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Chinese Yellow Dust and Korean infant health

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ABSTRACT

Naturally-occurring Yellow Dust outbreaks, which are produced by winds flowing to Korea from China and Mongolia, create air pollution. Although there is a seasonal pattern of this phenomenon, there exists substantial variation in its timing, strength, and location from year to year. 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 show that air pollution rises during Yellow Dust outbreaks and 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 born low weight. Public alerts about air quality during pregnancy help mitigate the adverse effect of pollution on fetal health. 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. We show that when the preventive effect of public health warnings is not accounted for, the estimated relationship between air pollution and infant health is reduced by more than fifty percent. In summary, air pollution has a deteriorating impact on newborns' health, and public alerts that warn individuals about increased air pollution help alleviate the negative impact.

1. 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 s/he was born. As explained by Bharadwaj et al. (2016), Currie (2011), Almond and Currie (2011), Currie (2009), infants who are heavier at birth end up being different in adulthood from those who have lighter birth weights. For example, they are taller as adults, have greater IQ scores, attain higher levels of education and earn more. Consequently, a sizable literature has investigated the impact on birth weight of its various determinants, ranging from smoking (Shoff and Yang, 2013; Grossman and Joyce, 1990) to prenatal care consumption (Mocan et al., 2015), to nutritional assistance for low-income families (Almond et al., 2011).

An important component of this investigation is the extent to which in-utero exposure to pollution impacts birth weight. The literature on the effect of air pollution on infant mortality is extensive (Greenstone and Hanna, 2014; Jayachandran, 2009; Currie and Neidell, 2005; Chay and Greenstone, 2003), there are relatively few studies examining the biological effect of pollution on birth weight. Examples of this limited area of inquiry include Currie et al. (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 toxic plant openings increase the incidence of low birth weight through detrimental effect on air pollution within a one-mile radius. Currie and Walker (2011) show that the introduction of E-ZPass (automated toll-collection) in highways of New Jersey and Pennsylvania reduced the incidence of low birth weight for infants born around the toll plazas due to the reduction in traffic congestion and the reduction in air pollution generated by it.

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

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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 allows 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. This weather event originates in the arid lands of Northern China and the desert regions of Mongolia Plateau. Winds with an abnormally high speed pick up dust and sand particles and carry them to the Korean peninsula. These winds, depending on their trajectory, may pick up other chemicals on the way. As a result, the Yellow Dust Events (YDEs) may cause an increase in PM (Particulate Matter) pollution whose chemical composition could be different from the PM pollution generated by manufacturing activity, or by fires (Choi et al., 2001; Li et al., 2012). Therefore, the impact on birth outcomes of PM pollution generated by YDEs could be different than that generated by industry (Chay and Greenstone, 2003), automobiles (Currie and Walker, 2011) or forest/agricultural fires (Rangel and Vogl, 2016).

Although there is a seasonal pattern of Yellow Dust Events, 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, Fig. 1A displays the average concentration of PM10 (particles with a diameter of 10 μm or less) by month between 2003 and 2011. The values reported in Fig. 1A are the average PM10 levels, aggregated over hourly readings in about 130 weather stations across South Korea. While pollution generally rises in the 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. Fig. 1B presents the distribution of the number of Yellow Dust Events during the same period. High levels of PM10 in a month coincide with more frequent Yellow Dust Events.

