NBER WORKING PAPER SERIES

# GRAY MATTERS: FETAL POLLUTION EXPOSURE AND HUMAN CAPITAL FORMATION

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Working Paper 20662
http://www.nber.org/papers/w20662

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2014

The authors wish to thank the Departamento de Estasticas e Informacion de Salud del Ministerio de Salud (MINSAL) and Ministry of Education (MINEDUC) of the government of Chile for providing access to the data used in this study. We have also benefited from discussions with Matthew Neidell, Reed Walker and participants at PERC Workshop on Environmental Quality and Human Health, NBER Environmental Meetings, University of Southern California, UC Irvine, Yale and the IZA Workshop on Labor Market Effects of Environmental Policies. Financial support from the UC Center for Energy and Environmental Economics is gratefully acknowledged. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w20662.ack

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NBER Working Paper No. 20662
November 2014
JEL No. I10,Q53

## ABSTRACT

This paper examines the impact of fetal exposure to air pollution on 4th grade test scores in Santiago, Chile. We rely on comparisons across siblings which address concerns about locational sorting and all other time-invariant family characteristics that can lead to endogenous exposure to poor environmental quality. We also exploit data on air quality alerts to help address concerns related to short-run time-varying avoidance behavior, which has been shown to be important in a number of other contexts. We find a strong negative effect from fetal exposure to carbon monoxide (CO) on math and language skills measured in 4th grade. These effects are economically significant and our back of the envelope calculations suggest 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

A long literature in economics has emphasized the important role of human capital in determining labor market activity and economic growth.[1] It is widely believed that the information age has only increased the private and social returns to education, which may partly explain why governments around the world spend an average of 5% of their GDP on education (World Development Indicators 2010) and why Americans alone spend more than $7B on private tutoring every year (Dizik, 2013). Yet, human capital formation depends on many inputs and growing literatures in public health and economics highlight the important role played by prenatal and early childhood health in this process (Cunha and Heckman 2008, Currie and Hyson 1999, Almond and Currie 2011). Since pollution adversely affects contemporaneous childhood health,[2] the impacts of early-life pollution exposure on long-term human capital outcomes is of particular interest as pollution could have a sizable cost to society through its contemporaneous and dynamic effects on the production of human capital. If short run changes in pollution lead to lifelong changes in well-being, they may constitute a sizable, and heretofore largely unmeasured, cost of pollution.

Estimating the relationship between fetal environmental exposures 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 more pristine location. As a result research in this area has been extremely limited,[3] relying on quasi-experimental variation in exposure induced by nuclear accidents/testing in data-rich Scandinavian countries (Almond, Edlund and Palme 2009; Black et al. 2013), or policy-induced variation in pollution 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 school. The richness of our data allows us to overcome the core estimation challenges in this line of research and

[1]See Heckman, Lochner and Todd (2006) for a review on the links between human capital and wages; Romer (1986) and Lucas (1988) form some of the important work showing the importance of human capital for economic growth.

[2]For recent examples see Currie and Walker (2009), Schlenker and Walker (2011), Knittel, Miller, and Sanders (2012), Arceo-Gomez, Hanna, and Oliva (2012), Currie et al. (2013).

[3]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, Rau, Reyes and Urzua 2014).

improve upon the existing literature in several important dimensions. First, we can directly link vital statistics and education data through unique individual identifiers. Geographic identifiers allow us to further link to data from 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. In particular, we rely on sibling comparisons which allow us to address concerns about locational sorting and purge estimates of all other 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.[4] 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, Greenstone and Shapiro 2012; Graff Zivin, Neidell and Schlenker 2011).

Finally, our paper may shed light on the micro-foundations underpinning the recently documented relationship between early life pollution exposure and labor market outcomes (Isen, Rossin-Slater, and Walker 2014). It may also help underscore the implicit tradeoffs across economic development paths by highlighting potential feedback loops between industrialization, human capital formation, and economic growth. The evidence presented in this paper is also of direct policy relevance. To the extent academic achievement in school can be linked to labor productivity, we develop a quantitative estimate of the social costs of pollution through its effects on human capital production and highlight the sizable benefits incurred from pollution abatement policies implemented during the last two decades. Carbon monoxide is regularly emitted as a byproduct of fossil fuel combustion and subject to regulation across the world. The human capital impacts from pollution along with any attending avoidance behaviors constitute additional costs that should be weighed against the relevant benefits from the generation of air pollution.

[4]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.

The remainder of the paper is organizing as follows. The next section provides a brief description of the relevant scientific background. Section 3 describes our data and Section 4 details our econometric approach. Our results are described in Section 5. Section 6 offers some concluding remarks.

