Gray Matters: Fetal Pollution Exposure and Human Capital Formation

Prashant Bharadwaj, Matthew Gibson, Joshua Graff Zivin, Christopher Neilson

Abstract: This paper examines the impact of fetal exposure to air pollution on fourth-grade test scores in Santiago, Chile. We rely on comparisons across siblings which address concerns about locational sorting (for nonmovers) 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) and correlated pollutants (like PM10) on math and language skills measured in fourth 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 US$100 million per birth cohort.

JEL Codes: I24, J24, Q53, Q56

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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 be-

Prashant Bharadwaj and Joshua Graff Zivin are at the University of California, San Diego. Matthew Gibson (mg17@williams.edu) is at Williams College. Christopher Neilson is at Princeton University. We 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 Francisco Gallego, Matthew Neidell, Reed Walker, and participants at PERC Workshop on Environmental Quality and Human Health, NBER Environmental Meetings, University of Southern California, University of California, Irvine, Yale University, and the IZA Workshop on Labor Market Effects of Environmental Policies. Financial support from the University of California Center for Energy and Environmental Economics is gratefully acknowledged.

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.

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lieved that information technology has 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 $7 billion 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 (Currie and Hyson 1999; Cunha and Heckman 2008; Almond and Currie 2011). Pollution has been known to have adverse effects on contemporaneous childhood health,[2] which raises the question of whether early-life pollution exposure affects long-term human capital outcomes. If so, pollution could have a sizable cost to society through its contemporaneous and dynamic effects on the production of human capital. Such effects 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, data sets 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 data set from Santiago, Chile, to examine how fetal exposure to carbon monoxide (and correlated pollutants like PM10 and PM2.5) affects children's performance on high-stakes national tests in primary school.[4] The richness of our data allows us to overcome the core estimation challenges in this line of research and improve upon the existing literature in several important dimensions. First, we can directly link vital statistics and education data through unique in-

2. For recent examples, see Currie and Walker (2011), Knittel, Miller, and Sanders (2011), Arceo-Gomez, Hanna, and Oliva (2012), Currie, Graff Zivin, Meckel, et al. (2013), Currie, Graff Zivin, Mullins, and Neidell (2013), Schlenker and Walker (2015).

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 et al. 2009). Long-term consequences include negative impacts on schooling outcomes, criminal behavior, and economic productivity (Rogan and Ware 2003; Reyes 2007; Nilsson 2009; Rau, Reyes, and Urzúa 2013).

4. Outcomes in primary school are important to consider as they predict future outcomes like dropping out of high school (Ensminger and Slusarcick 1992; Garnier, Stein, and Jacobs 1997). Research shows that parents are willing to pay more in local school taxes for modest increases in test performance in elementary school (Black 1999).

dividual 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 2001, 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 multipronged approach to address the endogeneity of pollution exposure. In particular, we rely on sibling comparisons which allow us to address concerns about locational sorting (insofar as households do not endogenously move between sibling births) 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 (FE) yields results that are quite a bit larger than ordinary least squares (OLS) estimates, suggesting an important role for family-level characteristics.[5] We also exploit data on air quality alerts to address short-run time-varying avoidance behavior, which has proved to be important in a number of other contexts (Graff Zivin and Neidell 2009; Neidell 2009; Graff Zivin, Neidell, and Schlenker 2011; Deschenes, Greenstone, and Shapiro 2012).

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 trade-offs 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. Drawing on previous work linking academic achievement and 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 accrued from pollution abatement policies implemented during the last two decades. Carbon monoxide is regularly emitted as a by-product of fossil fuel combustion and subject to regulation across the world.[6] 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.

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5. 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.

6. It is worth mentioning that an important caveat here is that while we estimate the impacts of carbon monoxide exposure, CO is emitted along with other pollutants and we are unable to separately identify the impacts of CO versus PM10 versus PM2.5, etc. Later in the paper we show estimates for these other correlated pollutants as well as a composite index of pollutants (AQI).

The remainder of the paper is organized as follows. The next section provides a brief description of the relevant scientific background. Section 2 describes our data, and section 3 details our econometric approach. Our results are described in section 4. Section 5 offers some concluding remarks.

1. SCIENTIFIC BACKGROUND

Carbon monoxide is an odorless and colorless gas that is largely emitted through motor vehicle exhaust (EPA 2008). 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 (Plopper and Fanucchi 2000; Neidell 2004; Mortimer et al. 2008). 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).

Animal studies have shown that CO can disrupt critical processes in the developing brain. The limited evidence suggests that the first and third trimesters of pregnancy may be particularly important. During the first trimester, exposure to CO can impair the migration of neuroblasts during neurogenesis and thus impede brain development (Woody and Brewster 1990). Exposure to CO during the third trimester can block important receptors that regulate neuronal cell death, leading to neurodegeneration in the developing rat brain (Ikonomidou et al. 1999). Most directly relevant for our study, a recent epidemiological study of human exposure to wood smoke, of which CO is a major constituent component, found that third-trimester exposure led to long-term deficits in neuropsychological performance (Dix-Cooper et al. 2012). Whether exposure to outdoor CO pollution translates into cognitive impairment in humans is largely unknown and the focus of this study.

A common challenge for all nonlaboratory studies of the impacts of air pollution is confounding due to other pollutants. Some pollutants are co-emitted as a by-product 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 nor 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 multipollutant 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.[7] To address this, 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 interpret 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.[8] Finally, we note that weather, particularly temperature, can impact pollution formation as well as child health (Deschenes, Greenstone, and Guryan 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 3 where we discuss our empirical specification and strategy.

2. 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 data set 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 the corresponding test scores between 2002 and 2010.

2.1. Birth Data

Birth data come from a data set (essentially the vital statistics of Chile) provided by the Health Ministry of the government of Chile. This data set 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, marital status, and municipality of residence. (Note that a Chilean municipality is a neighborhood, not a city.) Impor-

7. CO and ozone are negatively correlated. Assume for the moment that both pollutants negatively affect long-run human capital. If we were to omit the ozone control from our regression, our estimated effect of CO would conflate the harm from high CO with the benefit from low ozone. The CO estimate would be biased downward in magnitude.

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

tantly, these data contain a unique code for the mother, allowing us to identify offspring from the same mother and thus implement sibling fixed effects.

2.2. Environmental Data

Air pollution data for the period from 1998 to 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 1992–97 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 three Santiago monitors that operate during our entire study period.[9] 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 since inversion layers, which are correlated with extremely high pollution events, occur at altitudes that are lower than this monitor (Gramsch et al. 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.[10]

CO data during our study period are 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 (O_3, 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.

