Environment and Human Capital:
The Effects of Early-Life Exposure to Pollutants in the Philippines

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Abstract

Human capital, a determining factor in individual labor market and macroeconomic outcomes, is malleable to early-life investments and insults. This study examines the long-term human capital impacts of early-life exposure to common air pollutants in the Philippines. A three-decade, longitudinal survey provides life course measures of human capital and the combination of a macro- and a micro-environmental database characterizes exposure to carbon monoxide and ozone. Using an instrumental variable strategy of weather induced, spatial and temporal variation in emissions, I find that carbon monoxide exposure is consistently detrimental to physical and cognitive dimensions of human capital while the effects of ozone exposure are detrimental to cognition and earnings. In present value terms, a nationwide 10% reduction in carbon monoxide and ozone would generate $5.15 billion in discounted lifetime earnings per annual birth cohort.

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1 Introduction

Because human capital is a widely recognized factor in individual income (Schultz, 1990) as well as macroeconomic growth (Nelson and Phelps, 1966), it is critical to understand the factors influencing the development of human capital (Sanders, 2012). Among the potential factors is pollution exposure. Pollution is increasingly regulated because of widespread evidence that increased exposure directly impacts contemporaneous morbidity and mortality of vulnerable subpopulations, including the very young.[1] Additional evidence suggests that morbidity during early, critical periods of development has persistent, long-term impacts on human capital and labor market outcomes (Almond and Currie, 2011; Cunha and Heckman, 2010; Currie and Hyson, 1999). If early-life pollution exposure damages long-term human capital development, the cumulative effects could be quite large and imply that environmental regulations traditionally viewed as taxes may be investments fueling economic growth in developing economy contexts (Graff Zivin and Neidell, 2013; Nelson and Phelps, 1966; Schultz, 1990).

Despite evidence of pollution's effect on early-life morbidity and the long-term impacts of early-life morbidity, the links between early-life pollution exposure and long-term human capital and labor market outcomes have been assessed in only a few studies.[2] The research question addressed here is: what are the human capital impacts throughout life and the adult labor market effects of early-life pollution exposure to carbon monoxide (CO) and ozone (O_3). I explore this question by combining a longitudinal survey conducted in the Philippines assessing human capital over three decades with macro- and micro-environmental databases characterizing the emissions and resulting exposure of the survey respondents during early-life. An instrumental variable strategy is employed because linking the macro- and micro-environmental databases produce measurement error, and optimizing behaviors like residential sorting (Banzhaf and Walsh, 2008; Chay and Greenstone, 2005; Graff Zivin and Neidell, 2009) lead to non-random exposures. The resulting bias in estimates is unconventional because, in contrast to developed economies, higher socioeconomic status households in developing economies like the Philippines reside near areas of greater emissions (Azmi et al., 2012; Duflo et al., 2008; Graff Zivin and Neidell, 2013). Weather instruments isolate exogenous spatial and temporal variation in economic activity and pollution unrelated to measurement error and identify the long-term human capital and labor market effects.

This study focuses on the life course human capital and labor market impacts of early-life pollution exposure to CO and O_3. CO and ozone O_3 are common emissions of economic activities with biological pathways through which early-life exposure impacts human capital development.[3] Human capital, a multi-dimensional set of skills and resources which contribute to individual productivity (Becker, 1962; Cunha and Heckman, 2010; Graff Zivin and Neidell, 2013), is assessed in this study by various measures including anthropometrics and cognitive test scores. Birth weight and height are anthropometrics which demonstrate strong correlations to cognitive test scores, suggesting similar developmental inputs (Berger, 2001; Case and Paxson, 2008; Grantham-McGregor, 2002). Furthermore, both height and cognition demonstrate impacts on labor market outcomes.[4] Research concerning the environmental determinants of anthropometrics are inconsistent and limited in length (Bobak et al., 2004; Currie et al., 2013; Jedrychowski et al., 2004). Research concerning the environmental determinants of long-term cognition focus on lead

