1,450,696	1,417,975

Notes: Outcome variable is baby's weight at birth in grams. Variables Advisories, Warnings, Yellow dust events, PM10, Temperature and Precipitation measure the corresponding variables 30, 60, 90 and 120 days following the baby's birth in columns 1 to 4, respectively. Full set of controls are included in regressions. Standard errors clustered at the city level are in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 7: The Effect of Alerts and Air Pollution on Birth Weight in Subsamples

	(1)	(2)	(3)	(4)
	Infants Born in North West Korea	Infants Born in Rest of Korea	Infants Born in High PM10 Cities	Infants Born in Low PM10 Cities
PM10	-0.982***	-1.216***	-1.079***	-0.743**
	(0.209)	(0.277)	(0.195)	(0.298)
Advisories	2.560	5.154***	1.580	7.102***
	(1.738)	(1.453)	(1.284)	(1.941)
Warnings	8.640***	17.078***	14.920***	12.292***
	(2.210)	(1.913)	(2.014)	(2.120)
Yellow dust events	11.425***	7.738***	10.611***	7.537***
	(0.801)	(0.457)	(0.614)	(0.475)
N	692,463	856,913	823,921	725,455

	(5)	(6)	(7)	(8)	(9)	(10)
	Infants Born to High Educated Mothers	Infants Born to Low Educated Mothers	First Born Infants	Non-First Born Infants	Infants Born to Working Mothers	Infants Born to Non-Working Mothers
PM10	-0.797***	-0.807***	-0.711***	-0.897***	-0.888***	-0.760***
	(0.146)	(0.198)	(0.176)	(0.164)	(0.220)	(0.148)
Advisories	4.000***	4.855***	4.109***	4.497***	3.282***	4.732***
	(0.993)	(1.277)	(1.018)	(1.116)	(1.110)	(1.078)
Warnings	13.568***	14.157***	14.404***	12.645***	13.780***	13.477***
	(1.528)	(2.344)	(1.674)	(1.744)	(1.664)	(1.638)
Yellow dust events	8.332***	9.077***	8.785***	8.359***	8.408***	8.652***
	(0.405)	(0.526)	(0.440)	(0.420)	(0.568)	(0.416)
N	1,020,987	528,389	835,108	714,268	445,974	1,103,402

Notes: Table 7 presents coefficients obtained from estimating the main specification over subsamples described at the top of each column. Outcome variable is baby's weight at birth in grams. Full set of control variables are included in all regressions. Standard errors clustered at the city level are presented in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Subsamples: Infants born in/to (1) Regions in North and North West Korea Seoul, Gangwon and Chungnam vs. (2) Rest of Korea; (3) Regions with average PM10 level greater than the median vs. (4) Regions with average PM10 level less than the median; (5) Mothers with at least a college degree vs. (6) Mothers with less than college degree; (7) Mothers of their first children vs. (8) Mother who have given birth before; (9) Working mothers vs. (10) Mother who are not working.

Table 8
Characteristics of Families Whose Infants are Born in Polluted Areas

	(1)	(2)
	Born in High PM10 city	Born in High PM10 city
White Collar Family		0.050***
		(0.015)
Second baby	-0.044***	-0.044***
	(0.010)	(0.010)
Third baby	-0.102***	-0.101***
	(0.020)	(0.020)
Married	0.033*	0.033*
	(0.019)	(0.020)
Mother working	0.035***	
	(0.012)	
Mother's age 20-30	0.059***	0.061***
	(0.012)	(0.012)
Mother's age 30-40	0.109***	0.111***
	(0.018)	(0.019)
Mother's age 40+	0.127***	0.130***
	(0.021)	(0.021)
Mother high sch. grad.	0.037***	0.038***
	(0.009)	(0.010)
Mother college grad.	0.002	0.002
	(0.018)	(0.018)
Father working	0.017	
	(0.013)	
Father's age 20-30	-0.015	-0.008
	(0.016)	(0.016)
Father's age 30-40	-0.003	0.004
	(0.018)	(0.017)
Father's age 40+	0.000	0.008
	(0.021)	(0.020)
Father high sch. grad.	0.000	0.002
	(0.010)	(0.010)
Father college grad.	-0.012	-0.013
	(0.019)	(0.018)
N	1,549,376	1,549,376

