GREY MATTERS
PRELIMINARY DRAFT. PLEASE DO NOT CITE.

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ABSTRACT. This paper examines the impact of fetal exposure to air pollution on 4th grade test scores in Santiago, Chile. Data on air quality alerts and the use of siblings fixed effects estimation allow us to address several potentially important concerns about endogenous exposure to poor environmental quality. We find a strong negative effect from fetal exposure to carbon monoxide (CO) on math and language skills. Sibling fixed effects estimates are larger than OLS estimates, suggesting that controlling for unobserved, time invariant characteristics of families is important in this context. Consistent with theory, controlling for avoidance behavior modestly increases the magnitude of our estimates. We estimate that the 50% reduction in CO in Santiago between 1990 and 2005 increased lifetime earnings by approximately 100 million USD per birth cohort.

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1. Introduction

Human capital has long been recognized as an important contributor to aggregate income and economic growth (Schultz 1963, Nelson and Phelps 1966, Romer 1986). Moreover, growing literatures in public health and economics suggest that prenatal and early childhood health play an important role in human capital formation over the lifecycle (Cunha and Heckman 2008, Currie and Hyson 1999, Almond and Currie 2011, Graff Zivin and Neidell 2012). Yet, despite a large literature documenting the adverse effects of pollution on contemporaneous childhood health,[1] only a handful of studies have examined the impacts of early-life exposures on long-term human capital outcomes (Almond, Edlund, and Palme 2009, Sanders 2012, Black, Bütikofer, Devereux, and Salvanes 2013).[2] Elucidating this relationship is particularly important from a policy perspective because short run changes in pollution can lead to lifelong changes in well-being. Such changes may well be an important addition to the acute morbidity costs that form the basis of current regulatory standards. Moreover, this research may shed light on the micro-foundations that underpin the relationship between early life exposure to pollution and labor market outcomes found in recent literature (Isen, Rossin-Slater, and Walker 2014).

Estimating the relationship between fetal pollution exposure and human capital outcomes later in life is challenging for two reasons. First, datasets that link environmental and human capital measures over an extended period of time are quite rare. Second, exposure to pollution levels is typically endogenous. Families can engage in both short- and long-run avoidance behaviors to reduce exposure: for example, curtailing outdoor activities or moving to a cleaner location. To avoid these difficulties, research in this area has focused on quasi-experimental variation in exposure induced by nuclear accidents or nuclear testing in data-rich Scandinavian countries (Almond et al., 2009; Black et al., 2013), or policy-induced variation coupled with strong assumptions about individual mobility (Sanders 2012).

In this paper, we employ a unique panel dataset from Santiago, Chile, to examine the impacts of fetal carbon monoxide exposure on children's performance on high-stakes national tests in primary and middle school. The richness of our data allows us to overcome these challenges and improve upon the existing literature in several important dimensions. First, we can directly link vital statistics and education

[1]For recent examples see Currie and Walker (2009), Schlenker and Walker (2011), Knittel, Miller, and Sanders (2011), Arceo-Gomez, Hanna, and Oliva (2012), Currie, Graff Zivin, Meckel, Neidell, and Schlenker (2013).

[2]A notable exception is the literature focused on exposure to lead, a neurotoxin with well documented impacts on brain development even at modest concentration levels (Sanders, Liu, Buchner, and Tchounwou 2009). Long-term consequences include negative impacts on: schooling outcomes, criminal behavior, and economic productivity (Reyes 2007, Nilsson 2009, Rogan and Ware 2003).

data through unique individual identifiers. Geographic identifiers allow us to further link to data from a network of pollution monitors operated by the Chilean Ministry of Environment. Moreover our study period, which includes the universe of births between 1992 and 2002, corresponds to a period when sustained economic growth and new environmental policy allowed Santiago to transition from high levels of pollution to more modest ones.

Second, we exploit a multi-pronged approach to address the endogeneity of pollution exposure. Endogeneity of pollution exposure is a common problem in such an exercise; while prior studies have used instrumental variables approaches to solving this problem(Schlenker and Walker 2011, Knittel, Miller, and Sanders 2011, Currie and Walker 2009), we address this threat to identification through sibling comparisons that purge estimates of all time-invariant family characteristics, including those that might spuriously influence our core relationship of interest in ways that would otherwise be unobservable to the econometrician. As we will detail below, using sibling fixed effects yields results that are quite a bit larger than OLS estimates, suggesting an important role for family level characteristics.[3] We also exploit data on air quality alerts to address short-run time-varying avoidance behavior, which has been shown to be important in a number of other contexts (Neidell, 2009; Graff Zivin and Neidell, 2009; Deschenes and Greenstone, 2011; Graff Zivin et al., 2011).

Finally, this paper is novel in at least two additional ways. We are the first to examine the impacts of fetal pollution exposure on cognitive outcomes outside of a developed country setting. With pollution becoming an important issue in developing countries, particularly China and India, understanding how environmental quality impacts human capital and the implicit tradeoffs across economic growth paths is of critical importance. It is also worth noting that our estimates are readily useful for modern-day environmental policymakers in the developed world. The pollutants we study are criteria air pollutants that are regularly emitted as a byproduct of fossil fuel combustion and subject to regulation across the developed and developing world.

2. Scientific Background

A large literature in medicine and epidemiology has linked exposure to various pollutants and toxins in utero to poor birth outcomes as well as health later in life (see Currie et al. 2014 for an excellent

[3]Note that Almond, Edlund, and Palme (2009) also use a sibling FE framework. Since endogenous exposure to fallout from the Chernobyl accident in their setting is a minimal concern, while exposure was made quite salient to individuals ex post, they interpret their findings as shedding light on parental investments rather than sorting.

review). We focus on carbon monoxide (CO) exposure because CO is the only criteria air pollutant known to cross the placental barrier. Moreover, a recent multi-pollutant study that included data on PM, CO, O3 found that only CO exhibited consistent negative effects on infant and child health (Currie, Neidell, and Schmieder 2009). While the precise mechanism via which CO exposure results in mortality or decreased cognitive function is unknown, a potential mechanism linking in utero exposure to pollutants and long term outcomes such as cognitive achievement is cardiovascular and respiratory function. Exposure to carbon monoxide in utero and in early childhood has been linked with lower pulmonary function (Mortimer et al 2008, Neidell 2004, Plopper and Fanucchi 2000). In addition, there are several studies that suggest a link between various pollutants, including CO, and the development of other vital organs in-utero (Sly and Flack 2008).