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[1] Brunekreef et al. (1995); Chay and Greenstone (2003a,b); Chen et al. (2013); COMEAP (1998); Dockery and Pope (1994); Glinianaia et al. (2004); Holgate et al. (1999); Katsouyanni et al. (1997); Lebowitz (1996); Pope et al. (1995); Schwartz (1994); Schlenker and Walker (2011)

[2] Almond et al. (2009); Bharadwaj et al. (2014); Black et al. (2013); Isen et al. (2014); Sanders (2012).

[3] Altshuler et al. (2003); Baccarelli and Bollati (2009); Block and Calderon-Garciduenas (2009); Chen and Schwartz (2009); Genc et al. (2012); Gluckman et al. (2008); Gonzalez-Flecha (2004); Hewitt and Tellier (1998); Jedrychowski et al. (2004); Mezzacappa et al. (2011); Paustenbach (2001); Ritz and Wilhelm (2008); Sheldon and Cohen-Hubal (2009)

[4] Alderman et al. (2006); Case and Paxson (2008); Foster and Rosenzweig (1993); Haddad and Bouis (1991); Hoddinott and Kinsey (2001); Magnusson et al. (2006); Martorell and Habicht (1986); Strauss and Thomas (1998); Walker et al. (2007)

(Liu and Lewis, 2014), a small portion of pollutants, or leverage unpredictable, uncommon environmental shocks such as epidemics, famines, and nuclear disasters (Almond, 2006; Almond et al., 2009; Scholte et al., 2012). Previous studies have exploited quasi-experimental variation to assess the impact of early-life pollution exposure on later childhood test scores (Bharadwaj et al., 2014) and same-day exposure on test scores (Lavy et al., 2012), however this is the first study to trace multiple dimensions of human capital effects of early-life exposure over time and and examine their translation to the labor market. Moreover, this is the first study to perform the analysis of pollution and human capital in a developing country context where recourses such as health care are limited and the marginal return to human capital is higher (Duflo, 2001).

The first contributions of the study come from circumventing the lack of longitudinal exposure, human capital and labor market data by combining and linking multiple data sources. The Cebu Longitudinal Health and Nutrition Survey collected frequent anthropometric, cognitive and labor market measures of a cohort born in 1983-1984 and followed for three decades. Missing early-life (conception to age 2) exposure data is addressed by the RETRO (REanalysis of the TROpospheric chemical composition over the past 40 years (1960-2000)) database (Schultz et al., 2007c), and historical polluter source data. RETRO specifies spatially aggregated, monthly emissions by economic sector of CO and O_3 precursors.[5] RETRO historical emissions for Metro Cebu do not provide spatial variation across the micro-environments where CLHNS respondents reside. In order to generate spatial variation across micro-environments the historical pollution sources are identified from archived telephone directories, pollution permits, land use, zoning and road network maps and the per source contributions to aggregate RETRO emissions are estimated. Within each micro-environment of CLHNS respondents exposures temporally vary by the early-life exposure window (conception to age 2).[6]

Additional contributions include the use of multiple, high frequency weather variables[7] as instruments exploiting the link between weather and economic activity, and the assessment of the exclusion restriction by placebo tests, subsample analyses, and a test of overidentification. Deviations from seasonal averages and extreme incidences of temperature, humidity, wind speed, and precipitation influence economic activities and resulting emissions.[8] The differential impact of each weather variable on sectoral emissions and the location of sources isolate exogenous spatial variation within urban-rural areas. Exogenous temporal variation in exposure within micro-environments is isolated by the combination of the exposure window timing and the timing of weather extremes and seasonal deviations. However, because extreme weather and seasonal deviations which may also directly impact morbidity and consequently human capital (Deschenes and Moretti, 2009; Maccini and Yang, 2009), validation of the exclusion criteria for the instruments is assessed by placebo tests, subsample analyses, and a test of overidentification. The placebo tests assess the impact of instrumented exposures on outcomes with and without biological mechanisms through which pollution exerts effects. Subsample assess the consistency of the results across subsamples whose livelihood and health are directly impacted by weather. The test of overidentification estimates the impacts of CO and O_3 exposure excluding the instruments least likely to meet the exclusion restriction. Each of these analyses validate the instrumental variable strategy.