## 2. Scientific Background

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. 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). Moreover, 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). The degree to which these physiological impacts translate into cognitive outcomes is entirely unknown and the focus of this study.

A common challenge for all non-laboratory studies of the impacts of air pollution is confounding due to other pollutants. Some pollutants are co-emitted as a byproduct of combustion processes. Others follow opposing seasonal patterns due to heating and cooling patterns and weather more generally. During our study period, Santiago regularly experienced episodes where carbon monoxide, particulate matter (PM), and ozone pollution levels were elevated. While neither PM or ozone cross the placental barrier, it is still possible that they could damage fetal health through respiratory and cardiovascular impacts on the mother. A recent study that found CO to be the only pollutant to consistently impair infant and child health (Currie, Neidell, and Schmieder 2009) bolsters the case for our focus on CO, but also underscores the importance of utilizing a multi-pollutant framework to address potential confounding.

In our setting, environmental confounding could take several distinct forms. In Santiago, like most urban environments, CO exhibits a strong seasonal pattern, with high levels in winter and lower levels in summer. Ozone exhibits the opposite pattern, with high levels in summer and lower levels in winter. Thus, if ozone exposure also inhibits cognitive formation, ignoring it would lead us to understate the impacts of CO pollution. As such, all of our regressions will control for seasonality as well as directly control for ozone pollution levels. Ideally, we would include similar controls for PM, but given the extremely high correlation between ambient levels of CO and PM in our setting, which typically exceeds 0.9, that is not possible. Rather, we urge the reader to view our results as the composite effect of CO and PM, recognizing that the epidemiological literature points toward CO as the primary culprit in this population.[5] Finally, we note that weather, particularly temperature, can impact pollution formation as well as child health (Deschenes et al., 2009). Thus, we add a wide range of controls for weather in order to isolate the deleterious effect of CO. Additional details on these controls can be found in Section 4 where we discuss our empirical specification and strategy.

## 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, environmental conditions, 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 marital 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.

[5]As will be clarified later, our results are largely unchanged when we repeat our core analyses using PM rather than CO as our dependent variable.

### 3.2. **Environmental Data**

Air pollution data for the period from 1998-2001 come from the Sistema de Informacion Nacional de Calidad del Aire (SINCA), a network of monitoring stations operated by the Chilean Ministry of Environment. Data from 1992-1997 come from the Monitoreo Automatica de Contaminantes Atmosfericos Metropolitana (MACAM1) network, also operated by the Ministry.

Given concerns about the endogeneity of monitor "births" and "deaths" (Auffhammer and Kellogg, 2011), our analysis is based on data from the balanced panel of 3 monitors that operate during our entire study period. Two of the monitors – Parque O'Higgins and La Independencia – are centrally located and representative of general pollution patterns in metropolitan Santiago (Osses, Gallardo, and Faundez, 2013). The third monitor is located in Las Condes, a wealthy suburb in the foothills of the Andes that sits at high elevation. Pollution patterns at this monitor are quite different in this municipality since inversion layers, which are correlated with extremely high pollution events, occur at altitudes that are lower than this monitor (Gramsch, Cereceda-Balic, Oyola, and Von Baer, 2006). As a result, we limit our assignment of pollution from the Las Condes monitor to residents in the Las Condes municipality. All other residents in Santiago are assigned the pollution readings from the nearest monitor based on municipality centroids.[6]

CO data during our study period is reported as an 8-hour moving average. We construct a daily average measure of CO from these readings and then compute the mean exposure at the trimester level. 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. We follow a similar procedure to construct mean exposure at the trimester level.

In order to provide a sense of aggregate pollution patterns in Santiago, we use data on CO, PM10 and O3, to compute a daily Air Quality Index (AQI) using the algorithm developed by the U.S. Environmental Protection Agency (EPA 2006). The AQI is a composite measure of pollution that ranges from 0 to 500 in order to rank air quality based on its associated health risks. 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.

[6]We have also constructed an alternative exposure measure by taking an inverse-distance weighted average over the remaining two monitors for births outside Las Condes. Results are qualitatively similar. In addition, assigning all high elevation municipalities (as determined by the mean or median altitude of the municipality) to the Las Condes monitor and using nearest monitor assignment among remaining municipalities yields very similar results.

Figure 1 also shows long-run levels of CO and the AQI. As in the seasonal graphs, the two series track each other closely. The steep declines that occur in the mid- to late-90s are the result of a concerted government effort to address the serious pollution concerns from the previous decade. The most serious of these measures started in 1997 under the PPDA (Mullins and Bharadwaj 2014). Meteorological data for this study period come from the NOAA Summary of the Day for the monitor at Comodoro Arturo Merino Benitez International Airport (SCL). Our analysis makes use of daily maximum temperature measures as well as daily average data on rainfall, dew point, wind speed, and an indicator for the presence of fog. Each is converted to a trimester level measure and used as a non-linear control in our regressions, as detailed in Section 4.