Carbon monoxide is an odorless and colorless gas that is largely emitted through motor vehicle exhaust (Environmental Protection Agency, January 1993, 2003b). CO binds to the iron in hemoglobin, inhibiting the body's ability to deliver oxygen to vital organs and tissues. The detrimental effects of CO exposure are magnified in utero. First, the reduced oxygen available to pregnant women means less oxygen is delivered to the fetus. Second, carbon monoxide can directly cross the placenta where it more readily binds to fetal hemoglobin (Margulies 1986) and remains in the fetal system for an extended period of time (Van Housen et al., 1989). Third, the immature fetal cardiovascular and respiratory systems are particularly sensitive to diminished oxygen levels. Indeed, most of the damaging effects of smoking on infant health are believed to be due to the CO contained in cigarette smoke (World Health Organization, 2000).

Because carbon monoxide is a combustion byproduct, it typically occurs together with fine particulate matter (PM), a mixture of solid particles and liquid droplets found in the air. (In our setting the correlation between ambient levels of CO and PM typically exceeds .9; see Table A1.) Particulates less than 10 micrometers in diameter (PM10) - the width of a single human hair - pass through the lungs and enter the bloodstream, causing potentially serious health problems. Unlike CO, PM has no direct effects on the fetus, as fine particles cannot cross the placenta. (Any damage to the fetus from PM would be indirect, through impaired function in the mother.) This important physical difference helps motivate our focus on CO.

In most urban environments, CO exhibits a strong seasonal pattern, with high levels in winter and lower levels in summer. Ozone exhibits the oppostite pattern, with high levels in summer and lower levels in winter. If we failed to control for ozone, we might erroneously find that high CO was beneficial because it was correlated with low ozone. Ozone affects respiratory morbidity by irritating lung airways, decreasing lung function, and increasing respiratory symptoms (Environmental Protection Agency, 2006). As with PM10, the principal route through which ozone might affect the fetus is indirect, through the diminished health of the mother. We control for these indirect ozone effects in order to isolate the deleterious effect of CO.

3. Data

In order to measure the effect of in utero pollution exposure on middle school test scores, we require data from several broad categories. This section describes how we construct a dataset that links data on births, pollution, and test scores. Our analysis is based on the universe of births in Santiago, Chile between 1992 and 2001 and their subsequent test scores in 2002-2010.

3.1. **Birth Data**

Birth data come from a dataset (essentially the Vital Statistics of Chile) provided by the Health Ministry of the government of Chile. This dataset includes information on all the children born in the years 1992-2001. It provides data on the sex, birth weight, length, and weeks of gestation for each birth. It also provides demographic information on the parents, including their age, education and occupational status. Importantly, these data contain a unique code for the mother, allowing us to identify offspring from the same mother, and thus implement sibling fixed effects.

3.2. **Environmental Data**

Air pollution data for the period from 1998-2002 come from the Sistema de Informacion Nacional de Calidad del Aire (SINCA), a network of monitoring stations operated by the Chilean Ministry of Environment. Earlier data 1992-1997 come from the Monitoreo Automatica de Contaminantes Atmosfericos Metropolitana (MACAM1) network, also operated by the Ministry. Our analysis is based on data from the balanced panel of 3 monitors that operate during our entire study period. Using municipality centroids, we match municipalities to the nearest monitor, with the exception of the monitor in Las Condes. The monitor in Las Condes experiences dramatically different pollution patterns due to its high altitude, as it is on the foothills of the surrounding Andes. According to Gramsch, Cereceda-Balic, Oyola, and Von Baer (2006), inversion layers, which are correlated with extremely high pollution events, occur at altitudes that are *lower* than this monitor; as a result, this monitor shows much lower readings of CO than other monitors in Santiago. Hence, we match residents in Las Condes to the readings of the Las Condes monitor, but match residents in other parts of Santiago to either of the two more centrally located monitors in Parque O'Higgins and La Independencia. According to Osses, Gallardo, and Faundez (2013), these two monitors in the downtown area are representative of the pollution patterns in Santiago, and the Las Condes monitor while "specific" to the pollution patterns of that area, is not representative.

CO data during our study period is consistently available as an 8-hour moving average. We take the daily average CO and then compute the mean exposure at the trimester level. We apply a similar procedure to construct weather and atmospheric controls. Meteorological data come from the NOAA Summary of the Day for the monitor at Comodoro Arturo Merino Benitez International Airport (SCL). Data on particulate matter less than 10 microns in diameter (PM10, measured as a 24-hour moving average) and ozone (O3, measured hourly) come from the same monitoring sites as our CO data.

Using consistently measured data on CO, PM_{10} and O_3, we compute daily AQI measures for Santiago using the algorithm employed by the EPA (EPA 2006). Seasonality in the AQI correlates well with the patterns seen in CO during the year, as is evident from Figure 1. Air quality is worst during the winter months in Santiago when thermal inversions are common.

Figure 1 also shows long-run levels of CO and AQI, where both pollutants have been standardized to 1 starting in 1992 (the first year of data). As in the seasonal graphs, the two series track each other closely. Starting in the mid 1990's the government of Chile implemented a wide range of measures to curb the drastically high levels of pollution, particularly PM_{10} and associated pollutants like CO. The most serious of these measures started in 1997 under the PPDA (Bharadwaj and Mullins 2013). As a result, in the time period we study, we see a rather steep decline in levels of CO and the AQI.

3.3. **Education Data**

The data on school achievement come from the SIMCE database, which includes administrative data on test scores for every student in the country between 2002 and 2008.[4] The SIMCE is a national standardized test administered to all schools in Chile. The SIMCE test covers three main subjects: mathematics, science, and language arts. It is administered to every student in grade 4, as well as 8 and 10 depending on the year. It is used to evaluate the progress of students against the national curriculum goals set out by

[4] This database was kindly provided by the Ministry of Education of Chile (MINEDUC).