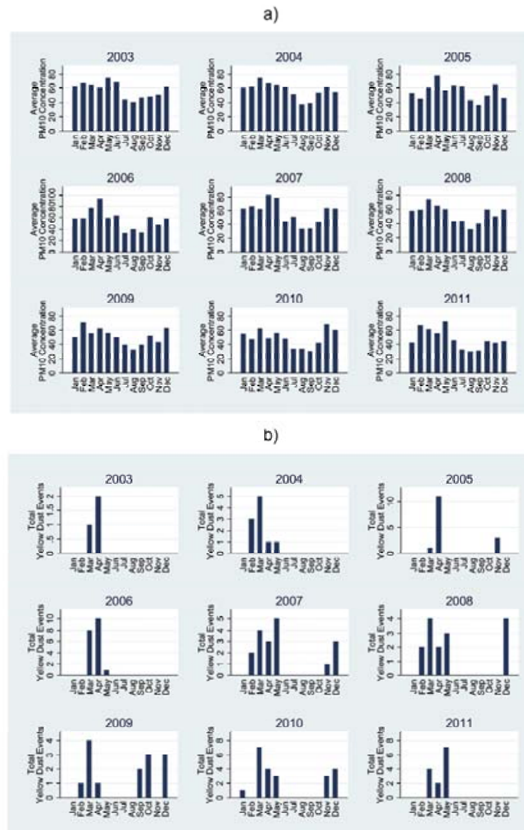

Fig. 1. A) Average Hourly PM10 Concentrations between 2003 and 2011. B) Number of Yellow Dust Events between 2003 and 2011.
Fig. 1A and B, respectively, present the monthly distribution of average hourly PM10 concentrations and the number of Yellow Dust Events between 2003 and 2011 in Korea.

Although the link between negative health outcomes and PM10 is well documented in the medical literature, the definitive biological mechanisms through which exposure to PM10 during pregnancy affects birth outcomes is unknown (Shah and Balkhair, 2011). However, according to one suspected mechanism, PM10 particles settle into expecting mother's lungs, and they are absorbed into blood. The bloodstream carries these particles to organs including placenta where the fetus is maintained. Such entry of particles leads to oxidative inflammation and it results in adverse birth outcomes (AHA, 2010; Liu et al., 2003). Another possible mechanism involves the entry of toxic matters into mother's body on the surface of the inhaled particles. These toxic matters ultimately interfere with the nourishment of the fetus and reduce the blood flow to the placenta (Liu et al., 2003). Also, Latzin et al. (2009) suggest a reduced lung function in newborns due to mother's PM10 exposure during her pregnancy.

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 avoidance behavior, although there are exceptions (e.g. Janke, 2014; Moretti and Neidell, 2011; Neidell, 2009). A contribution of our paper is the ability to account for avoidance behavior and to obtain estimates of the relationship between pollution avoidance and birth outcomes. We utilize various pollution alerts at the local level, issued by Korean authorities, to obtain estimates of association between pollution and infant health, as well as estimates of the improvement of infant health generated by pollution avoidance. Although Neidell (2009) and Moretti and Neidell (2011) implemented a similar approach when analyzing the impact of ozone on respiratory-related hospitalizations and asthma, our paper is the first to investigate the effectiveness of public air quality alerts on *birth outcomes*. Janke (2014), Moretti and Neidell (2011); Neidell (2009, 2004) also consider public warnings, but these papers focus on the effects of smog and ozone alerts on respiratory illnesses such as asthma in the general population, rather than birth outcomes. Furthermore, using the regression results, we obtain estimates of the willingness to pay to reduce air pollution and the cost of the avoidance behavior.

2. Yellow Dust, air pollution, and pollution alerts

Yellow Dust is a weather phenomenon originated in Northern China and the deserts of the Mongolian 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 they also take place irregularly during the winter months. These dust and sand particles are detrimental to human health, and they have adverse respiratory health effects, particularly among children and the elderly. Epidemiological literature has identified negative health consequences of Yellow Dust (Park et al., 2005; Lee et al., 2007). These studies typically suffer from small sample sizes and they focus on a small geographic area.