The final contributions arise from the results which provide the first estimates of the long-term impacts to human capital and labor market outcomes of early-life pollution exposure. Confirming previous results, early-life exposure

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[5] O_3 precursors include nitrogen oxides (NO_x) and volatile organic compounds (VOCs)

[6] Typically, individual exposures are derived by matching the individual to the closest pollution monitor by residential information (Currie et al., 2009; Currie and Walker, 2011), whereas the process of assessing exposure in this study incorporates additional information regarding the sectors and locations of pollution sources.

[7] Obtained from the National Climatic Data Center (NCDC) and the Water Resources Center of the University of San Carlos (WRC).

[8] Bennett and McMichael (2010); Dell et al. (2011, 2013); Hassan and Barker (1999); Hsiang (2010); Hsiang and Jina (2014); Sudarshan and Tewari (2013)

to CO consistently and negatively affects short-term measures such as birth weight and length while early-life O_3 exposure does not exhibit significant effects. The effects of early-life CO exposure remain consistent throughout life and in adulthood a decrease by 10% of the mean exposure increases adult height by .5 cm, test scores by up to 1.5%, and weekly hours worked by 2 to 4%. The effects of O_3 exposure become more pronounced over time particularly in the non-physical components of human capital; a decrease by 10% of the mean O_3 early-life exposure reduces language and math scores by 1 and 2% respectively. In the labor market, CO reduces hours worked and O_3 reduces earnings. A decrease by 10% of the mean O_3 early-life exposure reduces earnings by 6.2%. Assuming a constant effect over the lifecycle, the results suggest that the cumulative discounted lifetime earnings gains of reducing exposure to CO and O_3 emissions by 10% is approximately \$3,434 per person in the birth cohort (Chetty et al., 2011; Isen et al., 2014).[9] Assuming that the estimated parameters are average treatment effects (ATE)[10] and generalizing outside of the sample, the provincial and national impact of a 10% reduction in CO and O_3 indicate an annual provincial discounted lifetime earnings benefit of \$116.76 and an annual national benefit of \$5.15 billion (or 5.7% of 2005 GDP).[11]

The paper will proceed as follows. Section 2 describes the criteria air pollutants assessed in this study, the fetal origins of health and human capital making early-life a critical exposure window, and the context of the study: Metropolitan Cebu of the Philippines. Next, the methods section 3 will describe the data and the econometric specification. In section 4 the results are described and subsequently discussed in section 5. Finally, section 6 concludes the study.

2 Background

2.1 Pollutants

Carbon monoxide (CO) and ozone (O_3) are among the most common air pollutants. CO is an odorless, colorless gas that is primarily emitted from combustion processes (EPA, 2013b). CO bonds with hemoglobin more easily than oxygen, reducing the body's ability to deliver oxygen to organs and tissues (Blumenthal, 2001). Consequently, during pregnancy the amount of oxygen transported to the fetus is reduced by CO (WHO, 2000). Because oxygen is needed for proper growth and development (Clark and Sokoloff, 1999), CO exposure has demonstrated consistent associations with low birth weight (Currie et al., 2013; Shah and Balkhair, 2011; Stieb et al., 2012) and early-life height/length (Ghosh et al., 2011; Kyu et al., 2009; Mishra and Retherford, 2007). Other studies demonstrate an association to diminished cognitive function (Lavy et al., 2012; Amitai et al., 1998; Bharadwaj et al., 2014), however the biological mechanism is unclear and in epidemiological studies the effects of CO disappear when sociodemographic factors are included as controls (Chen and Schwartz, 2009; Gatto et al., 2014).[12]

Ozone (O_3), another colorless, odorless gas, is not emitted directly but is formed by chemical reactions in the sunlight with nitrogen oxides, NO_x and volatile organic compounds, $VOCs$ (EPA, 2013c). O_3 and its precursors[13]

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[9] Earnings gain is a combination of the impact to hours worked and earnings per hour. For a more detailed description of this calculation see section 5 and Table 10.