The outcome variable is an indicator that takes the value of one if the baby is born in a city where the average PM10 level is greater than the median. Regressions also include month and year of conception dummies. High Family Income is equal to one if both parents of the infant have white collar jobs such as managers, engineers and office workers, and it is equal to zero if at least one parent has a blue collar job such as laborer or technician or an agricultural job. Standard errors clustered at the city level are presented in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 9: The Effect of Alerts and Air Pollution on Birth Outcomes Controlling for Housing Price Index and a Proxy for the Productive Efficiency of the Family

Panel A

	(1)	(2)	(3)	(4)	(5)
	Birth Weight	Low Birth Weight	Gestation	Premature Birth	Fetal Growth
PM10	-1.241***	0.0005***	-0.008***	0.001***	-0.016***
	(0.202)	(0.000)	(0.002)	(0.000)	(0.003)
Housing Price Index$_{t-9}$	0.333***	-0.000***	0.003***	-0.0005***	0.004**
	(0.113)	(0.000)	(0.001)	(0.000)	(0.002)
White Collar Family	1.880*	-0.001	0.003	0.0001	0.042*
	(0.998)	(0.000)	(0.003)	(0.0004)	(0.023)
Advisories	5.399***	-0.003***	0.046***	-0.006***	0.054***
	(1.090)	(0.000)	(0.006)	(0.001)	(0.019)
Warnings	15.094***	-0.005***	0.094***	-0.007***	0.209***
	(1.418)	(0.001)	(0.008)	(0.001)	(0.028)
Yellow dust events	8.662***	-0.003***	0.058***	-0.006***	0.114***
	(0.427)	(0.000)	(0.002)	(0.000)	(0.007)
N	1,376,282	1,376,282	1,376,282	1,376,282	1,376,282

Panel B

	(1)	(2)	(3)	(4)	(5)
	Birth Weight	Low Birth Weight	Gestation	Premature Birth	Fetal Growth
PM10	-1.265***	0.0005***	-0.009***	0.001***	-0.016***
	(0.204)	(0.000)	(0.002)	(0.000)	(0.003)
Advisories	4.757***	-0.002***	0.041***	-0.005***	0.046**
	(1.103)	(0.000)	(0.006)	(0.001)	(0.019)
Warnings	16.213***	-0.006***	0.103***	-0.009***	0.222***
	(1.501)	(0.001)	(0.008)	(0.001)	(0.029)
Yellow dust events	8.585***	-0.003***	0.058***	-0.006***	0.113***
	(0.413)	(0.000)	(0.002)	(0.000)	(0.007)
N	1,376,282	1,376,282	1,376,282	1,376,282	1,376,282