To reduce the risk of the Yellow Dust exposure, the Korean government has developed a warning system with behavioral guidelines. Since 2002, Korea 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 predicted to be between 500 and 1000 $\mu m/\mathrm{m}^3$ for over 2 h in a given day. A *Warning* is issued when the PM10 level is predicted to rise above 1000 $\mu m/\mathrm{m}^3$ for over 2 h. In February 2007, these thresholds were reduced to 400 and 800 $\mu m/\mathrm{m}^3$, 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. As documented by international media, during a Yellow Dust Event, Koreans respond by wearing preventive masks and staying indoors (The New York Times, April 12th, 2002, p.3. "China's Growing Deserts Are Suffocating Korea.").

PM10 concentrations in a city rise due to YDEs (as shown in Fig. 1A and B which display the monthly distributions of average PM10 concentrations and YDEs in our sample period 2003–2011, respectively). To investigate the relationship between YDEs and PM10 more formally, we estimate a regression where the unit of observation is a city-day. In this regression, the outcome variable is the average PM10 level in a city on a specific day. The control variables include a dummy variable for whether a YDE is observed in the city on that day, this variable's 3-day lags and leads as well as city fixed effects, and month and year dummies. This estimation procedure is similar to that of Goel and Gupta (2015) who estimate the impact of metro expansions on air pollutants in Delhi, India. Fig. 2 summarizes the results. The PM10 concentration in a city starts rising one day before the YDE, and it peaks on the day of the YDE (denoted by the vertical line). On the day after the YDE, the PM10 level starts to decrease but remains higher than the average of the city. PM10 concentration returns to its baseline only after two days following the Yellow Dust Event. These results indicate that average daily PM10 concentrations increase by about 40 $\mu m/\mathrm{m}^3$ within the 3-day window of a Yellow Dust Event.

3. Methods

3.1. Empirical specification

Following past literature (Arceo et al. 2016; Lepeule et al., 2012; Linares and Díaz, 2010; Samoli et al., 2005), which suggests a linear relationship between PM10 exposure and health outcomes, we estimate the equation depicted below:

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

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 2500 g), 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). The Korean birth certificate data released to us contain 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 by 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 mother throughout the duration of her pregnancy that ended with the birth of the child on day t in city c.

The vector $\boldsymbol{Alerts_{ict}}$ represents the two variables that measure the total number of days in which a public notification has been issued in the mother's city of residence during her pregnancy that ended at time t. There are two types of public alerts: *Advisories* (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 1000 $\mu m/m^3$ [800 since 2007]). These alerts are issued based on the Korean Meteorological Administration's *predictions* of future PM10 levels. That is, there is no mechanical relationship between the alerts and PM10 levels. We also include in the regressions the number of days a Yellow Dust Event is observed in the mother's city during her pregnancy. This is denoted by YDE_{ict} in equation (1).

$\boldsymbol{X}$ 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 potentially impact health outcomes, and they 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).

The vector $\boldsymbol{X}$ also contains other variables that impact infant's birth weight, including infant's gender and indicators for whether

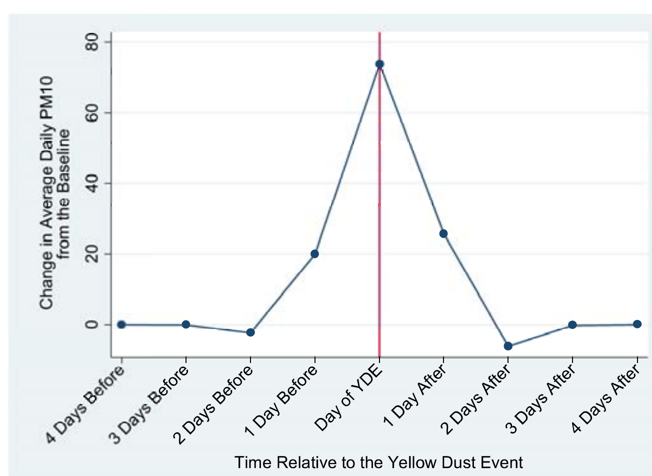

Fig. 2. Effect of Yellow Dust Events on PM10.
The figure displays the results obtained from a regression where the unit of observation is a city-day. The outcome variable is the average daily PM10 concentration. The connected line presents the point estimates of lags and leads of a dummy variable that takes the value of one if there was a Yellow Dust Event in that city on a specific day (YDE). We include three lags, three leads and the current YDE. We also control for city fixed effects, month and year dummies.