[10] The assumption is supported by the subsample analysis (see section 5) and stylized contextual facts describing an area and time without effective environmental regulations, measured emissions/concentrations, and no research linking pollution to human capital outcomes such that respondents were plausibly uninformed and incapable of reacting to the instruments based on determinants of their idiosyncratic gains/losses (Heckman, 1997).

[11] Calculations are based on provincial and national birth cohort size in 1983-1984 (HIS, 1985).

[12] One systematic review of epidemiological evidence has demonstrated that hypoxia, a condition in which the body or a region of the body is deprived of adequate oxygen supply as results from the binding of CO to hemoglobin, adversely affects cognitive development and academic outcomes (Bass et al., 2004).

[13] While this study refers to the effects of O_3 exposure for convenience and brevity, the effects estimated are those of exposure during the relevant early-life period to total emissions of NO_x and the $VOCs$ benzene, toluene and xylene. *In vivo* animal studies have demonstrated that NO_x affects

are demonstrated to be neurotoxins in both *in vivo* and *in vitro* models operating through inflammation, oxidative stress, and neurotoxicity.[14] However, in contrast to CO, systematic reviews indicate that prenatal O_3 exposure does not affect birthweight (Shah and Balkhair, 2011; Stieb et al., 2012). In epidemiological studies, O_3 exposure demonstrates consistent, negative impacts on cognition (Chen and Schwartz, 2009; Gatto et al., 2014).

2.2 Early-Life Origins of Human Capital

Extensive human epidemiologic and animal research indicate that during critical periods of prenatal and postnatal development, environmental exposures such as CO and O_3 influence developmental trajectories of lifetime health (Waterland and Michels, 2007).[15] Rapid cell division, epigenetic programming, and development of diverse bodily systems during early-life magnify the potential impacts of environmental toxins (Altshuler et al., 2003; Baccarelli and Bollati, 2009; Gluckman et al., 2008; Ritz and Wilhelm, 2008; Sheldon and Cohen-Hubal, 2009). Moreover, the behaviors (crawling, time outdoors) and the small mass of children increase their proportional exposure pushing them further along the dose-response curve (Hewitt and Tellier, 1998; Paustenbach, 2001). The economics literature has expanded upon the health outcomes typically assessed in order to include human capital and labor market outcomes (Almond and Currie, 2011).

2.3 Metropolitan Cebu

Because environmental quality data is scarce in developing economies where regulation is often non-existent or ineffective, the contexts of most fetal origins studies in economics are developed countries (Graff Zivin and Neidell, 2013). The current study is the first to examine the effects of early-life pollution exposure on human capital and labor market outcomes in a developing economy context: Metropolitan Cebu. Metro Cebu is located on the island of Cebu in the Central Visayas region of the Philippines, and in 1983-84 Metro Cebu consisted of five cities and five municipalities: Cebu City, Mandaue City, Talisay City, Lapu-lapu City, Naga City, Consolacion, Liloan, Cordova, Minglanilla and Compostela (see Figure 1). It is the only area of high population and economic density on the island of Cebu.[16]