MINEDUC, and is constructed to be comparable across schools and time. The education data sets were subsequently matched to the birth data using individual level identifiers. For more on the match quality please see Bharadwaj, Loken and Neilson (2013).

4. Econometric Approach

Our goal is to estimate the effect of in utero pollution exposure on human capital outcomes later in life. The primary estimating equation uses test scores as the dependent variable and pollution exposure in each trimester as the independent variables of interest. Trimesters are computed using the birth date and the baby's estimated gestational age. The median gestational age in our data is 39 weeks. We assign weeks 1-13 to trimester 1, weeks 14-26 to trimester 2, and weeks 27-birth to trimester 3.[5] Since we have the exact date of birth and gestational age, we are able to accurately construct the history of gestational exposure to ambient air quality. We include all trimester exposure measures in a single specification, along with relevant temperature and other weather variables. Our basic estimating equation is:

$$S_{ijrt} = \beta E_{rt} + \overline{\theta_t} + \overline{\chi_i} + \bar{\gamma}\overline{W_t} + \epsilon_{ijrt} \tag{1}$$

The dependent variable S_{ijrt} is 4th grade test score in either math or language of child i, born to mother j, in municipality r, at time t. $\overline{\theta_t}$ is a vector of year and month dummies interacted with three monitor dummies (month dummies capture important seasonal effects, which differ markedly by monitor), and $\overline{\chi_i}$ is a gender dummy. $\overline{W_t}$ includes a host of weather controls (temperature, precipitation, fog, dewpoint and wind), measured at the trimester level. Since it is important to control for weather in a flexible manner, we use a polynomial in the trimester average of precipitation, fog, dew point and wind. Given its role in forming ozone, we pay special attention to temperature. For ozone and for human health and performance, controlling for higher temperatures is very important. Hence we create 10 degree bins for each trimester, which are based on the *maximum* temperature, and count the number of days in each bin. For example, we include three variables (one per trimester) counting the number of days with a maximum temperature between 20 and 30 degrees Farenheit. These weather variables are important not only because they are correlated with air quality, but also because they have direct effects on maternal behavior and fetal health.

[5]While it is easier to interpret and aggregate coefficients at the trimester level, results at the gestational month level also show similar results.

E_{rt} contains the average level of one or more pollutants, also measured at the level of gestational trimester. Our analysis will focus on the impacts of CO on educational outcomes. As described earlier, CO is the only one of our pollutants that is known to cross the placental barrier. In all specifications, we control for O3 levels but omit those for PM10 due to their high correlation with CO levels in our study area. Our analysis of CO should be *interpreted* as capturing the composite effects of CO and PM10, as is universal in studies of this type due to the co-emission of many pollutants (Currie et al., 2013).[6] Appendix Table A1 shows the correlations across our three pollutant measures.

The seasonal patterns in pollution in Santiago are an important reason behind the inclusion of month and year fixed effects in equation 1. As mentioned earlier, Figure 1 shows that there are strong monthly patterns to CO and overall air quality as captured by the AQI. Since these seasonal patterns could exist for other unmeasured pollutants or weather variables (like temperature or rainfall), month fixed effects are an important control in all our specifications. Our approach requires residual variation in the measures of pollution after controlling for seasonality (month fixed effects) and year fixed effects. Figure 2 shows the distribution of CO after removing these fixed effects; we see that substantial variation remains in the pollution measures. It is this variation that predominantly drives the identification in this paper. The first modification we make to equation 1 is the introduction of observable mother's characteristics. Hence, we estimate:

$$S_{ijrt} = \beta E_{rt} + \overline{\theta_t} + \overline{\chi_i} + \bar{\gamma}\overline{W_t} + \overline{\delta X_j} + \epsilon_{ijrt} \tag{2}$$

Where X_j includes mother's characteristics like age and education.

The identifying assumption in the above equation is that after controlling for observable maternal characteristics, seasonality and flexible weather controls, exposure to pollution is uncorrelated with ϵ_{ijrt}. One concern with this assumption is that parents may respond to pollution levels, either directly by limiting exposure to pollution or indirectly through ex post investments designed to mitigate harmful effects. While such responses would not bias our results, they imply that all estimates will capture pollution impacts net of these potentially costly behaviors.[7] To clarify the interpretation of β in our estimation strategy, it is useful to describe a simple education production function.

[6]As will be shown later, repeating our analysis replacing CO with PM10 measures provides qualitatively similar results.
[7]See Graff Zivin and Neidell (2012) for a detailed conceptual model of the environmental health production function.

We begin by specifying a production function for school achievement, similar in spirit to Todd and Wolpin (2007). Test score achievement of student i born to mother j in region r at time t[8] is a function of early childhood health (H), investments made from birth to time of test taking (P) and parental characteristics (X).

$$S_{ijrt} = f(H_{ijrt}, \sum_{k=t}^{k=T} P_{ijrk}, X_j) \tag{3}$$

Early childhood health is a function of in utero environmental conditions E (eg. pollution exposure from various pollutants), weather conditions W (eg. rainfall, temperature etc) and parental characteristics X. *Individual* environmental conditions are a function of regional ambient environmental conditions, mitigated by individual level avoidance behavior (A).

$$H_{ijrt} = h(E_{ijrt}, W_{ijrt}, X_j) \tag{4}$$

$$E_{ijrt} = e(E_{rt}, A_{ijrt}) \tag{5}$$

Taking a linear approach to estimating equation 3 and plugging in linear functions of equations 4 and 5, and recognizing that weather variables are also observed at the regional level, we can express student performance as:

$$S_{ijrt} = \beta E_{rt} + \gamma W_{rt} + \sum_{k=t}^{k=T} \nu_k P_{ijrk} + \eta A_{ijrt} + \delta X_j + \epsilon_{ijrt} \tag{6}$$

Equation 1 is essentially a modified version of equation 6. While test scores still depend on fetal environmental conditions and parental characteristics, they also depend on time-varying parental investments in human capital as well as pollution avoidance behaviors during the prenatal period. While educational investments in response to early life insults are not observable in our setting (they will be subsumed in our error term), studies in other similar contexts have found those responses to be small and if anything largely compensatory (see Bharadwaj, Eberhard and Neilson (2013) and Halla and Zweimüller (2014)). Thus, to the extent that Chilean parents make investments to overcome cognitive deficiencies due to in utero pollution exposure, they will be reflected in our estimated effects from pollution. This is desirable - it captures

[8] In our specification, t always refers to time of birth, not time of test taking. For the most part everyone born at time t takes the test at the same later time (T), since we use scores from the national fourth grade exam.

the realized impacts of pollution - but it is worth noting that the costs of those parental investments may constitute a sizable welfare cost due to pollution.