the infant was the mother's second, or third or higher pregnancy. $\boldsymbol{W}$ 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 time-invariant characteristics of cities such as the extent of economic development, urbanization and access to health care. In addition, Equation (1) contains $\boldsymbol{\theta_t}$ which represents a vector of dummies for year-of-conception and month-of-conception of the infant who is born on day *t*. Standard errors are clustered at the city level. We also experimented with clustering at the birth-month level. We found that while standard errors increase somewhat, the conclusions of the paper are unchanged.

3.2. Data

We have information on all births in Korea between 2003 and 2011, obtained from Vital Statistics-Natality Files provided by Statistics Korea MicroData Service System. Birth certificates provide information about the infant (such as gender, birth weight, gestational length and the birth order) and the parents (such as their age, education level, employment status, and marital status). Also, the month, year and the city of the birth are reported. The birth certificate data set only includes month and year of birth, but not day of birth. In our analyses, we assumed that infants are born on the 15th day of the month reported in the certificate. Following the literature, we restrict our sample to singleton births with gestational age between 27 and 42 weeks.

We augment the birth certificate data with data on city's air quality, Yellow Dust Events public notifications and weather conditions. To proxy for air quality, we use PM10 (objects in the air that are smaller than or equal to 10 μm in diameter) concentration which is measured hourly by the monitoring stations in cities. These PM10 data are obtained from National Institute of Environmental Research in Korea. The variable *PM10* is the average hourly PM10 concentration in the city of residence of the mother during her pregnancy. If there are multiple stations in a city, we use the average of their measures. Fig. 3 shows the average daily PM10 concentrations in each region across Korea between years 2003 and 2011 in our sample. 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 in Geoje-si, the most-Southeastern region used in our sample, the ambient PM10 level was about 36 $\mu m/m^3$ during the same time period. We obtain weather conditions data (precipitation and temperature) from the annual climatological report provided by the Korea Meteorological Administration (KMA).

Although there are about 4 million births between 2003 and 2011, our estimation sample contains about 1.5 million of these births because of two reasons. First, births in most locations cannot be matched reliably with measures of air pollution because PM10 is not measured or not measured consistently in these locations. Second, some regions such as Jeong-eup in North-Jeolla province are excluded at the advice of the KMA because of the inaccuracy of the Yellow Dust outbreak indicators in those areas.

One might also be concerned that birth weight data could be systematically missing for children born at home rather than in a hospital or in a medical institution. However, this is not the case for our data set. We observe the universe of birth certificates data, regardless of the type or location of delivery. Also, home births make up a very small share of the births in Korea. For example, in our sample, the share of home births (reported on birth certificates) among all births is only 1.09%.

The descriptions and the summary statistics of the variables are presented in Table 1. The average Korean infant was born just above 3200 g with gestational age of 39 weeks. This is similar to the average birth weight of U.S. born babies, 3320 g (Mocan et al., 2015). Average hourly PM10 exposure of a mother during pregnancy is about 54 $\mu m/m^3$. Due to Yellow Dust outbreaks, mothers experienced about 1.7 *Advisories* and 0.5 *Warnings* during pregnancy. The average Korean mother experienced 7 *Yellow Dust Events*. 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.

4. Results

4.1. 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 control variables that measure temperature and precipitation in the city where the birth took place, sex and birth order (second, third+) of the newborn, and attributes of the parents such as their marital status, age, employment status and educational attainment. To preserve space, we only report the coefficients of the variables of interest. The estimates of the full set of control variables are presented in Web Appendix Table 1. The regressions additionally 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 2500 g (column 2), gestational age in weeks (column 3), an indicator for whether the infant's gestational age is fewer than 37 weeks (column 4), and the ratio of birth weight to gestational age (column 5). Standard errors, reported in parentheses, are clustered at the city level. Similar results are obtained when we cluster standard errors at the birth-month 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 g reduction in newborn's birth weight. This indicates that a 10-percent increase in the average hourly PM10 exposure reduces birth weight by about 0.13% (from the baseline of 3,257 grams).