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oxidative stress, leading to impaired cognition (He et al., 2013; Pratico et al., 2002). $VOCs$ including benzene, toluene and xylene, cause structural and numerical chromosomal aberrations and target the central nervous system to produce attention deficits, and craniofacial and limb anomalies (EPA, 2013a,d). Additionally, VOC exposures have demonstrated associations to decreased physical growth (Dejmek et al., 2000). In addition to the similar biological mechanisms and results for human capital, the study focuses on O_3 as the combination of these precursors because of the high level of correlation between NO_x and VOC emissions in the data (see Appendix Table A.1) and factor analysis demonstrating the correlated variation between the two emissions. Additionally, the catalyst of the conversion process is sunlight and Appendix Figure A.1 demonstrates that over 90% of the hourly weather observations describe the cloud cover as less than 20% and over 90% of the observed clouds in the data are at altitudes exceeding 6000 meters.

[14] Block and Calderon-Garciduenas (2009); Genc et al. (2012); Gonzalez-Flecha (2004); Dorado-Martinez et al. (2001); Rivas-Arancibia et al. (1998); Sirivelu et al. (2006); Sorace et al. (2001)

[15] This vein of literature takes multiple names, from the "fetal origins hypothesis" Barker (1995) to the "developmental origins hypothesis" (Waterland and Michels, 2007). Numerous studies recognize the prenatal period and the first few years of life as critical periods of human capital development. Drawing on this insight as well as the structure of the CLHNS survey (high frequency observation until age 2 allowing correct exposure assignment), I focus on exposures between conception and age two (Altshuler et al., 2003; Almond and Currie, 2011). The current study uses the term "early-life" instead of "developmental origins" in order to avoid confusion when referring to economic development.

[16] By recent count, approximately 1,000 polluting industrial establishments are located in Metro Cebu, mainly concentrated in Cebu City, Mandaue and Lapu-Lapu. Allan Aranguez, Environmental Management Bureau, Region VII, quoted in Parco, B. "Metro Cebu's air quality as bad as Manila's," Cebu Daily News, June 2008.

3 Methods

The effects of early-life CO and O_3 exposure on human capital and labor market outcomes are estimated with an instrumental variables strategy. The first stage demonstrates that extreme weather and deviations from seasonal patterns are related to emissions levels, as predicted by previous studies.[17] The instrumental variables isolate exogenous spatial and temporal variation in early-life exposures conditional on the control covariates by comparing weather induced variation in exposure to proximate emissions sources across urban-rural areas and within micro-environment variations by exposure timing. The challenge of this identification strategy is the exclusion restriction: weather has demonstrated a direct impact on early-life morbidity (Deschenes and Moretti, 2009; Maccini and Yang, 2009) and early-life morbidity impacts long-term human capital development (Almond, 2006; Baird et al., 2011; Maccini and Yang, 2009). The validity of the instrumental variables is explored by placebo tests, subsample analysis, and an overidentification test.

3.1 Data

The analysis utilizes the combination of four types of data: human capital and labor market data from the Cebu Longitudinal Health and Nutrition Survey (CLHNS), historical emissions data from the RETRO (REanalysis of the TROpospheric chemical composition over the past 40 years) database, polluter source location and industry/sector data collected specifically for this study from various governmental and non-governmental agencies in Cebu, and weather data from the National Climatic Data Center (NCDC) and Water Resources Center of the University of San Carlos (WRC). The CLHNS provides birth outcomes including birth weight, measures of length/height throughout life, test scores measuring cognitive development, and labor market outcomes including labor sector participation, hours worked and hourly earnings. Combining the RETRO database describing historical emissions of the Metro Cebu macro-environment with specific information on the locations and industries of point and non-point sources of pollution within micro-environments of Metro Cebu generates both temporal and spatial variation in emissions. Micro-environmental emissions are translated into individual exposures using detailed residential and exposure window information for individuals in the CLHNS birth cohort. High frequency weather data from the NCDC and WRC identify extremes and deviations from seasonal patterns in precipitation, temperature, wind speed and humidity.