### 3.3. **Education Data**

The data on school achievement are obtained from the SIMCE database, which includes administrative data on test scores for every student in the country between 2002 and 2010.[7] The SIMCE is a national standardized test administered in all schools in Chile. The SIMCE test covers three main subjects: mathematics, language, and science. It is administered to every student in grade 4, and episodically in grades 8 and 10. The SIMCE scores are used to evaluate the progress of students against the national curriculum goals set out by 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.[8]

## 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.[9] Since we have the exact date of birth and gestational age, we are able to accurately construct the history of gestational exposure to ambient

[7]This database was kindly provided by the Ministry of Education of Chile (MINEDUC).
[8]More details on the match quality can be found in Bharadwaj, Loken and Neilson, 2013.
[9]While it is easier to interpret and aggregate coefficients at the trimester level, analysis at the gestational month level yields similar results.

air quality. We include all trimester exposure measures in a single specification, along with temperature and other weather variables. Our basic estimating equation is:

$$S_{ijrt} = \beta E_{mt} + \theta_t + \alpha \chi_{ijrt} + \gamma W_t + \epsilon_{ijrt} \quad (1)$$

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. $\theta_t$ 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 $\chi_{ijrt}$ is a gender dummy. $W_t$ includes a host of weather controls (temperature, precipitation, fog, dewpoint and wind), measured at the trimester level. We use a polynomial in the trimester average of precipitation, fog, dew point and wind in order to capture potential nonlinear impacts. Since temperature extremes can have a direct effect on maternal behavior and fetal health (Deschenes et al., 2009), and also play a role in pollution formation, we control for temperature more flexibly. In particular, we create 10 degree bins based on daily maximum temperatures and count the number of days per trimester in each bin. For example, we include three variables (one per trimester) counting the number of days with a maximum temperature between 70 and 80 degrees Fahrenheit.

$E_{mt}$ contains the average level of pollution, also measured at the level of gestational trimester based on the nearest monitor assignment. As discussed in the previous section, our analysis will focus on the impacts of carbon monoxide on educational outcomes, but will also include controls for ozone pollution levels. As a robustness check, we will repeat the same analysis using PM10 as our primary pollutant, with controls for ozone levels.[10] We will also take a more structured approach to the multi-pollutant problem by using the air quality index, which provides a composite measure of environmental conditions based on the health dangers associated with CO, PM10, and O3 levels (EPA, 2006).

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 variables that might impact our outcome of interest (e.g. income-specific timing of childbirth), month fixed effects are an important control in all our specifications. Our approach requires

[10]Recall that the correlation between CO and PM10 levels are 0.9.

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 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:

$$S_{ijrt} = \beta E_{mt} + \theta_t + \alpha \chi_{ijrt} + \gamma W_t + \delta X_j + \epsilon_{ijrt} \tag{2}$$

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 $\epsilon_{ijrt}$. 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.[11] To clarify the interpretation of $\beta$ in our estimation strategy, it is useful to describe a simple education 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 $t$ [12] 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 pollution exposure $E$, weather conditions $W$ (e.g. rainfall, temperature, etc.) and parental characteristics $X$. Individual environmental conditions are a function of ambient pollution measured at the nearest monitor ($E_{mt}$), mitigated by individual level avoidance behavior ($A$).

[11] See Graff Zivin and Neidell (2012) for a detailed conceptual model of the environmental health production function.

[12] 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.

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

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

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

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

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 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 residential sorting can lead to non-random assignment of pollution, we employ family fixed effects models to make within household comparisons that hold geography fixed. This is a particular concern as air quality is capitalized into housing values (Chay and Greenstone 2005, Figueroa, Rogat, Firinguetti 1996), since families with higher income are more likely to sort into neighborhoods with better air quality and invest in human capital. Family fixed effects in this setting also play an important role insofar as our limited data on maternal characteristics is missing important unobservable family 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:

$$\Delta S_{ijrt-i'jrt'} = \beta \Delta E_{mt-mt'} + \gamma \Delta W_{t-t'} + \Delta u_{ijrt-i'jrt'} \tag{7}$$

Note that the above equation will capture all time-invariant investments in children, but ignores time-varying investments since we do not have data on parental investments across siblings. One time-varying activity that may influence outcomes is averting behavior. 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 PM10 levels (which are highly correlated with CO levels). For example, during May-August, the peak pollution months in Santiago, PM10 forecasts are broadcast on a regular basis, with alerts announced when this pollutant reaches certain thresholds (see Mullins and Bharadwaj 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.[13] If individuals engage in 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:

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

All of our core analyses will follow the same basic structure. The OLS regression described in equation (2) will serve as our base model specification. This will be followed by estimates of the sibling fixed effect regressions described in equation (7). Finally, we will present estimates of our fully saturated model, which includes sibling fixed effects and controls for air quality alerts to capture time-varying avoidance behavior, as described in equation (8).