The results of column (1) in Table 2 also indicate that each additional pollution *Advisory* and *Warning* that a mother experiences during her pregnancy is associated with an increase in the birth weight of the infant by 4.4 and 13.6 g, 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*. Therefore a warning, which is associated with stronger health risk, may prompt a stronger avoidance response. The coefficient of *Yellow Dust Events* in column (1) indicates that the birth weight of the infant increases by about 8.6 g for each additional day a Yellow Dust Event is declared during pregnancy. 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 expecting mother.

Similar to those in column (1), the results presented in columns (2)–(5) in Table 2 provide evidence for the detrimental effect of PM10 exposure and the preventative 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 are associated with an increase in the gestational age of the infant, the probability of premature birth and its average fetal growth, while a rise in PM10 exposure reduces them.

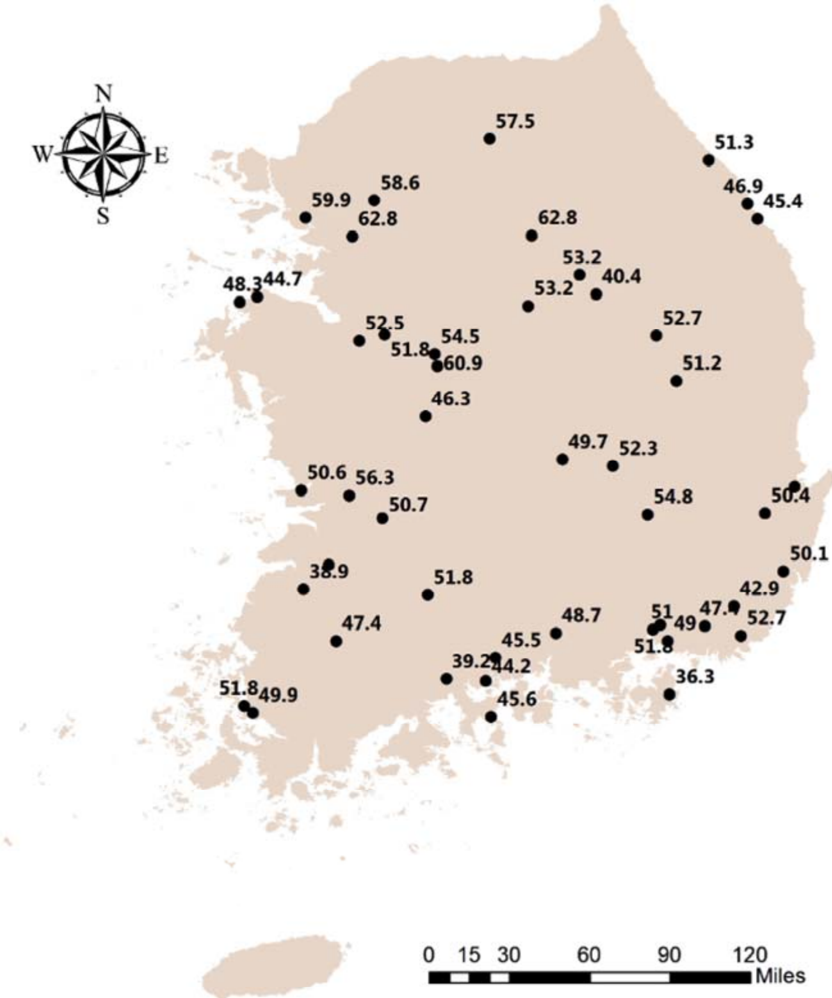

Fig. 3. Average Daily PM10 Concentrations in each Region across Korea 2003–2011.
The Figure presents the average hourly PM10 concentrations in different regions of Korea during our sample period between 2003 and 2011. Although PM10 concentrations are available at the weather station level in a region, 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.