3.1.1 Cebu Longitudinal Health and Nutrition Survey

The combination of survey length and anthropometric, cognitive and labor market measures frequently collected in the CLHNS provides the unique opportunity to assess the human capital and labor market effects of early-life environmental exposures in a developing economy context. The CLHNS randomly sampled 33 barangay (17 urban and 16 rural) in Metro Cebu in order to form a cohort of pregnant women (see Figure 1). Barangays are the smallest administrative district in the Phillipines. The 33 sampled barangay contained in total roughly 28,000 households in 1982, all of which were canvassed in search of pregnant women. Women of the selected barangays who gave birth between May 1, 1983, and April 30, 1984, are included in the baseline sample taking place during the 6th or 7th month of pregnancy.[18] In total, 3,327 women were surveyed at baseline and 3,122 were resurveyed at childbirth.[19] Following the child's birth,

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[17] Bennett and McMichael (2010); Dell et al. (2011, 2013); Hassan and Barker (1999); Hsiang (2010); Sudarshan and Tewari (2013)

[18] Two methods are used to determine the gestational period. First, conception date is estimated by women's report of their last menstrual period when surveyed at 6-7 months of pregnancy. However, as these reports may be inaccurate, gestation is alternatively measured as beginning 40 weeks prior to the child's birth. The results of these specifications are not significantly different.

[19] In each sample barangay informants were stationed who reported births to survey interviewers who then performed the birth survey and collected the measures of birth length, weight and others (Feranil et al., 2008).

the mother-child pair was resurveyed every two months for the first two years of the child's life, and then in 1991, 1994, 1998, 2002, and 2005.[20]

Table 1 provides summary statistics of mothers, fathers, household characteristics, residence, migration, attrition, and children's health and human capital at birth, adolescence, and in adulthood. Anthropometrics such as height and weight were collected for women beginning with the baseline survey and for children beginning at birth. Parents in the sample are young (26-28 years old on average), and not highly educated (approximately 50% with primary or less education). 53% of children born in the sample were male and the majority of children were born in the lengthier Amihan season between September/October and May/June. Mothers are relatively small (151 centimeters tall) and 12% of children are low birth weight (less than 2500 grams). Height and length until adulthood are expressed in z-scores; the z-score system expresses the anthropometric value as a number of standard deviations or z-scores below or above the international age and sex specific reference means (WHO, 2014). Between birth and ages 1 and 2, child height z-scores go from -.32 to -1.43 and -2.11. Miscarriages, stillbirths, and deaths within a week of birth represent only 2% of pregnancies in the sample, and infant mortality within the first year is only 4%[21] Just under 50% of the sample reside in Cebu City at birth and over three-quarters of the sample reside in urban barangays.[22] Furthermore, 24% of the sample permanently attrit from the three-decade long survey, while 17% temporarily attrit for a period of time and are observed in later periods.

3.1.2 RETRO emissions

The RETRO database of estimated historical emission describes the temporal variation in CO and O_3 precursors for the macro-environment of Metro Cebu encompassing all of the 33 micro-environments, or barangay, in which the CLHNS birth cohort reside during gestation and the first two years of life. RETRO contains global monthly emissions by sectors for the years 1960-2000 at a $0.5x0.5$ latitude-longitude degree of spatial resolution.[23] RETRO combines five global-scale numerical models of atmospheric transport and chemistry to achieve statistically robust and temporally consistent estimates of emissions (Schultz et al., 2007c).[24] The bottom panel of Figure 1 shows the $0.5x0.5$ RETRO grid, 55 km on each side, covering the Metro Cebu area and the 400 subdivisions into $0.025x0.025$ latitude-longitude grids, each side 2.75 km long.[25] The $0.025x0.025$ grids describe the micro-environments where CLHNS respondents reside.[26] In addition to the numerous studies assessing its validity, the RETRO database is particularly relevant for the current study because the $0.5x0.5$ grid covering Metro Cebu does not cover any other land mass or population hub which would contribute to the overall emissions.