Avoidance behavior can take two broad forms and we employ two main techniques to capture them in our analysis. Since pollution levels can vary considerably within municipalities, e.g. pollution levels are higher near busy roads and bus stops, we employ family fixed effects models to make within household comparisons that hold geography fixed at a much finer scale. Family fixed effects in this setting also play an important role insofar as the X variables we observe are limited. It is likely that there are unobservable family or mother characteristics that might matter for test outcomes as well as pollution exposure (Currie, Neidell, and Schmieder 2009). Our estimating equation using family fixed effects (indexing another sibling i' born at t') is essentially a first difference across siblings and takes the form:

$$\Delta S_{ijrt-i'jrt'} = \beta \Delta E_{rt-rt'} + \gamma \Delta W_{rt-rt'} + \Delta u_{ijrt-i'jrt'} \tag{7}$$

Note that in the above equation we ignore parental investments since we do not have data on parental investments within siblings, and that municipality fixed effects are redundant since parents in our sample rarely move municipalities across different births. Hence, sibling fixed effects regressions capture the effects of sorting as well as unobserved family level characteristics.

In the short run, individuals can take deliberate actions to reduce their realized exposure to pollution by spending less time outside, wearing face masks, or engaging in a number of other activities (Neidell 2005, Neidell 2009). Such short-run responses require knowledge about daily or even hourly pollution levels. In our context, that knowledge is made available through a well-publicized system of air quality alerts based on PM_{10} levels (which are highly correlated with CO levels). For example, during May-August, the peak pollution months in Santiago, there are regular announcements and forecasts with regards to PM_{10}, and alerts are announced when this pollutant reaches certain thresholds (see Bharadwaj and Mullins 2014 for details). To the extent that these alerts generate behavioral responses, we can account for them by including controls for the number of alert days during the pregnancy for each trimester.[9] If individuals engage in

[9]Of course, individuals may also engage in avoidance behavior based on the visible signs of pollution (or its correlates). While we cannot control for those behaviors in this setting, they can be viewed as conceptually similar to unmeasured parental investments in human capital. They create a wedge between the “biological" and “in situ" impacts of pollution, and represent a potentially significant welfare cost attributable to pollution.

avoidance behavior, controlling for avoidance should make the estimates larger relative to estimates where this is not explicitly taken into account (Moretti and Neidell 2011).

We modify equation 7 to take transient avoidance into account as follows:

$$\Delta S_{ijrt-i'jrt'} = \beta \Delta E_{rt-rt'} + \gamma \Delta W_{rt-rt'} + \kappa \Delta Alerts_{rt-rt'} + \Delta u_{ijrt-i'jrt'} \tag{8}$$

5. Results

We begin our analysis by examining the impact of pollution on test scores using one pollutant at a time (i.e. a single pollutant model) in Table 2. Panel A presents the estimates using for 4th grade math scores as the dependent variable and CO as the independent variable, Panel B uses PM10 as the independent variable and Panel C uses O3 as the independent variable. Since subsequent tables follow the same pattern, it is useful to emphasize the difference in specifications across the three columns in Table 2. Column 1 estimates the baseline specification as in Equation 2, Column 2 adds sibling fixed effects as per Equation 7 and column 3 estimates the sibling fixed effects model with air quality alerts as described by equation 8.

The broad finding of Table 2 is that bad air quality in-utero leads to lower performance on math test scores. Sibling fixed effects play a substantial role in determining the magnitude of the estimates as we move from Column 1 to Column 2. This confirms the importance of maternal unobservables in determining pollution exposure and birth outcomes. The effect of sibling fixed effects on estimate magnitudes is greater for CO and PM10 than for O3. This pattern suggests that the sibling fixed effects may also capture some maternal avoidance behaviors, as most of the pollution alerts in Santiago are focused on PM levels (which are highly correlated with CO), and little or no attention is paid to O3 levels. In general, the coefficients show a negative and significant effect of pollution exposure on cognitive outcomes. However, in order to isolate the impact of CO, we move to tables that control for O3.

Table 3 shows our main specification, in which we control for O3 exposure. Table 3 Panel A shows negative and significant effects of in utero CO exposure on 4th grade math test scores in specifications that account for sibling fixed effects.[10] Most of the effects are concentrated in trimesters 2 and 3 (although estimates for trimester 2 are not statistically significant), which corresponds well with the medical literature

[10]As described later in this section, our results remain qualitatively similar when we repeat our core analysis replacing CO with PM10.

on fetal CO exposure and subsequent health impacts. Moving from Column 1 to Column 2 again shows the importance of accounting for unobservables in this setting. A 1 SD increase in CO in the third trimester is associated with a 0.002 SD decrease in 4th grade math scores (column 1); however adding sibling FE in Column 2 increases the estimates to 0.03 SD. Adding air quality alerts to the main specification with sibling fixed effects (Column 3) increases the magnitude of the estimates slightly (by about 6 to 8 percent in most cases). Panel B shows similar effects in both direction and magnitude on language test scores.

Taken as whole, the results in Table 3 reveal a strong negative effect from fetal exposure to CO. To place the magnitudes of these effects in context, they are equivalent to the effects of a 10% increase in birthweight in Chilean and US study populations (Bharadwaj et al. 2013, Figlio et al 2013) and quite a bit larger than estimates due to changes in TSP within the U.S. (Sanders, 2011). Moreover, they are roughly one-fifth the magnitude of successful interventions that specifically target educational outcomes in developing countries (JPAL 2014); however, in utero pollution exposure also affects a far greater number of children than most education-specific programs in developing countries. Hence, while the magnitudes are small in absolute terms, they are economically meaningful. Table 4 shows that the OLS coefficients (column 1) change very little when we restrict the sample to siblings (i.e. we omit singletons, just as when we estimate siblings FE estimates in columns 2-3).