9. In Santiago, new monitor placements arise endogenously from political and bureaucratic processes. Use of an unbalanced monitor panel could induce nonzero covariance between exposure measurement error and time-varying unobservable determinants of test scores, resulting in bias. Nonetheless we explore this approach in appendix table A2 (appendix and tables A1–A5 available online), which shows results using an unbalanced panel of Santiago monitors. Estimates are broadly similar, but somewhat smaller in magnitude for math scores. We do not have similarly consistent pollution measures for other Chilean cities, e.g., Valparaiso, over this period.

10. Appendix table A3 shows results when we constrain distance to the nearest monitor. Our OLS results are strongest (as expected) when the distance to the nearest monitor is smaller. 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.

In order to provide a sense of aggregate pollution patterns in Santiago, we use data on CO, PM10, and O_3, to compute a daily Air Quality Index (AQI) using the algorithm developed by the US Environmental Protection Agency (EPA 2006; Mintz 2012). 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.

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-1990s are the result of a concerted government effort to address the serious pollution concerns from the previous decade. The most important of these measures started in 1997 under the PPDA (Mullins and Bharadwaj 2014). Figure 2 shows the monitor-level time series for the three monitors that comprise our balanced panel. They exhibit similar seasonal patterns, but levels are much lower at the Las Condes monitor than at the Parque O'Higgins and La Independencia monitors.

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 nonlinear control in our regressions, as detailed in section 3.

2.3. 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.[11] 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 are constructed to be comparable across schools and time. The education data sets were subsequently matched to the birth data using individual-level identifiers.[12] We are unable to use the eighth- and tenth-grade results in this setting since for these later grades, the number of sibling groups is far too small: approximately 3,000 for eighth grade and still fewer for tenth grade.

The match rate between births and SIMCE files (the test score records) is approximately 0.8. This match rate, and the fact that Santiago has around 82,500 births per

11. This database was kindly provided by the Ministry of Education of Chile (MINEDUC).
12. More details on the match quality can be found in Bharadwaj, Løken, and Neilson 2013.

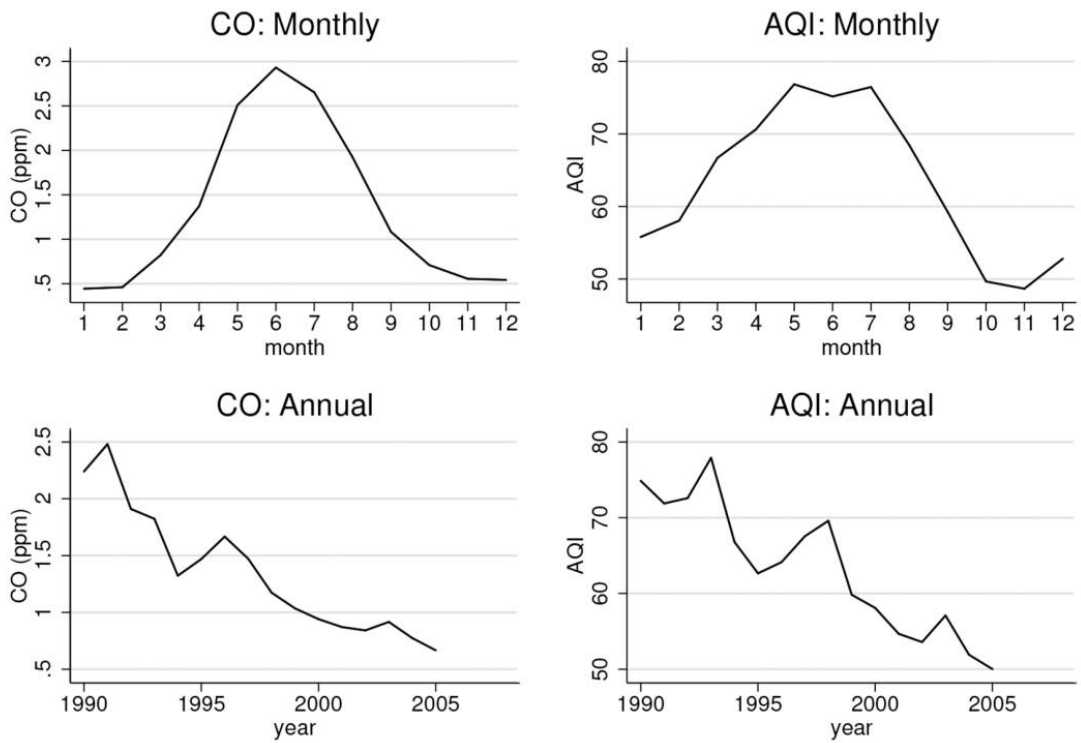

Figure 1. Pollution over time. The top panel shows that CO and AQI are higher in the winter months (Chile, being in the southern hemisphere, experiences winters from June through August).