Notes: The Housing Price Index pertains to the city of infant's birth, 9 months before the infant's birth date. White Collar Family is equal to one if both parents of the infant have white collar jobs such as managers, engineers and office workers, and it is equal to zero if at least one parent has a blue collar job such as laborer or technician or an agricultural job. Regressions in Panel A include Housing Price Index, and White Collar Family in addition to the control variables as in Table 2. Regressions in Panel B include all control variables except for Housing price Index and White Collar Family. The coefficients of the full set of control variables are listed in Appendix Table 2. Standard errors clustered at the city level are presented in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Figure 1
Average Hourly PM10 Concentrations in Our Sample between years 2003 and 2006
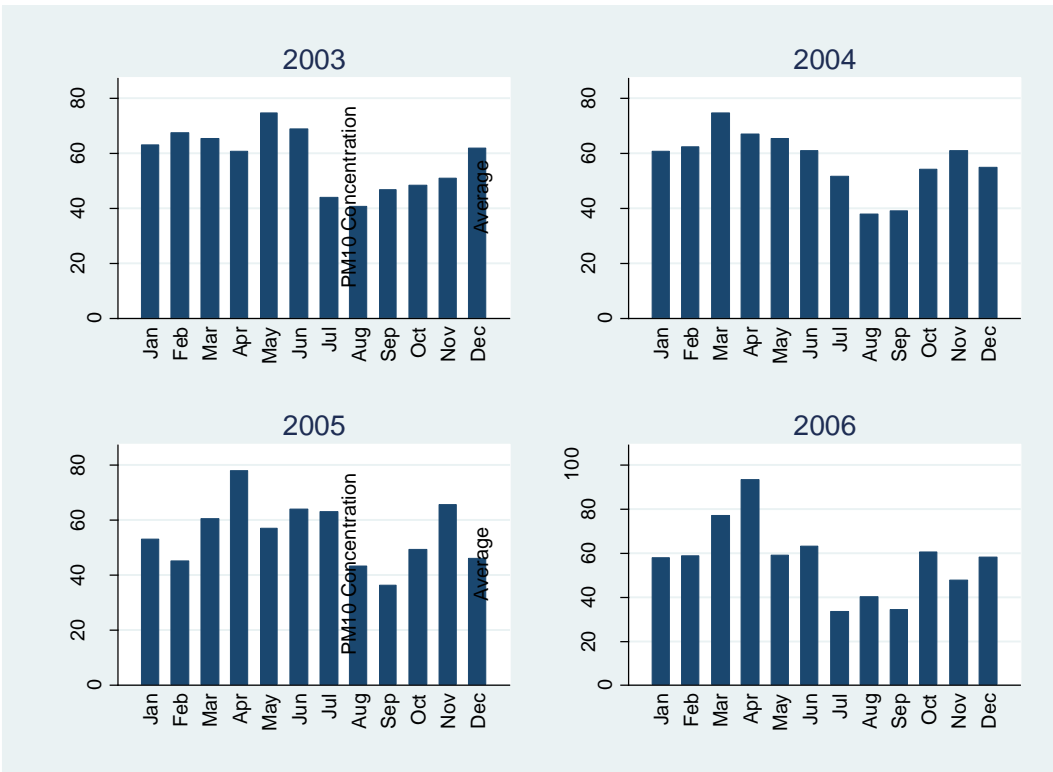
Figure 2
Average Daily PM10 Concentrations in each Region across Korea
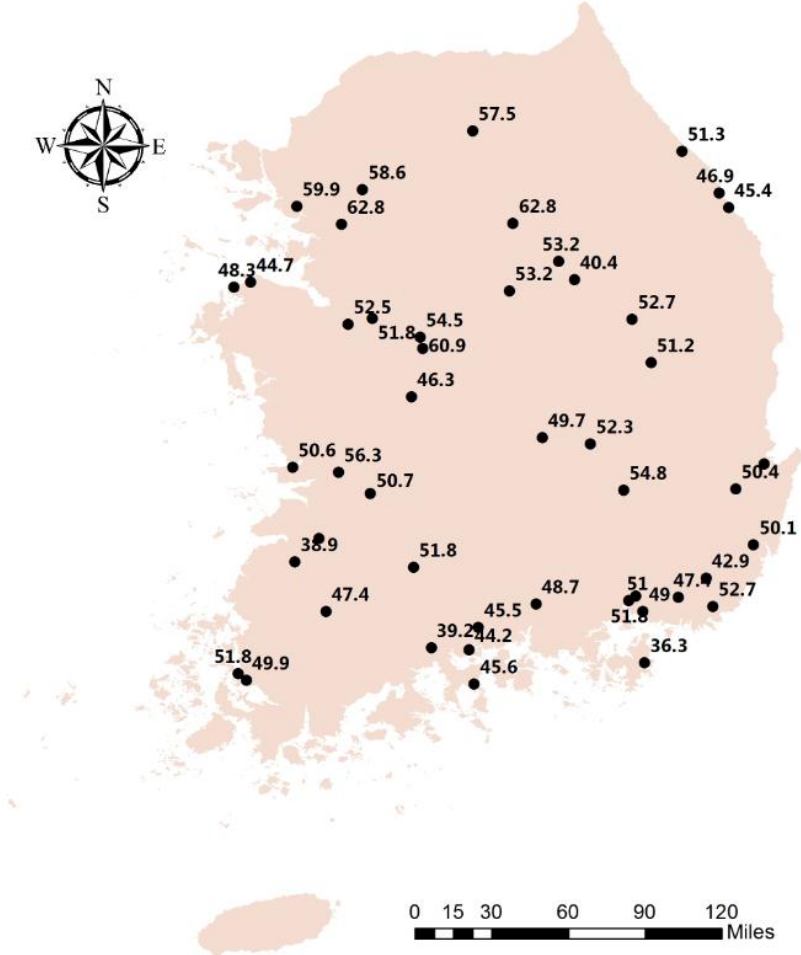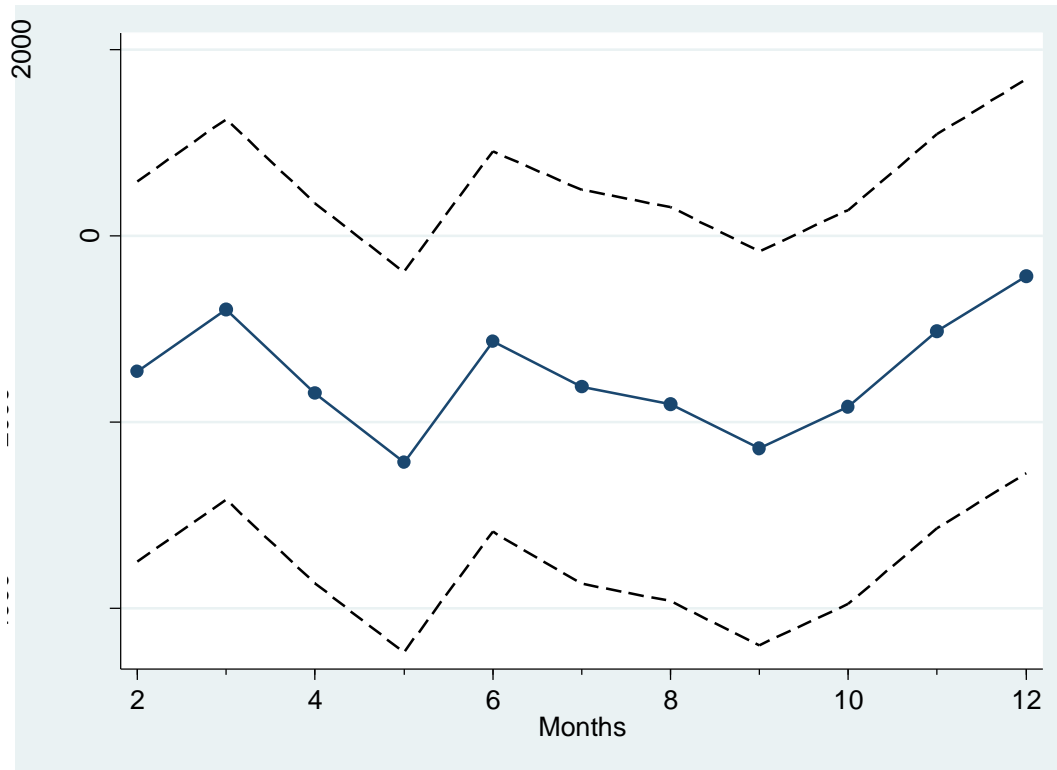**between years 2003 and 2011**