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 days in which a Yellow Dust outbreak impacts the city of the infant's birth.	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 (cm.)	125.26	46.77

Notes: Summary statistics and the descriptions of the full set of variables used in our estimations are presented. Sample consists of 1,549,376 observations. Unit of observation is newborn baby. Other control variables include indicators for whether the infant is a girl, birth order (2nd, 3rd+), and parental characteristics such as the marital status of the parents, parents' age, education and employment status.

4.2. The effect of pollution on birth outcomes when avoidance is omitted

In Table 3 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 3 is similar to Table 2, except for the pollution alert variables. In the interest of space, we only report the coefficients of the PM10 variable. The estimates of the remaining control variables are reported in Web Appendix

Table 2
The effect of alerts and air pollution on birth outcomes.

	(1) Birth Weight	(2) Low Birth Weight	(3) Gestation	(4) Premature Birth	(5) 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)
N	1,549,376	1,549,376	1,549,376	1,549,376	1,549,376

Outcome variables are baby's weight at birth in grams, an indicator for whether baby's birth weight is less than 2500 g, 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. In addition to the variables listed, regressions include control variables that measure temperature and precipitation in the city where the birth took place, sex and birth order (first vs. second … etc.) of the newborn, and attributes of the parents such as their marital status, age, employment status and educational attainment. We report only the coefficients of the variables of interest. Estimates of the control variables are reported in Web Appendix Table 1. 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 3
The effect of air pollution on birth outcomes without controlling for pollution alerts.

	(1) Birth Weight	(2) Low Birth Weight	(3) Gestation	(4) Premature Birth	(5) Fetal Growth
PM10	−0.232**	0.0001**	−0.001	0.0001***	−0.005*
	(0.101)	(0.0000)	(0.001)	(0.0000)	(0.003)
N	1,676,096	1,676,096	1,676,096	1,676,096	1,676,096

Outcome variables are same as Table 2. Regressions include the whole set of covariates as in Table 2 *except* Advisories, Warnings, and Yellow Dust Events. We report only the coefficients of the variable of interest. Estimates of the control variables are reported in Web Appendix Table 2. Standard errors clustered at the city level are presented in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 2. The coefficients of PM10 in columns (1)–(5) of Table 3 indicate that PM10 is harmful to 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 3 (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 g reduction in the newborn's birth weight. This same effect is estimated to be 0.8 g 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 3 reveals that the failure to account for the beneficial effect of pollution warnings on health generates a substantial underestimation of the negative impact of pollution on health.

4.3. Robustness checks and extensions

Fig. 1A and B clearly indicate that pollution levels increase and more YDEs occur in months of March and April. Because this seasonality may be known to parents, they could take preventive action. For example, parents may time the pregnancy such that the entire pregnancy period does not overlap with YDE seasons of March–April. If this is the case, then our estimates in Tables 2 and 3 are biased. We investigated this possibility by looking at the timing of conceptions. If parents try to time the pregnancy such that it does not overlap with the YDE seasons in March and April, then they should time the conception so that it takes place during May–June. This is because, the expected duration of pregnancy is about 40 weeks, and consequently, infants who are conceived in May and June of a given year are expected to be born in January–February of the next year. In this scenario, the entire pregnancy is expected to be outside of the high-pollution season. The upshot is that if parents time the pregnancy to avoid high-pollution months, then we should observe a spike in the number of conceptions in Mays and Junes.