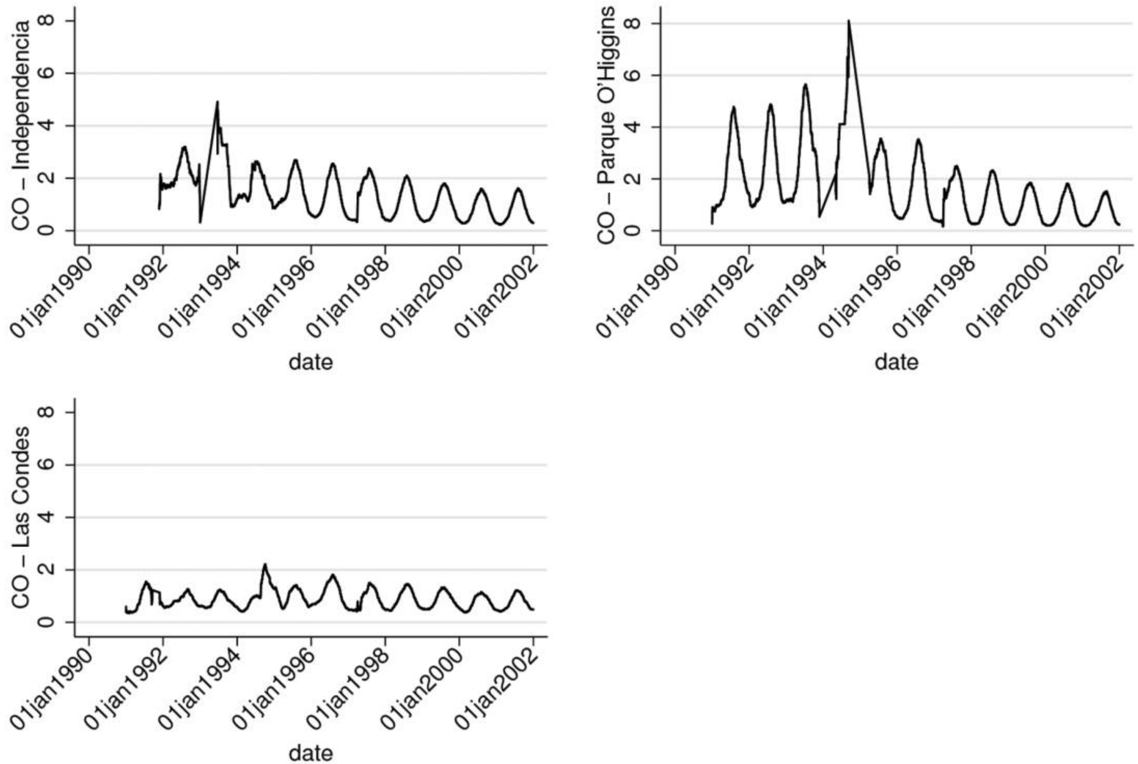

Figure 2. CO over time, by monitor. Each graph shows 90-day moving average CO (ppm) at one of the three monitors in our balanced panel.

year over our time period, leads to around 66,000 matched observations per year. Over a 10-year period, this is around 660,000 observations. After accounting for observations that are missing essential covariates, we arrive at a potential OLS sample of 623,002. Among these observations, the number that have siblings within the age range observable to us is 193,138. Descriptive statistics for all variables used in our empirical analysis are presented in table 1.

3. 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 all three trimesters 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.[13] 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 temperature and other weather variables. Our basic estimating equation is:

$$S_{ijrt} = \beta E_{mt} + \theta_t + \alpha \chi_{ijrt} + \gamma W_t + \varepsilon_{ijrt}. \tag{1}$$

The dependent variable S_{ijrt} is fourth-grade test score in either math or language of child i, born to mother j, in municipality (neighborhood) r, at time t. The term θ_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 χ_{ijrt} is a gender dummy. The term W_t includes a host of weather controls (temperature, precipitation, fog, dew point, 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.[14]

13. While it is easier to interpret and aggregate coefficients at the trimester level, analysis at the gestational month level yields similar results.

14. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables.

Table 1. Descriptive Statistics

	Mean	SD	Min	Max
Fourth-grade math	.16	1.01	−2.99	2.51
Fourth-grade language	.10	1.02	−3.28	2.33
CO—trimester 1	1.31	.95	.16	4.85
CO—trimester 2	1.30	.95	.16	5.76
CO—trimester 3	1.23	.93	.16	6.59
PM10—trimester 1	90.59	29.79	39.73	197.85
PM10—trimester 2	91.53	29.42	39.73	249.45
PM10—trimester 3	89.86	29.24	36.44	261.59
O_3—trimester 1	31.92	10.24	9.78	85.73
O_3—trimester 2	31.01	10.46	9.78	85.73
O_3—trimester 3	31.31	10.26	9.06	85.73
AQI—trimester 1	64.95	15.86	31.91	109.82
AQI—trimester 2	65.63	15.33	31.91	145.23
AQI—trimester 3	64.84	14.99	31.12	146.53
O'Higgins monitor dummy	.69	.46	.00	1.00
Independencia monitor dummy	.31	.46	.00	1.00
Las Condes monitor dummy	.06	.23	.00	1.00
Temperature—trimester 1	58.45	7.27	45.79	70.28
Temperature—trimester 2	57.74	7.39	45.79	70.28
Temperature—trimester 3	57.74	7.39	45.79	70.28
Rainfall—trimester 1	1.64	1.15	.00	4.57
Rainfall—trimester 2	1.76	1.21	.00	4.71
Rainfall—trimester 3	1.72	1.23	.00	5.29
Dew point—trimester 1	48.43	16.08	39.74	154.12
Dew point—trimester 2	49.66	19.59	39.74	154.12
Dew point—trimester 3	51.33	22.51	37.42	245.74
Fog—trimester 1	.24	.13	.01	.53
Fog—trimester 2	.25	.13	.01	.53
Fog—trimester 3	.25	.13	.00	.61
Wind speed—trimester 1	4.78	1.31	2.61	7.52
Wind speed—trimester 2	4.70	1.34	2.61	7.52
Wind speed—trimester 3	4.79	1.34	2.47	8.09
Air quality alert—trimester 1	4.86	7.41	.00	32.00
Air quality alert—trimester 2	5.56	7.73	.00	32.00
Air quality alert—trimester 3	5.39	7.56	.00	35.00
Gestational age (weeks)	38.78	1.38	33.00	41.00
Birth weight (g)	3342.28	497.23	270.00	6046.00
Low birth weight (<2.5 kg)	.05	.21	.00	1.00
Mother's age	27.19	5.75	12.00	51.00
Sex (1 = female)	.50	.50	.00	1.00
Observations	193,138			

The term E_{mt} contains the average level of pollution, also measured at the level of gestational trimester based on the nearest monitor. 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.[15] We will also take a more structured approach to the multipollutant 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 O_3 levels (EPA 2006; Mintz 2012).

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 residual variation in the measures of pollution after controlling for seasonality (month fixed effects) and year fixed effects. Figure 3 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.[16]

The first modification we make to equation (1) is the introduction of observable mother's characteristics. Hence, we estimate:

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

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 would capture pollution impacts net of these potentially costly behaviors.[17] To clarify the interpre-

15. Recall that the correlation between CO and PM10 levels is 0.9 (see appendix table A1). Also, our results are not sensitive to the use of ozone as a control variable. This is likely due to the fact that ozone and CO are inversely correlated and seasonal controls do enough to capture the effects of ozone.

16. Note that while feasible, including year of birth × month of birth fixed effects leaves us with little residual variation. Results including year × month of birth fixed effects are insignificant in the OLS and sibling fixed effects specifications. Results available on request.