[13]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.

## 5. RESULTS

We begin our analysis by examining the impact of CO on test scores in Table 2. Panel A presents the estimates using for 4th grade math scores as the dependent variable and Panel B uses 4th grade language scores as the dependent variable. Column 1 is our base OLS specification where we control for seasonality (year and month fixed effects interacted with monitor dummies), environmental controls at the trimester level (maximum temperature in 10 degree F bin days and a second degree polynomial in mean precipitation, fog, wind speed and dew point), demographic controls (mother's age and education, student gender) and trimester average ozone levels. Standard errors for OLS specifications are clustered at the year of birth and month of birth level. We add to this base model, sibling fixed effects in column 2 and further add the total number of trimester level air quality alert days in column 3. Standard errors for specifications including sibling fixed effects are clustered at the family level.

Table 2 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.[14] The effects are concentrated in trimesters 2 and 3 (although estimates for trimester 2 are not statistically significant). Moving from Column 1 to Column 2 illustrates the importance of accounting for sorting behavior and other time-invariant unobserved family characteristics in this setting, as the magnitude of our estimates increase significantly in Column 2. A 1 SD increase in CO in the third trimester is associated with a statistically insignificant 0.003 SD decrease in 4th grade math scores (column 1); however adding sibling FE in Column 2 increases the estimates to a statistically significant 0.034 SD. Adding air quality alerts to our sibling fixed effects specification (Column 3) increases the magnitude of the estimates slightly (by about 6 to 8 percent in most cases), suggesting that insofar as the alerts induce avoidance behavior, this appears to have a rather modest impact on child outcomes. Panel B shows similar effects in both direction and magnitude on language test scores.

Taken as whole, the results in Table 2 reveal a strong negative effect from fetal exposure to CO. While the magnitudes may appear small, it is important to note that test performance is notoriously difficult to move, even via input based schooling policies (Hanushek 2003). To place the magnitudes of these effects in context, they are roughly one-fifth the magnitude of successful interventions that specifically target educational outcomes in developing countries (JPAL 2014). The economic importance of these results is

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

underscored by the size of the exposed population – far more children are exposed to pollution than well-designed education-specific programs in developing countries. It is also worth noting that our effects are quite a bit larger than estimates based on changes in total suspended particulates pollution within the U.S. (Sanders 2012). [15]

In Table 3, we examine heterogeneity in these human capital impacts by mother's education. For both math and language test scores, we see that the effects of CO exposure are quite a bit larger for children of mothers without a high school diploma. Indeed, the point estimates under the sibling FE specifications are roughly 2.5 times larger for children of less-educated mothers. While the diminished sample size drives the sibling FE results for math to statistical insignificance, the statistical significance for language remains. A direct comparison of coefficients for the third-trimester across the education gradient is presented in the bottom row of Table 3. The OLS estimates for language are significantly different from one another; and the sibling FE estimates are nearly significantly different at the 10% significance level. Together, these results provide suggestive evidence that less educated families are more vulnerable to the detrimental effects of pollution. Whether this is due to increased exposure or a diminished ability to invest in their children to help offset early life deficits remains an open question.

All of our previous analysis treated the relationship between CO exposure and test scores as linear. In Table 4, we explore this relationship by using the U.S Environmental Protection Agency's National Ambient Air Quality thresholds for CO (9 parts-per-million for an 8-hr average).[16] In particular, for each trimester we sum the number of days on which the EPA's safety threshold is exceeded. For both math and language, we find that for every extra day of EPA threshold violation during the third trimester, test scores decrease significantly, with a consistent magnitude around 0.002 SD using the fixed effects estimates. It is worth noting that violations of the EPA standard were a regular occurrence in the 1990s in Santiago. For example, in 1997 approximately 47 days exceeded the EPA CO limit, which, linearly would imply an effect of nearly 0.1SD. The average number of EPA violations during a third trimester in our sample is 2.3, which translates to a 0.004 SD reduction in test scores for the average child exposed to such a third trimester.

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

[15]The estimates in Sanders (2012) may be smaller due to measurement error issues. Sanders (2012) infers in utero pollution by assuming all students were born in the place they attended high school.