In Tables 5 and 6, we examine heterogeneity in these human capital impacts by mother's education. The effects of CO exposure are quite a bit larger for mothers without a high school diploma, although the diminished sample size drives the sibling FE results to statistical insignificance in Table 5. However in Table 6, the results for lower-educated mothers are not only larger and also statistically significant, they are two to three times the size of the coefficients for the more educated sample. Taken together, Tables 5 and 6 suggest that less educated families are more vulnerable to the detrimental effects of pollution exposure. They are also consistent with the notion that less educated families may have fewer resources to invest in their children to help offset early life deficits. These results may help explain the persistence of poverty in many parts of the world, as poor environmental quality can create a vicious cycle of low education and thus diminished economic opportunities.

In Table 7, we examine some potential non-linearity in the relationship between CO exposure and test scores. To address this question in a readily interpretable way, we use EPA determined thresholds (9ppm for an 8-hr average and 35ppm for a 1-hr average – note that the average CO levels over a trimester are around 1ppm). More specifically, for each trimester we sum the number of days that exceeded EPA's safety threshold. For both math and language, we find that for every extra day of EPA threshold violation, test scores decrease between 0.013-0.015 SD. This is a substantial effect since violations of the EPA standard regularly occurred in the 1990s in Santiago. For example, in 1997 approximately 47 days exceeded the EPA CO limit.

Thus far our analysis has largely been silent on the various mechanisms that might underpin our results. While our data do not allow us to formally disentangle possible channels, they do allow us to probe one important one. Since birth weight has been shown to be an important determinant of school performance (Figlio et al. 2013, Bharadwaj et al. 2013), we directly explore the effects of in utero pollution exposure on birth weight in a specification similar in spirit to Equations 7 and 8. Our OLS specifications in Table 8 show that exposure to in utero pollution significantly decreases birth weight and increases the probability of being low birth weight (less than 2500 grams). Sibling FE estimates also show negative and significant effects of CO exposure, although the magnitudes are again quite a bit larger than the OLS estimates. While this provides suggestive evidence that some of the long term effects seen are via the channel of health at birth, it is important to note that these birth weight effects are much too small to explain all of the relationship between pollution and scores. Indeed, point estimates from Bharadwaj, Eberhard and Neilson (2013) of the impact of birthweight on test scores imply that this channel explains no more than 10% of the cognitive impacts due to pollution.

5.1. **Robustness Checks**

As mentioned earlier, due to the high correlation between CO and PM_{10}, our main specifications do not control for PM_{10}. Hence, replacing CO with PM_{10} should yield qualitatively similar results. In Table 9, we find that this is indeed the case. Across all three of our specifications, we find that exposure to PM_{10} in utero is associated with significant negative effects on 4th grade math and language scores. The coefficient again increases in size across columns 1 and 2, suggesting an important role of underlying family characteristics in confounding OLS estimates.

Finally Table 10 shows that CO exposure in trimesters *prior* to conception does not play a role in determining test scores. This is important and reassuring, as it shows that our time dummies and other controls are effective in capturing serial correlation in pollution exposure.

6. CONCLUSION

In this paper, we merge data from the Chilean ministries of health and education with pollution and meteorological data to assess the impact of fetal air pollution exposure on human capital outcomes later in life. Data on air quality alerts and the use of siblings fixed effects estimation allow us to address several potentially important concerns about endogenous exposure to poor environmental quality. We find a strong negative effect from fetal exposure to CO on math and language skills, with timing that is broadly consistent with the medical literature. Our richest model specification suggests that a 1 standard deviation increase in CO exposure during the third trimester of pregnancy is associated with a 0.036 standard deviation decrease in 4th grade math test scores and a 0.042 SD decrease in 4th grade language test scores. Given the inherent challenges associated with improving education outcomes, these impacts are sizable - roughly one-fifth the magnitude of successful interventions that directly target educational performance in developing countries (JPAL 2014).

Since school performance is an important driver of employment and wage outcomes later in life (Chetty et al 2011, Currie and Thomas 2012), the legacy of acute pollution exposure in utero can be long-lasting and economically significant. In developing countries where pollution levels tend to be higher, those impacts may be particularly large. In that regard, the dramatic transformation of air quality in Chile from the early-90s to the mid-2000s is instructive. During this period average CO levels in Santiago dropped by more than 50 percent. A back-of-the envelope calculation using our estimated human capital effects and estimates on the returns to test scores from the U.S. (Blau and Kahn, 2005) suggests that, ceteris paribus, this drop could account for as much as $1000 additional lifetime earnings per child born under the cleaner regime. During our sample period on average 100,000 children are born every year, suggesting a lifetime increase of 100 million USD per cohort.[11] Such results may help explain patterns of wealth accumulation around the world, where the poor tend to live in neighborhoods with low environmental quality, which diminishes

[11]This number is calculated as follows. The change in average CO levels between 1992 and 2002 is equivalent to an 1 standard deviation change in CO pollution levels. Using our sibling FE results for math performance in the third trimester (this is conservative, as the improvement we imagine will apply for the entirety of the pregnancy, rather than a specific trimester) implies that this change in pollution levels generates a 0.036 SD improvement in test scores. Blau and Kahn (2005) find that a 1 SD change in U.S. adult test scores averaged across math and verbal reasoning yields a 16.36 percent change in adult earnings after controlling for education levels (see table 2, column 4). Applying this relationship between U.S. adult test scores and earnings to Chilean children yields an annual wage increase of 0.65%. Finally, we apply this figure to average adult wages in Chile (around 11000 USD) and discount at a 5% rate over 30 years.

cognitive attainment and thus limits opportunities to rise out of poverty. The sizable non-pecuniary benefits from education (Oreopoulos and Salvanes, 2009) only serve to magnify these welfare impacts.