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

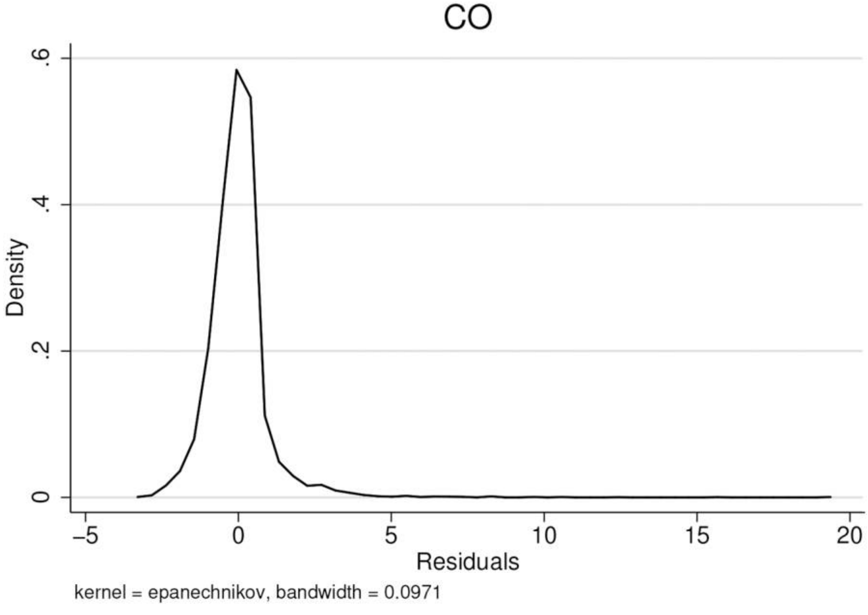

Figure 3. Residualized pollution (year and month dummies). Figure based on the residuals of a regression using daily CO as the dependent variable and year and month dummies as independent variables. We then plot the probability distribution function of the residuals using the Stata command "kdensity" with default options: an Epanechnikov kernel and MSE-minimizing bandwidth under an assumed Gaussian distribution.

tation of β 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 is a function of early childhood health (H),[18] investments made from birth to time of test taking (P), and parental characteristics (X).

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

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

18. 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.

environmental conditions are a function of ambient pollution measured at the nearest monitor (E_{mt}), mitigated by individual-level avoidance behavior (A).

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

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

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 city wide, we can express student performance as:

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

Equation (1) is essentially a modified version of equation (6). Test scores still depend on environmental conditions and parental characteristics and now 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; Halla and Zweimuller 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 nonrandom assignment of pollution, we employ sibling 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 (Figueroa, Rogat, and Firinguetti 1996; Chay and Greenstone 2005). Families with higher incomes are more likely to sort into neighborhoods with better air quality and invest in human capital.[19] Sibling fixed effects in this setting also play an important role insofar as our limited data on maternal characteristics are missing important unobservable family characteristics that might matter for test outcomes as well as pollution exposure (Currie et al. 2009). Our estimating equation us-

19. Note that our results are robust to the inclusion of municipality (neighborhood) linear time trends.

ing sibling fixed effects (indexing another sibling i' born at t') is essentially a first difference across siblings and takes the form:

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

In general the addition of granular fixed effects can exacerbate measurement error problems (Griliches and Hausman 1986). In studies of air pollution exposure, however, a spatial error component is often the primary concern. If measurement error is an additively separable function of location, our sibling fixed effects estimates will reduce rather than exacerbate bias from measurement error. In this vein, Jerrett et al. (2005) find that community fixed effects reduce attenuation in estimates of the pollution-mortality relationship. In addition, our sibling fixed effects will capture all time-invariant investments in children. Equation (7) ignores time-varying investments, however, 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, 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.[20] 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). These avoidance controls also reduce exposure measurement error arising from differences in indoor and outdoor air quality (Zeger et al. 2000).

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

$$\Delta S_{ijrt-i'jrt'} = \beta \Delta E_{mt-mt'} + \gamma \Delta W_{t-t'} + \kappa \Delta Alerts_{t-t'} + \Delta u_{ijrt-i'jrt'}. \tag{8}$$

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

20. 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.

Table 2. CO Effects on Scores

	OLS	Sib FE	Sib FE
		A. Math	
CO—trimester 1	−.025	−.001	−.000
	(.017)	(.018)	(.019)
CO—trimester 2	−.002	−.021	−.022
	(.011)	(.016)	(.016)
CO—trimester 3	−.005	−.034**	−.036**
	(.013)	(.015)	(.016)
CO—whole pregnancy	−.032	−.055	−.059*
	(.027)	(.034)	(.036)
		B. Language	
CO—trimester 1	−.040**	−.018	−.018
	(.018)	(.017)	(.018)
CO—trimester 2	−.017	−.015	−.018
	(.013)	(.015)	(.016)
CO—trimester 3	−.025*	−.040**	−.042**
	(.014)	(.019)	(.020)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	193,138	193,138	193,138
CO—whole pregnancy	−.082***	−.073**	−.078**
	(.031)	(.037)	(.039)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

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).

4. RESULTS

We begin our analysis by examining the impact of CO on test scores in table 2. Panel A presents the estimates using fourth-grade math scores as the dependent variable, and panel B uses fourth-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 Fahrenheit 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.[21] Standard errors are clustered on family and municipality (neighborhood) in all columns. To this base model we add sibling fixed effects in column 2 and further add the total number of trimester level air quality alert days in column 3. Here and throughout our empirical analysis, we estimate our OLS specification using the sibling sample, facilitating ceterus paribus comparisons across specifications.

Table 2, panel A, shows negative and significant effects of in utero CO exposure on fourth-grade math test scores in specifications that account for sibling fixed effects.[22] The effects are concentrated in trimesters 2 and 3 (although estimates for trimester 2 are not statistically significant), but taken together, the effect over the entire pregnancy is sizable and statistically significant in our preferred specification. 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 magnitudes of our estimates increase significantly in column 2. A 1 standard deviation increase in CO in the third trimester is initially associated with a statistically insignificant 0.005 standard deviation decrease in fourth-grade math scores (col. 1); however, adding sibling FE in column 2 increases the magnitude to a statistically significant 0.034 standard deviations. Adding air quality alerts to our sibling fixed effects specification (col. 3) increases the magnitude of the estimates slightly (by about 6%–8% in most cases), suggesting that insofar as the alerts induce avoidance behavior, this appears to have a rather modest impact on child outcomes.[23] Panel B shows similar effects in both direction and magnitude on language test scores. The bottom line in each panel presents

21. As discussed in section 1, this study focuses on CO rather than ozone because the scientific literature documents the mechanism by which CO harms a developing fetus. Ozone may also be harmful to the fetus, but the mechanisms are unknown. Appendix table A4 reports the estimated ozone coefficients from our preferred specification.