[16]The average CO levels over a trimester in our sample is approximately 1 part-per-million.

an 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 5 show that exposure to in utero pollution significantly decreases birth weight. The magnitude of these effects is amplified in the sibling FE framework, which also finds modest and marginally significant effects on the probability of being low birth weight (less than 2500 grams). While these results suggest 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**

We begin our assessment of the robustness of our results, by confirming that the differences between our OLS and sibling FE estimates are not being driven by sample composition. Table 6 reproduces our core analysis (from Table 2), with our OLS sample restricted to the population of siblings (i.e. we omit singletons,[17] just as when we estimate siblings FE models). Reassuringly, our OLS coefficients change very little, thus preserving the basic pattern as we move from our OLS (column 1) to our sibling FE specifications (columns 2 and 3) in our analysis.

As mentioned earlier, due to the high correlation between CO and PM10, our main specifications do not control for PM10. Hence, replacing CO with PM10 should yield qualitatively similar results. In Table 7, we find that this is indeed the case. Across all three of our specifications, we find that exposure to PM10 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 that residential sorting and underlying family characteristics are confounding OLS estimates.

An alternative approach to addressing multiple pollutants is to aggregate them into a single index. In this case, we use the U.S. Environmental Protection Agency's Air Quality Index (AQI), which is constructed by taking the maximum over piecewise-linear transformations of daily readings for all individual pollutants (EPA, 2006). As can be seen in Table 8, higher AQI exposure in utero leads to lower test scores.

[17]Note that 'singletons' in our sample are not necessarily only children, but rather those that cannot be matched to siblings during the time period that spans our data.

While this approach does not allow us to identify which particular pollutant is driving the index on any given day, these results follow the same patterns as prior tables – most of the effects are concentrated in the second and third trimester and the coefficients are much larger after accounting for sibling fixed effects.

Finally, Table 9 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 and robust negative effect from fetal exposure to CO on math and language skills. 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 these acute pollution exposures 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-1990s to the mid-2000s is instructive. During this period, which can be viewed as a transition from typical developing country urban pollution levels to levels that are closer to those found in typical developed country cities, 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 in Santiago, suggesting a lifetime increase of 100 million USD per cohort.[18] It is important to realize that most of the costs of pollution exposure might be borne by the less fortunate. 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 cognitive attainment and thus limits opportunities to rise out of poverty. The sizable non-pecuniary benefits from education (Oreopoulos and Salvanes 2011) only serve to magnify these welfare impacts.

Our empirical results are also of direct importance for policy makers. Carbon monoxide is 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 health, mortality and hospitalizations.[19] 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 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 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

[18]This number is calculated as follows. The change in average CO levels between 1992 and 2002 is equivalent to a 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 in Blau and Kahn 2005). Applying this relationship between U.S. adult test scores and earnings to Chilean children yields an annual wage increase of 0.58%. Finally, we apply this figure to average adult wages in Chile (around 11000 USD) and discount at a 5% rate over 30 years.

[19]Two examples of such work in the context of Santiago, Chile are worth mentioning. The first is Dessus and O'Connon (2003) who examine the welfare implications of climate policy in Santiago by including health costs. The second is the work of Figueroa, Gomez-Lobo, Jorquera and Labrin (2012), who estimate the benefits due to reduced pollution in Santiago due to better public transit infrastructure.

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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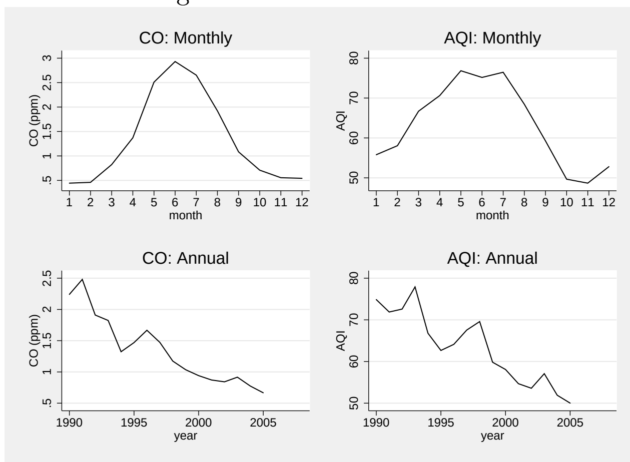
# Descriptive figures

Figure 1: Pollution over time




Top panel shows CO and AQI are higher in the winter months (Chile, being in the southern hemisphere, experiences winters from March through August).