Our empirical results are also of direct importance for policy makers. Carbon monoxide and its associated pollutants like PM10 are directly regulated throughout the developed and an increasing share of the developing world. Nearly all of these regulations are based on the benefits associated with reductions in pollution-related mortality and hospitalizations. Our results suggest that such an approach underestimates regulatory benefits for at least two reasons. First, it completely ignores the human capital effects, which have been largely invisible, but may well rival the more dramatic health effects in magnitude since they affect a much broader swath of the population. Second, it fails to account for the costs of short- and long-run avoidance behaviors for which we find considerable evidence. While our empirical framework does not allow us to assess the magnitude of these costs, they have been found to be substantial in other settings (Graff Zivin et al., 2011). The degree to which these “additional" benefits imply stricter regulation will, of course, depend upon the costs of pollution reduction.

While this paper provides new evidence in support of the so called fetal origins hypothesis and its lasting legacy on human capital formation, many questions remain unanswered. From a scientific perspective, the mechanisms behind these impacts remain murky. Our evidence suggests that birth weight is one important channel for these impacts, but it offers only a partial explanation. In more economic matters, much more work is needed to understand the role that households play in shaping outcomes. The effects we measure are net of any parental investments that take place between birth and test taking. The scale of these investments as well as their costs and effectiveness are largely unknown. Do they vary by identifiable household characteristics or over the lifecycle of a child? A deeper understanding of the persistence of these effects within and across generations is of paramount importance. Together these comprise a future research agenda.

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Main results

Table 1: Descriptive statistics

	Mean	Stdev	Min	Max
CO - trimester 1	1.30	0.96	0.16	4.85
CO - trimester 2	1.29	0.95	0.16	5.76
CO - trimester 3	1.22	0.93	0.16	6.74
O3 - trimester 1	31.67	9.93	9.78	85.73
O3 - trimester 2	30.80	10.19	9.78	85.73
O3 - trimester 3	31.13	10.00	8.71	85.73
Temperature - trimester 1	58.43	7.27	45.79	70.28
Temperature - trimester 2	57.75	7.38	45.79	70.28
Temperature - trimester 3	57.91	7.33	44.29	70.85
Rainfall - trimester 1	1.64	1.15	0.00	4.57
Rainfall - trimester 2	1.75	1.20	0.00	4.71
Rainfall - trimester 3	1.73	1.23	0.00	5.29
Gestational age (weeks)	38.88	1.33	33.00	41.00
Birth weight (g)	3362.51	483.58	240.00	6395.00
Mother's age	27.19	6.44	11.00	59.00
Sex (1=female)	0.50	0.50	0.00	1.00
Observations	627530			

Table 2: Single-pollutant models

Panel A: CO only			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0179	-0.00768	-0.00570
	(0.0126)	(0.0160)	(0.0166)
CO - trimester 2	-0.00844	-0.0295**	-0.0305**
	(0.0104)	(0.0143)	(0.0153)
CO - trimester 3	-0.00431	-0.0347**	-0.0369**
	(0.0119)	(0.0146)	(0.0152)
Panel B: PM only			
	OLS	Sib FE	Sib FE
PM10 - trimester 1	-0.000714	-0.000177	-0.000117
	(0.000472)	(0.000462)	(0.000467)
PM10 - trimester 2	-0.000107	-0.000694*	-0.000652*
	(0.000372)	(0.000354)	(0.000367)
PM10 - trimester 3	0.000482	-0.000748*	-0.000872*
	(0.000422)	(0.000431)	(0.000460)
Panel C: O3 only			
	OLS	Sib FE	Sib FE
O3 - trimester 1	-0.00219*	-0.000574	-0.000724
	(0.00125)	(0.000998)	(0.00104)
O3 - trimester 2	-0.00350*	-0.00362***	-0.00366***
	(0.00183)	(0.00112)	(0.00115)
O3 - trimester 3	0.00161	-0.000244	-0.000326
	(0.00100)	(0.00120)	(0.00123)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	666947	218202	218202

SEs in parentheses, clustered at birth month in column 1.
All models include yr and mo FEs interacted with monitor dummies.
Other controls include sex, log mother's age, mother's edu,
temperature, rainfall, dew point, fog, and wind.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: CO effects on scores

Panel A: Math			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.00367	-0.00121	-0.000174
	(0.0110)	(0.0171)	(0.0174)
CO - trimester 2	0.000306	-0.0207	-0.0220
	(0.0103)	(0.0150)	(0.0158)
CO - trimester 3	-0.00286	-0.0336**	-0.0363**
	(0.0113)	(0.0151)	(0.0157)
Panel B: Language			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0115	-0.0177	-0.0178
	(0.0116)	(0.0179)	(0.0182)
CO - trimester 2	-0.00815	-0.0155	-0.0179
	(0.00996)	(0.0159)	(0.0167)
CO - trimester 3	-0.0195*	-0.0399**	-0.0424***
	(0.0103)	(0.0157)	(0.0164)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	627545	204486	204486

SEs in parentheses, clustered at birth month in column 1.
All models include yr and mo FEs interacted with monitor dummies.
Other controls include sex, log mother's age, mother's edu,
temperature, rainfall, dew point, fog, wind, and ozone.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: CO effects on scores - restricted to sibling FE sample

Panel A: Math			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0243	-0.00121	-0.000174
	(0.0152)	(0.0171)	(0.0174)
CO - trimester 2	-0.000983	-0.0207	-0.0220
	(0.0121)	(0.0150)	(0.0158)
CO - trimester 3	-0.00460	-0.0336**	-0.0363**
	(0.0152)	(0.0151)	(0.0157)
Panel B: Language			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0398**	-0.0177	-0.0178
	(0.0153)	(0.0179)	(0.0182)
CO - trimester 2	-0.0167	-0.0155	-0.0179
	(0.0132)	(0.0159)	(0.0167)
CO - trimester 3	-0.0257*	-0.0399**	-0.0424***
	(0.0146)	(0.0157)	(0.0164)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	204486	204486	204486

SEs in parentheses, clustered at birth month in column 1.

All models include yr and mo FEs interacted with monitor dummies.