Figure 3
Conceptions by Month

The figure presents the estimates obtained from a regression with outcome variable Number of Conceptions in a month. The unit of observation is a month-year. The independent variables are month and year dummies. January is the omitted category. The solid connected line is the coefficient estimates of the month dummies. The dashed lines represent 2 standard deviation confidence intervals.

Appendix Table 1: Characteristics Infants and Parents in and out of Sample

Variable	In the Sample		Out of Sample	
	Mean	Std. Dev.	Mean	Std. Dev.
Birth weight	3257	430	3262	439
Low birth weight	0.030	0.180	0.030	0.180
Gestation	38.94	1.48	38.85	2.55
Premature	0.040	0.200	0.040	0.200
Fetal growth	83.54	10.20	83.63	10.43
Singleton	1.000	0.000	1.000	0.000
Girl	0.480	0.500	0.480	0.500
Second baby	0.380	0.480	0.390	0.490
Third baby	0.080	0.280	0.100	0.300
Married	0.990	0.100	0.980	0.140
Mother working	0.290	0.450	0.230	0.420
Mother's age 20-30	0.410	0.490	0.470	0.500
Mother's age 30-40	0.570	0.490	0.510	0.500
Mother's age 40+	0.020	0.120	0.020	0.120
Mother high school grad.	0.320	0.470	0.410	0.490
Mother college grad.	0.660	0.470	0.560	0.500
Father working	0.950	0.210	0.960	0.200
Father's age 20-30	0.180	0.380	0.220	0.420
Father's age 30-40	0.750	0.430	0.710	0.460
Father's age 40+	0.070	0.250	0.070	0.250
Father high school grad.	0.290	0.450	0.360	0.480
Father college grad.	0.690	0.460	0.610	0.490

Number of observations in the sample of births that are not included in the regressions is about 2.5 million.