Figure 2: Residualized pollution (year and month dummies)

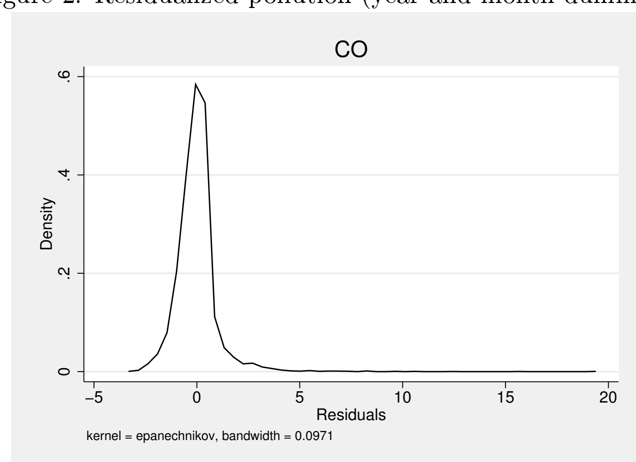



Figure based on the residuals of a regression using daily CO as the dependent variable and year and month dummies as independent variables. We then plot the probability distribution function of the residuals using the Stata command "kdensity" with default options: an Epanechnikov kernel and MSE-minimizing bandwidth under an assumed Gaussian distribution.

# Main results

Table 1: Descriptive statistics

| | Mean | Stdev | Min | Max |
|---|---|---|---|---|
| CO - trimester avg | 1.30 | 0.96 | 0.16 | 4.85 |
| PM10 - trimester avg | 90.87 | 29.86 | 39.73 | 197.85 |
| O3 - trimester avg | 31.67 | 9.93 | 9.78 | 85.73 |
| EPA CO violations - trimester avg | 0.17 | 0.73 | 0.00 | 5.00 |
| AQI - trimester avg | 65.03 | 15.92 | 31.91 | 109.82 |
| Temperature - trimester avg | 58.43 | 7.27 | 45.79 | 70.28 |
| Rainfall - trimester avg | 1.64 | 1.15 | 0.00 | 4.57 |
| Gestational age (weeks) | 38.88 | 1.33 | 33.00 | 41.00 |
| Birth weight (g) | 3362.51 | 483.58 | 240.00 | 6395.00 |
| Low birth weight (<2.5kg) | 0.04 | 0.19 | 0.00 | 1.00 |
| 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: CO effects on scores

| | | | |
|---|---|---|---|
| Panel A: Math | | | |
| | OLS | Sib FE | Sib FE |
| CO - trimester 1 | -0.004 | -0.001 | -0.000 |
| | (0.011) | (0.017) | (0.017) |
| CO - trimester 2 | 0.000 | -0.021 | -0.022 |
| | (0.010) | (0.015) | (0.016) |
| CO - trimester 3 | -0.003 | -0.034** | -0.036** |
| | (0.011) | (0.015) | (0.016) |
| Panel B: Language | | | |
| | OLS | Sib FE | Sib FE |
| CO - trimester 1 | -0.012 | -0.018 | -0.018 |
| | (0.012) | (0.018) | (0.018) |
| CO - trimester 2 | -0.008 | -0.015 | -0.018 |
| | (0.010) | (0.016) | (0.017) |
| CO - trimester 3 | -0.019* | -0.040** | -0.042*** |
| | (0.010) | (0.016) | (0.016) |
| Sibling FE | No | Yes | Yes |
| Air quality alerts | No | No | Yes |
| Observations | 627545 | 204486 | 204486 |

Standard errors are in parentheses, clustered on birth year-month in column 1 and clustered on family in columns 2-3. The dependent variable is the 4th grade math/language SIMCE test score. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Table 3: CO effects on math scores, by mother's education

| Panel A: less than HS | Math OLS | Math Sib FE | Math Sib FE | Language OLS | Language Sib FE | Language Sib FE |
|---|---|---|---|---|---|---|
| CO - trimester 1 | -0.022 | -0.017 | -0.015 | -0.040** | -0.096** | -0.100** |
| | (0.017) | (0.046) | (0.047) | (0.017) | (0.048) | (0.049) |
| CO - trimester 2 | -0.008 | -0.021 | -0.013 | 0.006 | -0.023 | -0.025 |
| | (0.018) | (0.040) | (0.044) | (0.018) | (0.042) | (0.045) |
| CO - trimester 3 | -0.019 | -0.052 | -0.047 | -0.046*** | -0.082** | -0.081* |
| | (0.016) | (0.039) | (0.040) | (0.014) | (0.040) | (0.041) |
| Observations | 125588 | 37513 | 37513 | 125588 | 37513 | 37513 |
| Panel B: HS or more | | | | | | |
| | OLS | Sib FE | Sib FE | OLS | Sib FE | Sib FE |
| CO - trimester 1 | 0.008 | 0.012 | 0.013 | 0.004 | 0.004 | 0.006 |
| | (0.010) | (0.019) | (0.019) | (0.011) | (0.020) | (0.020) |
| CO - trimester 2 | 0.002 | -0.021 | -0.023 | -0.012 | -0.017 | -0.017 |
| | (0.009) | (0.017) | (0.017) | (0.009) | (0.018) | (0.018) |
| CO - trimester 3 | -0.001 | -0.018 | -0.021 | -0.014 | -0.029* | -0.032* |
| | (0.011) | (0.017) | (0.018) | (0.011) | (0.018) | (0.018) |
| Sibling FE | No | Yes | Yes | No | Yes | Yes |
| Air quality alerts | No | No | Yes | No | No | Yes |
| Observations | 501295 | 166838 | 166838 | 501295 | 166838 | 166838 |
| p-value, 3rd trim. t-test | 0.177 | 0.212 | 0.277 | 0.036** | 0.113 | 0.137 |