The monthly distribution of conceptions depicted in Fig. 4, however, suggests no significant increase in the number of conceptions during months favorable in terms of pollution avoidance. We also estimated a regression where the unit of observation is a month-year. The outcome variable is the number of conceptions. We included year and month dummies, omitting May and June. The coefficients of five of the ten month dummies are positive (January, March, April, November and December), while the coefficients of the remaining months are negative. None of these month dummies were statistically significant. These findings provide evidence against the conjecture that parents time their pregnancies to avoid high-pollution seasons.

To investigate if the impact of air pollution and of alerts are different in different developmental stages of the fetus, we include in the regressions variables gauging 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). The results, displayed in Web Appendix Table 3, are similar to those reported in Table 2. The number of *Advisories, Warnings* and *Yellow Dust Events* experienced in any trimester have a positive and significant impact on birth weight. These effects are not statistically different from each other between trimesters. Consistent with Currie et al. (2009), we find that 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.

Exposure to pollution or avoidance of pollution *should not* impact birth outcomes *after the birth of the infant*. Thus, 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 include average PM10 and the number of alerts

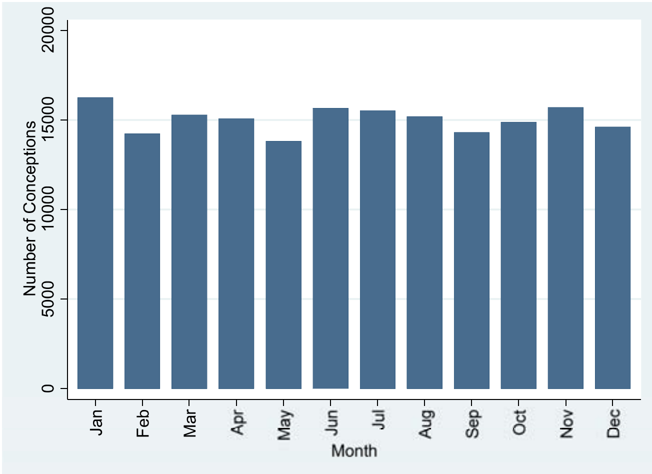

Fig. 4. Monthly Distribution of Number of Conceptions 2003–2011.
Distribution of number of conceptions over the months of the year, in our sample between 2003 and 2011.

30–120 days after the delivery of the baby in the regressions. As expected, the results, displayed in Web Appendix Table 4 show that mother's exposure to poor air quality or the pollution alerts *after* she delivered the baby does not have any influence on the birth weight of the baby.

Our main results in Table 2 indicate that air pollution alerts help reduce the detrimental effect of pollution on birth weight and gestational age. This finding is consistent with the hypothesis that mothers avoid/reduce outdoor 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 outdoors. No such data, however, are available. Instead, we use 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. We test this hypothesis using data from Korean soccer games between 2004 and 2011. Our results, displayed in Web Appendix Table 5, show that if a YDE is declared or a Warning is issued on a game day, attendance to that game is reduced by about 3400 and 7000 fans, respectively (from the mean of 12,500). Average PM10 and whether an advisory was issued on the game day were statistically insignificant. These results support the premise that individuals avoid spending time outside during days of pollution warnings and Yellow Dust Events.

We also tested whether the impact of PM10 and pollution alerts have differential impacts in subsamples that are separated by mother attributes (Llopa et al., 2011). The results indicate that there is no appreciable difference in the impact of pollution and that of alerts between the following groups: (1) Mothers who reside in North and North West Korea (Seoul, Gangwon and Chungnam) vs. the rest of Korea; (2) Mothers who live in regions with average PM10 level greater than the median vs. lower than the median; (3) Mothers with at least a college degree vs. mothers with less than college education; (4) Firstborn babies vs. non-firstborn babies (5) Working mothers vs. mother who are not working. We present the estimates in Web Appendix Table 6.

Other robustness checks, such as the potential geographical self-selection of parents by their income or education, and potential correlation between economic development and pollution are discussed in the Web Appendix.