Appendix Table 2: The Coefficients of the Full Set of Control Variables in Table 9

	(1)	(2)	(3)	(4)	(5)
	Birth Weight	Low Birth Weight	Gestation	Premature Birth	Fetal Growth
PM10	-1.241***	0.000***	-0.008***	0.001***	-0.016***
	(0.202)	(0.000)	(0.002)	(0.000)	(0.003)
Housing Price Index$_{t-9}$	0.333***	-0.000***	0.003***	-0.000***	0.004**
	(0.113)	(0.000)	(0.001)	(0.000)	(0.002)
White Collar Family	1.880*	-0.001	0.003	0.000	0.042*
	(0.998)	(0.000)	(0.003)	(0.000)	(0.023)
Advisories	5.399***	-0.003***	0.046***	-0.006***	0.054***
	(1.090)	(0.000)	(0.006)	(0.001)	(0.019)
Warnings	15.094***	-0.005***	0.094***	-0.007***	0.209***
	(1.418)	(0.001)	(0.008)	(0.001)	(0.028)
Yellow dust events	8.662***	-0.003***	0.058***	-0.006***	0.114***
	(0.427)	(0.000)	(0.002)	(0.000)	(0.007)
Temperature	-18.923***	0.005***	-0.141***	0.002	-0.203***
	(1.748)	(0.001)	(0.009)	(0.001)	(0.035)
Precipitation	-0.167***	0.000***	-0.001***	0.000***	-0.003***
	(0.031)	(0.000)	(0.000)	(0.000)	(0.001)
Girl	-98.022***	0.006***	0.134***	-0.008***	-2.795***
	(0.826)	(0.000)	(0.003)	(0.000)	(0.018)
Second baby	30.348***	-0.011***	-0.407***	0.000	1.677***
	(1.382)	(0.000)	(0.005)	(0.000)	(0.031)
Third baby	59.992***	-0.010***	-0.417***	0.007***	2.452***
	(1.983)	(0.001)	(0.006)	(0.001)	(0.049)
Married	31.388***	-0.011***	0.111***	-0.012***	0.591***
	(4.131)	(0.002)	(0.014)	(0.002)	(0.100)
Mother's age 20-30	67.169***	-0.007**	0.043*	-0.008*	1.626***
	(6.970)	(0.003)	(0.025)	(0.004)	(0.172)
Mother's age 30-40	65.313***	0.000	-0.029	-0.002	1.710***
	(6.911)	(0.003)	(0.025)	(0.004)	(0.171)
Mother's age 40+	22.993***	0.018***	-0.290***	0.021***	1.135***
	(7.428)	(0.004)	(0.030)	(0.005)	(0.183)
Mother high sch. grad.	44.026***	-0.010***	0.050***	-0.005***	1.034***
	(3.726)	(0.002)	(0.012)	(0.002)	(0.086)
Mother college grad.	51.570***	-0.016***	0.115***	-0.011***	1.100***
	(3.848)	(0.002)	(0.013)	(0.002)	(0.088)
Father's age 20-30	30.052**	-0.018**	0.028	-0.021***	0.740***
	(11.517)	(0.007)	(0.046)	(0.007)	(0.269)
Father's age 30-40	31.742***	-0.018**	0.036	-0.022***	0.766***
	(11.337)	(0.007)	(0.046)	(0.007)	(0.267)
Father's age 40+	22.727**	-0.011	-0.042	-0.013*	0.682**
	(11.062)	(0.007)	(0.046)	(0.007)	(0.258)
Father high sch. grad.	22.008***	-0.005***	0.015*	-0.003*	0.533***
	(3.146)	(0.001)	(0.009)	(0.001)	(0.077)
Father college grad.	28.682***	-0.009***	0.067***	-0.008***	0.606***
	(3.357)	(0.001)	(0.010)	(0.001)	(0.083)
N	1,376,282	1,376,282	1,376,282	1,376,282	1,376,282

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