Standard errors are in parentheses, clustered on birth year-month in column 1 and clustered on family in columns 2-3. The dependent variable is the 4th grade math/language SIMCE test score. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. "p-value, 3rd trim. t-test" denotes p value from a t-test of the difference between coefficients on 3rd-trimester CO, across education levels, against a null hypothesis of zero difference. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Table 4: EPA CO violations: effects on scores

| | | | |
|---|---|---|---|
| Panel A: Math | | | |
| | OLS | Sib FE | Sib FE |
| EPA CO violations - trimester 1 | -0.0010 | -0.0002 | 0.0003 |
| | (0.0006) | (0.0010) | (0.0011) |
| EPA CO violations - trimester 2 | 0.0001 | -0.0019* | -0.0019* |
| | (0.0008) | (0.0010) | (0.0011) |
| EPA CO violations - trimester 3 | -0.0001 | -0.0019** | -0.0020* |
| | (0.0006) | (0.0009) | (0.0011) |
| Panel B: Language | | | |
| | OLS | Sib FE | Sib FE |
| EPA CO violations - trimester 1 | -0.0011* | -0.0001 | 0.0003 |
| | (0.0006) | (0.0011) | (0.0012) |
| EPA CO violations - trimester 2 | -0.0013** | -0.0016 | -0.0012 |
| | (0.0006) | (0.0011) | (0.0012) |
| EPA CO violations - trimester 3 | -0.0013** | -0.0023** | -0.0024** |
| | (0.0006) | (0.0010) | (0.0011) |
| Sibling FE | No | Yes | Yes |
| Air quality alerts | No | No | Yes |
| Ozone violations | Yes | Yes | Yes |
| Observations | 627545 | 218871 | 218871 |

Standard errors are in parentheses, clustered on birth year-month in column 1 and clustered on family in columns 2-3. The dependent variable is the 4th grade math/language SIMCE test score. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. EPA violation dummy constructed based on 8hr standard of 9ppm, in force since the 1971 Clean Air Act. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Table 5: CO effects on birth weight

| | Birth weight | Birth weight (sibFE) | Low BW | Low BW (sibFE) |
|---|---|---|---|---|
| CO - trimester 1 | -6.72** | -18.1** | 0.00072 | 0.0061* |
| | (3.37) | (7.17) | (0.0016) | (0.0036) |
| CO - trimester 2 | -8.19** | -6.13 | 0.0028 | 0.0038 |
| | (3.82) | (6.68) | (0.0018) | (0.0033) |
| CO - trimester 3 | -4.71 | -18.1*** | 0.0010 | 0.0062* |
| | (3.72) | (6.53) | (0.0015) | (0.0034) |
| Sibling FE | No | Yes | No | Yes |
| Air quality alerts | Yes | Yes | Yes | Yes |
| Observations | 627532 | 204485 | 627545 | 204486 |

Standard errors are in parentheses, clustered on birth year-month in columns 1 and 3 and on family in columns 2 and 4. The dependent variables are birth weight in grams and an indicator for birth weight below 2500g. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Table 6: CO effects on scores - restricted to sibling FE sample

| Panel A: Math | | | |
|---|---|---|---|
| | OLS | Sib FE | Sib FE |
| CO - trimester 1 | -0.024 | -0.001 | -0.000 |
| | (0.015) | (0.017) | (0.017) |
| CO - trimester 2 | -0.001 | -0.021 | -0.022 |
| | (0.012) | (0.015) | (0.016) |
| CO - trimester 3 | -0.005 | -0.034** | -0.036** |
| | (0.015) | (0.015) | (0.016) |
| **Panel B: Language** | | | |
| | OLS | Sib FE | Sib FE |
| CO - trimester 1 | -0.040** | -0.018 | -0.018 |
| | (0.015) | (0.018) | (0.018) |
| CO - trimester 2 | -0.017 | -0.015 | -0.018 |
| | (0.013) | (0.016) | (0.017) |
| CO - trimester 3 | -0.026* | -0.040** | -0.042*** |
| | (0.015) | (0.016) | (0.016) |
| Sibling FE | No | Yes | Yes |
| Air quality alerts | No | No | Yes |
| Observations | 204486 | 204486 | 204486 |