Other controls include sex, log mother's age, mother's edu,

temperature, rainfall, dew point, fog, wind, and ozone.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: CO effects on math scores, by mother's education

Panel A: Low mother's edu			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0218	-0.0172	-0.0153
	(0.0169)	(0.0458)	(0.0473)
CO - trimester 2	-0.00804	-0.0214	-0.0135
	(0.0176)	(0.0404)	(0.0435)
CO - trimester 3	-0.0187	-0.0523	-0.0473
	(0.0156)	(0.0388)	(0.0404)
Observations	125588	37513	37513
Panel B: HS or more			
	OLS	Sib FE	Sib FE
CO - trimester 1	0.00783	0.0119	0.0131
	(0.0103)	(0.0189)	(0.0193)
CO - trimester 2	0.00198	-0.0210	-0.0226
	(0.00940)	(0.0167)	(0.0175)
CO - trimester 3	-0.000732	-0.0180	-0.0213
	(0.0112)	(0.0168)	(0.0175)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	501295	166838	166838

SEs in parentheses, clustered at birth month in column 1.
All models include yr and mo FEs interacted with monitor dummies.
Other controls include sex, log mother's age, mother's edu,
temperature, rainfall, dew point, fog, wind, and ozone.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: CO effects on language scores, by mother's education

Panel A: Low mother's edu			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0396**	-0.0958**	-0.100**
	(0.0169)	(0.0475)	(0.0491)
CO - trimester 2	0.00604	-0.0226	-0.0253
	(0.0181)	(0.0422)	(0.0454)
CO - trimester 3	-0.0459***	-0.0817**	-0.0811*
	(0.0136)	(0.0400)	(0.0414)
Observations	125588	37513	37513
Panel B: HS or more			
	OLS	Sib FE	Sib FE
CO - trimester 1	0.00407	0.00441	0.00597
	(0.0115)	(0.0198)	(0.0202)
CO - trimester 2	-0.0116	-0.0171	-0.0174
	(0.00927)	(0.0176)	(0.0185)
CO - trimester 3	-0.0140	-0.0293*	-0.0316*
	(0.0109)	(0.0176)	(0.0183)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	501295	166838	166838

SEs in parentheses, clustered at birth month in column 1.

All models include yr and mo FEs interacted with monitor dummies.

Other controls include sex, log mother's age, mother's edu, temperature, rainfall, dew point, fog, wind, and ozone.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: CO effects on scores

Panel A: Math			
	OLS	Sib FE	Sib FE
EPA CO violations - trimester 1	-0.00609	-0.00122	-0.00206
	(0.00646)	(0.00696)	(0.00710)
EPA CO violations - trimester 2	0.0127	-0.00912	-0.00775
	(0.00903)	(0.00690)	(0.00697)
EPA CO violations - trimester 3	-0.000769	-0.0143***	-0.0135**
	(0.00607)	(0.00552)	(0.00554)
Panel B: Language			
	OLS	Sib FE	Sib FE
EPA CO violations - trimester 1	-0.00599	-0.00344	-0.00432
	(0.00653)	(0.00734)	(0.00748)
EPA CO violations - trimester 2	0.00890	-0.00286	-0.00138
	(0.00800)	(0.00727)	(0.00735)
EPA CO violations - trimester 3	-0.00222	-0.0152***	-0.0145**
	(0.00598)	(0.00578)	(0.00582)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Ozone violations	Yes	Yes	Yes
Observations	668627	218871	218871

SEs in parentheses, clustered at birth month in column 1.

All models include yr and mo FEs interacted with monitor dummies.

Other controls include sex, log mother's age, mother's edu, temperature, rainfall, dew point, fog, wind, and ozone.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: CO effects on birth weight

	Birth weight	Birth weight (sibFE)	Low BW	Low BW (sibFE)
CO - trimester 1	-6.716**	-18.07**	0.000724	0.00611*
	(3.371)	(7.173)	(0.00160)	(0.00357)
CO - trimester 2	-8.189**	-6.135	0.00277	0.00376
	(3.821)	(6.681)	(0.00181)	(0.00328)
CO - trimester 3	-4.713	-18.08***	0.00104	0.00625*
	(3.716)	(6.526)	(0.00152)	(0.00339)
Sibling FE	No	Yes	No	Yes
Air quality alerts	Yes	Yes	Yes	Yes
Observations	627532	204485	627545	204486

Standard errors in parentheses

All models include yr and mo FEs interacted with monitor dummies.

Other controls include sex, log mother's age, mother's edu,

temperature, rainfall, dew point, fog, wind, and ozone.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: PM10 effects on scores

Panel A: Math			
	OLS	Sib FE	Sib FE
PM10 - trimester 1	-0.000394	0.0000643	0.0000831
	(0.000425)	(0.000471)	(0.000474)
PM10 - trimester 2	-0.0000417	-0.000569	-0.000593
	(0.000341)	(0.000373)	(0.000387)
PM10 - trimester 3	0.000181	-0.000914**	-0.00108**
	(0.000390)	(0.000452)	(0.000475)
Panel B: Language			
	OLS	Sib FE	Sib FE
PM10 - trimester 1	-0.000957**	-0.000596	-0.000550
	(0.000407)	(0.000495)	(0.000498)
PM10 - trimester 2	-0.000418	-0.000519	-0.000458
	(0.000308)	(0.000393)	(0.000407)
PM10 - trimester 3	-0.000455	-0.00105**	-0.00107**
	(0.000391)	(0.000477)	(0.000499)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	666947	218202	218202

SEs in parentheses, clustered at birth month in column 1.

All models include yr and mo FEs interacted with monitor dummies.

Other controls include sex, log mother's age, mother's edu,

temperature, rainfall, dew point, fog, wind, and ozone.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: CO effects on scores, placebo trimesters

	OLS	Sib FE	Sib FE
CO - trimester -3	0.00385	0.0140	0.0157
	(0.0135)	(0.0250)	(0.0257)
CO - trimester -2	0.0101	-0.0188	-0.0128
	(0.0138)	(0.0277)	(0.0280)
CO - trimester -1	0.0171	-0.00807	-0.0102
	(0.0176)	(0.0289)	(0.0296)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	561852	182799	182799

Standard errors in parentheses

Standard errors clustered at birth date level. All models include yr and mo FEs.