5. 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 by reducing the negative impact of pollution on birth weight. Therefore, an increase in PM10 affects birth weight both directly and indirectly. Thus, holding constant other determinants of birth weight (BW), the total change of BW with respect to a change in $PM10$ is given by equation (2):

$$\frac{dBW}{dPM10} = \frac{\partial BW}{\partial PM10} + \frac{\partial BW}{\partial Avoid}\frac{\partial Avoid}{\partial Alert}\frac{\partial Alert}{\partial PM10} \tag{2}$$

The first term on the right-hand side of Equation (2) 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

$$WTP = \frac{\partial BW}{\partial PM10} \times B \tag{3}$$

where B is the economic benefit associated with a one-gram increase in birth weight. The term ($\frac{\partial BW}{\partial PM10}$) in equation (3) is the direct biological effect of pollution on birth weight. The coefficient β_1 in Equation (1) is an estimate of $\frac{\partial BW}{\partial PM10}$ because the regression in Equation (1) controls for the impact of avoidance (*Advisories, Warnings* and *Yellow Dust Events*). Thus, the estimate of the WTP in Equation (3) provides the loss associated with the decline in infant health due to an increase in PM10.

Re-writing equation (2) and multiplying both sides with B yields Equation (4):

$$\frac{\partial BW}{\partial PM10} \times B = WTP = \left(\frac{dBW}{dPM10} \times B\right) - \left(\frac{\partial BW}{\partial Avoid}\frac{\partial Avoid}{\partial Alert}\frac{\partial Alert}{\partial PM10} \times B\right) \tag{4}$$

Equation (4) 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 t, $\left(\frac{dBW}{dPM10}\right)$.

Given that one can calculate WTP, as well as the first component of WTP on the right-hand side of Equation (4), 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 by pregnant women. The derivation of the cost of avoidance is discussed in the Web Appendix.

Our results in Table 2 (column 1) show that the impact of a 10% increase in PM10 on birth weight ($\frac{\partial BW}{\partial PM10}$), conditional on avoidance, is 4.3 g (using the coefficient of −0.8 in column 1 of Table 2). This represents a 0.13% decrease from the baseline average of 3257 g. Black et al., (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 (OECD Statistics). 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 $18. 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 annual birth cohort of Koreans is $8.5 million.

The estimated coefficient of PM10 reported in column (1) of Table 3 corresponds to $\left(\frac{dBW}{dPM10}\right)$. This is because the models reported in Table 3 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 0.04%; and using the same B as above, this produces a cost of $2.5 million for one annual birth cohort of Korean babies ($\frac{dBW}{dPM10} \times B$ in equation (4)). This implies that the cost of avoidance is $6 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.

6. Summary and conclusion

In this paper, we investigate the impact of air pollution on infant health using information on more than 1.5 million live births in Republic of Korea. The novelty of our analysis 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. We show that PM10 level in a city increases by 40 $\mu m/\mathrm{m}^3$ around the 1-day window around the Yellow Dust Event (one day prior, day of and subsequent day). Although there is a seasonal pattern of this phenomenon, 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.

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.

We find that, controlling for temperature and precipitation, and for a host of attributes of the mother and the family, exposure to air pollution during pregnancy is negatively associated with birth weight, gestation weeks of the baby, and the propensity of the baby being low weight (less than 2500 gr). Specifically, we find that the elasticity of birth weight with respect to average exposure to PM10 during pregnancy is 0.013. This estimate is similar to elasticity estimates ranging between 0.01 and 0.05 in previous papers (e.g. Currie et al., 2009; Coneus and Spiess 2012). Public notifications about air quality mitigate the negative effect of air pollution on fetal health. Using data on professional soccer matches, we show that attendance at soccer games is significantly impacted by public notification on air quality, which demonstrates public's avoidance response to air pollution alerts.

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 more than 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 $8.5 million (in 2010 dollars) for one annual birth cohort of babies, and the corresponding cost of avoidance is $6 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.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.socscimed.2017.05.031.

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