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

23. The difference in coefficients from adding the alerts controls is similar for trimesters 2 and 3. We caution against overinterpreting this pattern, however. First, these differences are very small relative to the associated standard errors. Second, these differences reflect both the quantity of avoidance behavior and its effectiveness, which could vary over the course of a pregnancy.

whole-pregnancy effects (sums of trimester-level estimates), which are statistically significant for language but not for math.

While there are many potential reasons for OLS and sibling fixed effects results to vary in this setting, the fact that OLS seems to underestimate the effect of pollution exposure is worth noting. This is perhaps counterintuitive if we believe that parents with worse socioeconomic status live in areas that are more polluted and also have children who perform worse in school. We offer three potential explanations as to why OLS might underestimate in this context relative to sibling FE. First, measurement error (if classical) can bias OLS toward zero. In our case, if measurement error is differenced out when comparing siblings, then the estimates from sibling FE could be larger than OLS. The second is parental investments. If parents act in ways that try to compensate for health deficiencies, and parental investments are at least partially local public goods within the household, then we would expect sibling FE estimates to be larger than OLS. For example, books purchased for one child are likely to benefit others within the household. In this case, investments that differentially help disadvantaged children who were exposed to pollution early in life will produce a greater "catch up" compared to children in other households (i.e., OLS) than compared to children within the same household (i.e., sibling FE). A full exploration of these forces is considered in Bharadwaj et al. (2013). The third is avoidance behavior. This is the explanation used in Moretti and Neidell (2011). In their model, they show that avoidance behavior can introduce a downward bias in OLS. The intuition here is simple: if increased pollution leads to more avoidance (and more avoidance leads to better health/cognitive scores), then the OLS captures the net effect of exposure and avoidance. In strategies that account for avoidance (like the instrumental variables [IV] used in Moretti and Neidell [2011]), avoidance is held constant, and therefore the IV estimates are larger than OLS estimates. In our case, sibling fixed effects hold constant time-invariant avoidance (e.g., fixed cost or lumpy investments or routine patterns of variable cost avoidance behaviors) and hence could be yet another explanation as to why FE estimates are larger than OLS.

Taken as whole, the results in table 2 reveal a strong negative effect from fetal exposure to CO.[24] 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 underscored by the size of the exposed population—far more chil-

24. An alternative measure is to measure pollution over the entire 9 months of the pregnancy. This measure yields similar negative and significant effects as seen in the graphs in appendix figures A1 and A2.

dren 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 United States (Sanders 2012).[25]

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. A 1 standard deviation increase in third-trimester CO affects the children of less educated mothers by more than twice as much as the children of more educated mothers (cols. 3 and 6). These results provide suggestive evidence that less educated families are more vulnerable to the detrimental effects of pollution. There are several possible explanations for this pattern, including but not limited to (1) increased susceptibility, perhaps due to poorer baseline health; (2) increased exposure; and (3) diminished ability to invest in children to offset early-life deficits. Our claims about the vulnerability of less educated families are based on evidence that air quality is capitalized into housing prices (Chay and Greenstone 2005; Banzhaf and Walsh 2008). We also note that Graff Zivin and Neidell (2013) discuss these issues of nonrandom pollution exposure more generally and provide direct empirical evidence that those households with higher socioeconomic status and higher levels of health investments generally live in neighborhoods with better air quality. Conditional on exposure, less educated families may be more susceptible to pollution due to a range of comorbid conditions, such as asthma and social stress, which are prevalent among less educated families, and are known to exacerbate the impacts of pollution (e.g., Eggleston et al. 1999; Clougherty et al. 2010). The relative importance of these and other mechanisms remains an open question.

All of our previous analysis treated the relationship between CO exposure and test scores as linear. Figures 4 and 5 show the relationship between pollution and test scores for the third trimester of pregnancy using local linear regressions. The figures confirm the negative result found in the previous tables and suggest nonlinearity is not first order in this setting. However, we note that there are many ways to model nonlinearity in this context. In order to avoid ad hoc searches for nonlinearity, we adopt counts of violations of the US Environmental Protection Agency's National Ambient Air Quality Standards for CO (9 parts per million for an 8-hour average)[26] as our nonlinear exposure measure. To be clear, for each trimester we sum the number of days on which the EPA's safety threshold is exceeded. Table 4 presents these results for both math and language. We find that for every extra day of EPA threshold violation

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

26. The average CO level over a trimester in our sample is approximately 1 part per million.

Table 3. CO Effects on Scores, by Mother's Education

	Math	Math	Math	Language	Language	Language
CO—trimester 1	−.014	−.000	.000	−.023	−.010	−.011
	(.015)	(.018)	(.019)	(.017)	(.017)	(.018)
CO—trimester 2	.003	−.021	−.022	−.011	−.014	−.017
	(.012)	(.017)	(.017)	(.014)	(.015)	(.016)
CO—trimester 3	−.007	−.025*	−.028*	−.024*	−.030	−.034*
	(.012)	(.015)	(.015)	(.014)	(.019)	(.020)
CO—trimester 1 × less than HS	−.029**	−.004	−.003	−.056***	−.033***	−.028**
	(.013)	(.012)	(.012)	(.013)	(.013)	(.012)
CO—trimester 2 × less than HS	−.028**	.006	.006	−.031**	−.003	−.000
	(.013)	(.014)	(.014)	(.013)	(.013)	(.013)
CO—trimester 3 × less than HS	−.018*	−.041***	−.038***	−.032***	−.045***	−.038***
	(.010)	(.010)	(.010)	(.009)	(.011)	(.011)
Sibling FE	No	Yes	Yes	No	Yes	Yes
Air quality alerts	No	No	Yes	No	No	Yes
Observations	193,138	193,138	193,138	193,138	193,138	193,138
CO—whole pregnancy	−.019	−.046	−.050	−.058**	−.054	−.063
	(.024)	(.035)	(.036)	(.029)	(.037)	(.039)
CO—whole pregnancy × less than HS	−.093***	−.085**	−.085**	−.176***	−.134***	−.129***
	(.030)	(.035)	(.036)	(.033)	(.038)	(.040)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