Controls include birth mo, birth yr, neighborhood, sex, log mother's age,

mother's edu, temperature, rainfall, dew point, fog, wind, and ozone.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Descriptive figures

Figure 1: Pollution over time

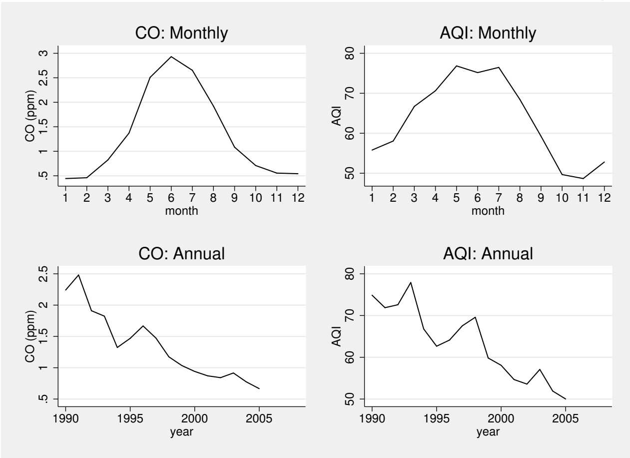
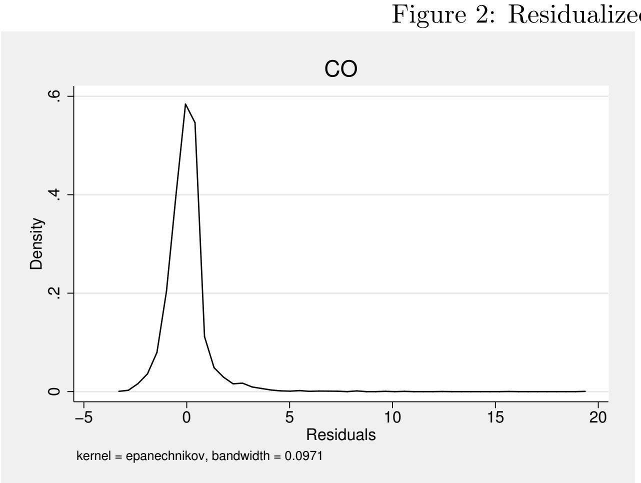


Figure 2: Residualized pollution (year and month dummies)



Appendix tables

Table A1: Pollutant Correlations

	CO - t1	CO - t2	CO - t3	O3 - t1	O3 - t2	O3 - t3	PM10 - t1	PM10 - t2	PM10 - t3
CO - t1	1								
CO - t2	0.235	1							
CO - t3	-0.361	0.212	1						
O3 - t1	-0.651	0.168	0.543	1					
O3 - t2	-0.141	-0.673	0.184	0.0643	1				
O3 - t3	0.594	-0.127	-0.655	-0.651	0.0691	1			
PM10 - t1	0.904	0.106	-0.525	-0.659	-0.185	0.611	1		
PM10 - t2	0.173	0.922	0.124	0.175	-0.645	-0.172	0.135	1	
PM10 - t3	-0.416	0.170	0.932	0.487	0.226	-0.616	-0.538	0.138	1

Table A2: CO effects on scores, by distance to nearest monitor

Panel A: Math					
	<4.5km	<6.2km	<11km	<16.9km	<22.1km
CO - trimester 1	-0.0174*	-0.0174**	-0.00301	-0.00442	-0.00324
	(-1.67)	(-2.39)	(-0.53)	(-0.97)	(-0.74)
CO - trimester 2	-0.00919	-0.0133**	-0.00787*	-0.00461	-0.00476
	(-1.15)	(-2.41)	(-1.84)	(-1.36)	(-1.46)
CO - trimester 3	-0.0101	-0.0219***	-0.0126**	-0.0129***	-0.0114***
	(-1.01)	(-3.02)	(-2.28)	(-2.95)	(-2.74)
Panel B: Language					
	<4.5km	<6.2km	<11km	<16.9km	<22.1km
CO - trimester 1	-0.0394***	-0.0183**	-0.0110**	-0.0109**	-0.00992**
	(-3.72)	(-2.51)	(-1.97)	(-2.42)	(-2.30)
CO - trimester 2	-0.0137*	-0.0132**	-0.00946**	-0.00759**	-0.00761**
	(-1.67)	(-2.38)	(-2.18)	(-2.19)	(-2.29)
CO - trimester 3	-0.0228**	-0.0221***	-0.0161***	-0.0150***	-0.0149***
	(-2.19)	(-2.98)	(-2.88)	(-3.42)	(-3.53)
Observations	82485	176501	316453	520407	577990

SEs in parentheses, clustered at birth date level.

All models include yr and mo FEs interacted with monitor dummies.

Controls include birth mo, birth yr, neighborhood, sex, log mother's age, mother's edu, temperature, rainfall, dew point, fog, wind, and ozone.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: CO effects on scores - restricted to sibling FE sample

Panel A: Math			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0243	-0.00121	-0.000174
	(0.0152)	(0.0171)	(0.0174)
CO - trimester 2	-0.000983	-0.0207	-0.0220
	(0.0121)	(0.0150)	(0.0158)
CO - trimester 3	-0.00460	-0.0336**	-0.0363**
	(0.0152)	(0.0151)	(0.0157)
Panel B: Language			
	OLS	Sib FE	Sib FE
CO - trimester 1	-0.0398**	-0.0177	-0.0178
	(0.0153)	(0.0179)	(0.0182)
CO - trimester 2	-0.0167	-0.0155	-0.0179
	(0.0132)	(0.0159)	(0.0167)
CO - trimester 3	-0.0257*	-0.0399**	-0.0424***
	(0.0146)	(0.0157)	(0.0164)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	204486	204486	204486

SEs in parentheses, clustered at birth month in column 1.
All models include yr and mo FEs interacted with monitor dummies.
Other controls include sex, log mother's age, mother's edu,
temperature, rainfall, dew point, fog, wind, and ozone.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$