Standard errors are in parentheses, clustered on birth year-month in column 1 and clustered on family in columns 2-3. The dependent variable is the 4th grade math/language SIMCE test score. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Table 7: PM10 effects on scores

| Panel A: Math | | | |
|---|---|---|---|
| | OLS | Sib FE | Sib FE |
| PM10 - trimester 1 | -0.0004 | 0.0001 | 0.0001 |
| | (0.0004) | (0.0005) | (0.0005) |
| PM10 - trimester 2 | -0.0000 | -0.0006 | -0.0006 |
| | (0.0003) | (0.0004) | (0.0004) |
| PM10 - trimester 3 | 0.0002 | -0.0009** | -0.0011** |
| | (0.0004) | (0.0005) | (0.0005) |
| **Panel B: Language** | | | |
| | OLS | Sib FE | Sib FE |
| PM10 - trimester 1 | -0.0010** | -0.0006 | -0.0005 |
| | (0.0004) | (0.0005) | (0.0005) |
| PM10 - trimester 2 | -0.0004 | -0.0005 | -0.0005 |
| | (0.0003) | (0.0004) | (0.0004) |
| PM10 - trimester 3 | -0.0005 | -0.0011** | -0.0011** |
| | (0.0004) | (0.0005) | (0.0005) |
| Sibling FE | No | Yes | Yes |
| Air quality alerts | No | No | Yes |
| Observations | 666947 | 218202 | 218202 |

Standard errors are in parentheses, clustered on birth year-month in column 1 and clustered on family in columns 2-3. The dependent variable is the 4th grade math/language SIMCE test score. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Table 8: AQI effects on scores

| Panel A: Math | | | |
|---|---|---|---|
| | OLS | Sib FE | Sib FE |
| AQI - trimester 1 | -0.0005 | -0.0005 | -0.0004 |
| | (0.0007) | (0.0007) | (0.0007) |
| AQI - trimester 2 | -0.0010* | -0.0013** | -0.0013** |
| | (0.0006) | (0.0005) | (0.0006) |
| AQI - trimester 3 | 0.0009 | -0.0013* | -0.0015** |
| | (0.0007) | (0.0007) | (0.0007) |
| **Panel B: Language** | | | |
| | OLS | Sib FE | Sib FE |
| AQI - trimester 1 | -0.0011* | -0.0010 | -0.0009 |
| | (0.0006) | (0.0007) | (0.0008) |
| AQI - trimester 2 | -0.0014** | -0.0015*** | -0.0014** |
| | (0.0006) | (0.0005) | (0.0006) |
| AQI - trimester 3 | -0.0004 | -0.0022*** | -0.0023*** |
| | (0.0007) | (0.0007) | (0.0008) |
| Sibling FE | No | Yes | Yes |
| Air quality alerts | No | No | Yes |
| Observations | 668627 | 218871 | 218871 |

Standard errors are in parentheses, clustered on birth year-month in column 1 and clustered on family in columns 2-3. The dependent variable is the 4th grade math/language SIMCE test score. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. Per EPA guidelines, AQI is the maximum over piecewise linear transformations of CO, PM10, and O3 readings. * (p<0.10), ** (p<0.05), *** (p<0.01)

Table 9: CO effects on scores, placebo trimesters

| | OLS | Sib FE | Sib FE |
|---|---|---|---|
| CO - trimester -3 | 0.004 | 0.014 | 0.016 |
| | (0.014) | (0.025) | (0.026) |
| CO - trimester -2 | 0.010 | -0.019 | -0.013 |
| | (0.014) | (0.028) | (0.028) |
| CO - trimester -1 | 0.017 | -0.008 | -0.010 |
| | (0.018) | (0.029) | (0.030) |
| Sibling FE | No | Yes | Yes |
| Air quality alerts | No | No | Yes |
| Observations | 561852 | 182799 | 182799 |

Standard errors are in parentheses, clustered on birth year-month in column 1 and clustered on family in columns 2-3. The dependent variable is the 4th grade math SIMCE test score. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummmies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature enters as a set of 10-degree F indicators in maximum daily temperature. We also control for ozone pollution (level). All environmental variables are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. Sample size is smaller than for our primary estimates because pollution data do not extend far enough to construct placebo trimesters for some early births. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)