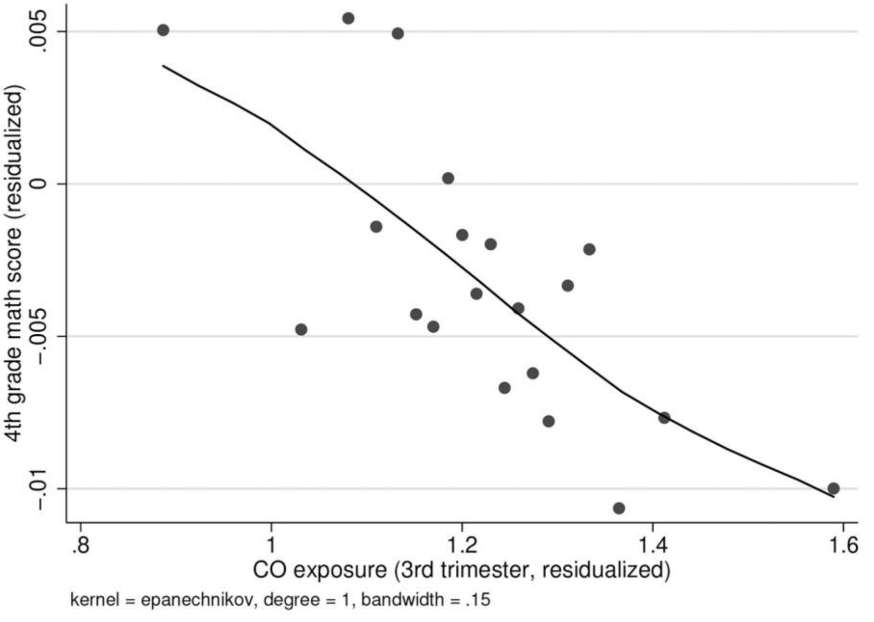

Figure 4. Residualized math scores and third-trimester CO. The vertical axis measures residualized fourth-grade math/language SIMCE test scores. The horizontal axis measures residualized third-trimester CO exposure, recentered around mean exposure for ease of interpretation. Residualized variables are constructed by regressing these two variables on the full set of controls from our preferred specification, including sibling fixed effects, alerts, and CO exposure in trimesters 1–2, then calculating residuals. Other controls include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. Points represent means within 20 equal-frequency bins. Fitted line is a local linear regression over these points, with default kernel and bandwidth. *$p < .10$; **$p < .05$; ***$p < .01$.

during the third trimester, test scores decrease significantly, with a consistent magnitude around 0.003 standard deviations 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 under linearity would imply an effect of nearly 0.15 standard deviations if all 47 violations happened in the second or third trimester. The average number of EPA violations during a third trimester in our sample is 2.3, which translates to a 0.007 stan-

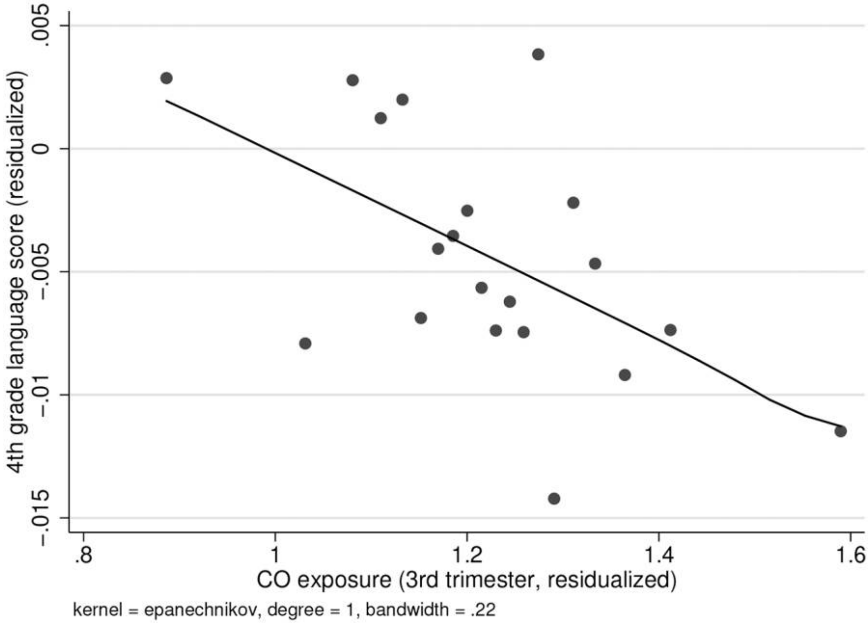

Figure 5. Residualized language scores and third-trimester CO. The vertical axis measures residualized fourth-grade math/language SIMCE test scores. The horizontal axis measures residualized third-trimester CO exposure, recentered around mean exposure for ease of interpretation. Residualized variables are constructed by regressing these two variables on the full set of controls from our preferred specification, including sibling fixed effects, alerts, and CO exposure in trimesters 1–2, then calculating residuals. Other controls include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. Points represent means within 20 equal-frequency bins. Fitted line is a local linear regression over these points, with default kernel and bandwidth. *$p < .10$; **$p < .05$; ***$p < .01$.

dard deviation reduction in test scores for the average child exposed to such a third trimester. Appendix table A5 adopts an alternative approach to nonlinearity, allowing CO exposure to enter as counts of third-trimester days in four bins. Consistent with our findings in table 4, there is suggestive evidence that harmful effects stem from the most polluted days, with ambient readings over 3.3 parts per million (ppm).

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

Table 4. EPA CO Violations: Effects on Scores

	OLS	Sib FE	Sib FE
	A. Math		
EPA CO violations—trimester 1	−.0020	−.0007	−.0006
	(.0013)	(.0014)	(.0015)
EPA CO violations—trimester 2	−.0012	−.0019*	−.0023*
	(.0010)	(.0012)	(.0013)
EPA CO violations—trimester 3	−.0002	−.0026**	−.0032**
	(.0008)	(.0012)	(.0014)
EPA CO violations—whole pregnancy	−.003	−.005*	−.006**
	(.002)	(.003)	(.003)
	B. Language		
EPA CO violations—trimester 1	−.0031**	−.0012	−.0016
	(.0013)	(.0013)	(.0015)
EPA CO violations—trimester 2	−.0027**	−.0020	−.0025
	(.0011)	(.0014)	(.0016)
EPA CO violations—trimester 3	−.0014*	−.0032***	−.0040***
	(.0008)	(.0012)	(.0015)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Ozone violations	Yes	Yes	Yes
Observations	193,138	193,138	193,138
EPA CO violations—whole pregnancy	−.007***	−.006**	−.008***
	(.002)	(.003)	(.003)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements 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 8-hour CO standard of 9 ppm, in force since 1971.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

channels, they do allow us to probe two possibilities. Since birth weight has been shown to be an important determinant of school performance (Bharadwaj et al. 2013; Figlio 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 specification in table 5 shows 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 2,500 grams). Similarly, in table 6 we find that pollution exposure increases the probability of low gestational age (birth before 36 weeks), with sibling FE estimates again larger than their OLS counterparts. This is in line with the finding that smoking and other maternal stressors can lead to earlier delivery. 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 effects are much too small to explain all of the relationship between pollution and scores. Indeed, point estimates from Bharadwaj et al. (2013) of the impact of birth weight on test scores imply that this channel explains no more than 10% of the cognitive impacts due to pollution. We also wish to point out that birth weight is a proxy measure of health at birth, but one that does not

Table 5. CO Effects on Birth Weight

	Birth Weight	Birth Weight	Low Birth Weight	Low Birth Weight
CO—trimester 1	−10.7*	−18.1*	−.00031	.0061
	(6.24)	(9.33)	(.0027)	(.0040)
CO—trimester 2	−13.9**	−6.13	.0024	.0038
	(6.67)	(6.44)	(.0029)	(.0030)
CO—trimester 3	−12.6**	−18.1***	.0028	.0062*
	(5.58)	(6.77)	(.0033)	(.0036)
Sibling FE	No	Yes	No	Yes
Air quality alerts	Yes	Yes	Yes	Yes
Observations	193,137	193,136	193,137	193,136
CO—whole pregnancy	−37.2***	−42.3**	.005	.016**
	(12.960)	(17.313)	(.006)	(.008)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variables are birth weight in grams and an indicator for birth weight below 2,500 g. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fehrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. Observation counts differ slightly from test score regression tables, and differ slightly across columns, because of small differences in completeness of test score and birth weight variables.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

Table 6. CO Effects on Low Gestational Age

	Low GA	Low GA	Low GA
CO—trimester 1	.0078***	.010***	.010***
	(.0028)	(.0027)	(.0030)
CO—trimester 2	.014***	.0081**	.0049
	(.0033)	(.0032)	(.0035)
CO—trimester 3	.010***	.0092***	.0059**
	(.0030)	(.0027)	(.0029)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	193,138	193,138	193,138
CO—whole pregnancy	.032***	.028***	.021***
	(.007)	(.006)	(.007)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is an indicator for gestational age below 36 weeks. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age, and dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

capture all aspects of fetal health or nutrition (Almond and Currie 2011). Moreover, maternal health stressors, such as pollution, can directly impact gene expression in the fetus through epigenetic channels that negatively impact intellectual growth and maturity (Petronis 2010).

4.1. Robustness Checks

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 fourth-grade math and language scores. An alternative approach to addressing multiple pollutants is to aggregate them into a single index. In this case, we use the US Environmental Protection Agency's Air Quality Index (AQI), which is constructed by taking the maximum over piecewise-linear transformations

Table 7. PM10 Effects on Scores

	OLS	Sib FE	Sib FE
		A. Math	
PM10—trimester 1	−.0004	−.0002	−.0001
	(.0005)	(.0005)	(.0006)
PM10—trimester 2	−.0006	−.0003	−.0003
	(.0004)	(.0005)	(.0005)
PM10—trimester 3	−.0009*	−.0010*	−.0011*
	(.0005)	(.0005)	(.0006)
PM10—whole pregnancy	−.002	−.001	−.001
	(.001)	(.001)	(.001)
		B. Language	
PM10—trimester 1	−.0010**	−.0008	−.0008
	(.0005)	(.0005)	(.0005)
PM10—trimester 2	−.0011**	−.0006	−.0006
	(.0005)	(.0004)	(.0004)
PM10—trimester 3	−.0013***	−.0013**	−.0013**
	(.0004)	(.0006)	(.0006)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	193,138	193,138	193,138
PM10—whole pregnancy	−.003***	−.003***	−.003***
	(.001)	(.001)	(.001)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

of daily readings for all individual pollutants (EPA 2006; Mintz 2012). As can be seen in table 8, higher AQI exposure in utero leads to lower test scores. While this approach does not allow us to disentangle the effects of different pollutants, these results follow the same patterns as prior tables—most of the effects are concentrated in the second

Table 8. AQI Effects on Scores

	OLS	Sib FE	Sib FE
	A. Math		
AQI—trimester 1	−.0006	−.0006	−.0006
	(.0008)	(.0007)	(.0008)
AQI—trimester 2	−.0022***	−.0010	−.0011
	(.0006)	(.0007)	(.0007)
AQI—trimester 3	−.0011*	−.0015*	−.0017*
	(.0006)	(.0008)	(.0009)
AQI—whole pregnancy	−.004***	−.003	−.003
	(.001)	(.002)	(.002)
	B. Language		
	OLS	Sib FE	Sib FE
AQI—trimester 1	−.0015**	−.0011	−.0011
	(.0007)	(.0009)	(.0009)
AQI—trimester 2	−.0031***	−.0016***	−.0018***
	(.0006)	(.0006)	(.0007)
AQI—trimester 3	−.0025***	−.0024***	−.0026**
	(.0006)	(.0009)	(.0010)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	193,138	193,138	193,138
AQI—whole pregnancy	−.007***	−.005**	−.005**
	(.001)	(.002)	(.002)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. All pollution measurements 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 O_3 readings.

* $p < .10$.

** $p < .05$.

** $p < .01$.

and third trimesters and the coefficients are larger after accounting for sibling fixed effects.

Table 9 adds controls for family size at birth to our preferred specification. Because we do not observe pre-1992 births, family size observed in our data will be weakly

Table 9. CO Effects on Math Scores, Family Size (Birth Order) Controls

	OLS	Sib FE	Sib FE
CO—trimester 1	−.025	−.002	−.001
	(.017)	(.018)	(.019)
CO—trimester 2	−.005	−.021	−.022
	(.011)	(.016)	(.016)
CO—trimester 3	−.009	−.036**	−.038**
	(.013)	(.015)	(.015)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	193,138	193,138	193,138
CO—whole pregnancy	−.038	−.059*	−.061*
	(.028)	(.034)	(.035)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. Family size controls are a set of dummies based on the running count of births (from one to six) to the same mother in our data. This count is an imperfect proxy, weakly less than true family size at the time of a birth we observe. Within the constraints imposed by our data, family size at birth and birth order are identical.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

smaller than true family size at birth. Note that this is equivalent to a birth order control, again with the caveat that we observe only relative birth order within our data. Estimates from the specification with family size controls, implemented as a series of dummy variables, are very similar to those from our preferred specification. Table 10 investigates the role of movers in our analysis. We define a mover dummy that equals 1 for a mother with births matched to two or more different monitors. Because our econometric analysis focuses on mothers with multiple births, we have a relatively large fraction of movers in the sample at 10%. In our sample, just 3,374 children are born to mover families in Las Condes. Because readings at the La Independencia and Parque O'Higgins monitors are similar, in most cases the pollution exposure we assign to a family does not change substantially as a result of the move. In table 10 the interactions of the mover dummy with CO exposure are small and not statistically significant at con-

Table 10. CO Effects on Math Scores, Interacted with Moving

	OLS	Sib FE	Sib FE
CO—trimester 1	−.029	−.000	.001
	(.019)	(.018)	(.019)
CO—trimester 2	−.001	−.020	−.021
	(.011)	(.016)	(.016)
CO—trimester 3	−.007	−.035**	−.037**
	(.013)	(.015)	(.015)
CO—trimester 1 × mover	.053*	−.010	−.010
	(.027)	(.014)	(.014)
CO—trimester 2 × mover	−.000	−.008	−.008
	(.016)	(.017)	(.017)
CO—trimester 3 × mover	.041*	.018	.018
	(.022)	(.012)	(.012)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	193,138	193,138	193,138
CO—whole pregnancy	−.037	−.055	−.058
	(.027)	(.034)	(.036)
CO—whole pregnancy, mover	.056	−.054	−.057
	(.041)	(.038)	(.039)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester. The movers dummy equals 1 for mothers matched to two or more pollution monitors.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

ventional levels. The sums of exposure coefficients for movers and nonmovers are nearly identical. This suggests that moves do not create a correlation between our CO exposure measures and time-varying unobservable determinants of test scores.

Table 11 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

Table 11. CO Effects on Math Scores, Placebo Trimesters

	OLS	Sib FE	Sib FE
CO—trimester −3	.021	.014	.016
	(.022)	(.022)	(.021)
CO—trimester −2	.021	−.019	−.013
	(.025)	(.029)	(.029)
CO—trimester −1	.045*	−.008	−.010
	(.024)	(.035)	(.037)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	171,946	154,744	154,744

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements 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 back in time to construct placebo trimesters for some early births.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

time dummies and other controls are effective in capturing serial correlation in pollution exposure. Table 12 shows that in years after birth, the effect of pollution is not generally statistically significant; however, the standard errors are too large to conclude whether postnatal exposure can truly be harmful or not. Future research on this topic would be useful to shed light on the importance of postnatal exposure, the role of avoidance behaviors undertaken by parents after birth has occurred, and its impacts on human capital production.[27] Finally, table 13 presents falsification tests, modeling predetermined variables as functions of CO exposure. Estimated effects on mother's

27. We also measure postnatal exposure in trimesters, examining the impacts from post trimesters 1 to 6. The effects in the sibling-based specifications are insignificant and small in magnitude (results available upon request).

Table 12. CO Effects on Math Scores, Postnatal Years

	OLS	Sib FE	Sib FE
CO—year 1	.032	.007	.008
	(.034)	(.042)	(.043)
CO—year 2	.040	.094**	.087**
	(.045)	(.044)	(.044)
CO—year 3	−.091	−.048	−.055
	(.060)	(.069)	(.068)
CO—year 4	.061	.038	.026
	(.159)	(.142)	(.142)
Sibling FE	No	Yes	Yes
Air quality alerts	No	No	Yes
Observations	193,138	193,138	193,138

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is the fourth-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 dummies for mother's education. Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester or year. Temperature controls are constructed as follows: for each trimester or year, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in (3 trimesters × 6 bins) + (4 years × 6 bins) = 42 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester or year of pregnancy. We represent an air quality alert with a dummy and sum within each trimester or year.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

age, father's age, and mother's education are near zero and statistically insignificant, revealing no evidence of bias from gross misspecification.

5. 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 sibling 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 results are also in line with the scientific literature suggesting the importance of the first and third trimesters in fetal brain development. Our richest model specification suggests that a 1 standard deviation increase in CO exposure during the third trimester of

Table 13. Falsification Tests

	Father's Age	Mother's Age	Low Mother's Education
CO—trimester 1	.024	−.021	.0019
	(.052)	(.015)	(.0033)
CO—trimester 2	−.0013	−.022	.0012
	(.045)	(.014)	(.0027)
CO—trimester 3	−.033	−.011	−.0037
	(.033)	(.013)	(.0037)
Sibling FE	Yes	Yes	Yes
Air quality alerts	Yes	Yes	Yes
Observations	193,138	193,138	193,138
CO—whole pregnancy	−.011	−.054	−.001
	(.098)	(.029)	(.007)

Note. Standard errors are in parentheses, clustered on family and municipality (neighborhood). The dependent variable is given in the column heading. All regressions include year and month fixed effects interacted with monitor dummies. Demographic controls include student gender, log of mother's age (omitted in col. 2), and dummies for mother's education (omitted in col. 3). Environmental controls include second-degree polynomials in precipitation, fog, wind speed, and dew point for each trimester. Temperature controls are constructed as follows: for each trimester, we count days for which maximum temperature falls in each of six 10-degree Fahrenheit bins, 40–49, 50–59, 60–69, 70–79, 80–89, ≥90. This results in 3 trimesters × 6 bins = 18 count variables. We also control for ozone pollution (level). All pollution measurements are averaged within each trimester of pregnancy. We represent an air quality alert with a dummy and sum within each trimester.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

pregnancy is associated with a 0.036 standard deviation decrease in fourth-grade math test scores and a 0.042 standard deviation decrease in fourth-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%. A back-of-the-envelope calculation using our estimated human capital effects and estimates on the returns to test scores from the United States (Blau and Kahn 2005) suggests that, ceteris paribus, this drop could account for as much as $1,000 in 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 US$100 million per cohort.[28] 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 nonpecuniary 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 problems, mortality, and hospitalizations.[29] 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

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28. 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 US adult test scores averaged across math and verbal reasoning yields a 16.36% change in adult earnings after controlling for education levels (see table 2, col. 4, in Blau and Kahn 2005). Applying this relationship between US 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 US$11,000) and discount at a 5% rate over 30 years.

29. 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 et al. (2013), who estimate the benefits due to reduced pollution in Santiago due to better public transit infrastructure.

et al. 2011). The degree to which these “additional” benefits imply stricter regulation will, of course, depend upon the costs and effectiveness of pollution reduction.[30]

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 and gestational age are important channels for these impacts, but they offer only a partial explanation. In the realm of human behavior, 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 life cycle 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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30. Gallego, Montero, and Salas (2011) provide a cautionary tale about well-intentioned policies aimed at reducing air pollution. They find that transportation policies in Santiago and Mexico City *increased* carbon monoxide levels, which given our findings would imply a reduction in human capital formation.

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