Available monitored emissions as well as descriptions of economic activity (energy and solvent usage, and biomass

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[20] Tracking surveys collecting a limited set of information, including education which is reflected in the summary statistics ofTable 1, were performed in 2007 and 2009.

[21] The low number of miscarriages, stillbirths and infant deaths may be a product of the sampling strategy which is likely to have oversampled healthier pregnancies. See section 4.5 for additional discussion.

[22] A more detailed description of residence is given in Table A.2.

[23] Typically, the literature utilizes measures of ambient concentrations given in weight per cubic meter, or m^3. RETRO differs in that it contains measures of CO and O_3 precursor emissions in nanograms per square meter per second ($ng/m^2/s$). As a result, the scale of exposure of CLHNS respondents to emissions is not directly comparable to other studies in the literature.

[24] See the RETRO emissions website for a full list of publications and reports for additional information.

[25] The total area of each $0.025x0.025$ grid is approximately 7.5 km^2. The $0.025x0.025$ latitude-longitude grids were chosen due to correspondence with average area of the barangay in which CLHNS respondents reside. Robustness checks of differently sized grids have been performed.

[26] Individual residence is determined by frequently repeated recording of residential barangay (highlighted areas in the top right panel of Figure 1. The emission levels corresponding to barangays which span multiple $0.025x0.025$ grids are area-weighted averages.

burning),[27] technology,[28] behavior (legislation, economic and industrial policies),[29] population, and meteorology form inputs to the atmospheric transport and chemistry models yielding monthly emissions by pollutant and sector for each $0.5x0.5$ latitude-longitude grid. Figures 2 and 3 display regional and global maps of sectoral CO and O_3 precursor emissions for a randomly selected month; power generation and residential/commercial are provided as sectoral examples. Comparisons to regional observational data have demonstrated the validity of the estimated RETRO emissions database and shown accurate representation of temporal atmospheric variability and chemical state (Schultz et al., 2007c).[30] Where deviations from existing databases exist, the RETRO estimated emissions are generally conservative.[31] The current study excludes all spatial variation with the RETRO database and focuses solely on temporal variation by month between the years 1982-1986 because the study area of the CLHNS is covered by a single $0.5x0.5$ grid located at the 10.25 degrees North and 123.75 degrees East latitude-longitude.[32]

Table 1 provides summary statistics of the fetal and early-life monthly average exposure to emissions.[33] Table 2 provides annual means and standard deviations of monthly emissions of CO and O_3 precursors by source type (point and non-point) and sector.[34] Encompassing various industries and activities, the sectors represented in the RETRO database are: industrial combustion, power generation, manufacturing with solvents/chemicals, fossil fuel extraction and distribution, agriculture, residential and commercial, shipping, road and other land transportation, and waste disposal. Among point sources, monthly emissions of O_3 precursors exceed those of CO and the majority of emissions come from the power generation sector, which is entirely composed of two coal-fired power plants in Metro Cebu (see Table A2 of the appendix). CO is the most commonly emitted pollutant by non-point sources, the majority emitted by residential and commercial sources.

3.1.3 Pollution sources

While the RETRO emissions database provides temporal variation in total emissions of CO and O_3 precursors for the macro-environment of Metro Cebu, the database contains no spatial variation within Metro Cebu to determine individual CLHNS respondent exposure. Spatial variation in exposure is generated by linking RETRO to the locations of point and non-point sources of pollution in Metro Cebu. Because Metro Cebu is the only area of economic and

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[27] International Energy Agency data on energy and fuel usage; Global Emissions Inventory Activity and the Emission Database for Global Atmospheric Research describing solvent use and biomass burning data (IEA, 2014; GEIA, 2014; Schultz et al., 2007b).

[28] Emissions rates by technology, year, region and sector from the Tropospheric Ozone and Precursors database (Monks, 2003; Schultz et al., 2007b).

[29] Novel database for each country between the years 1960-2000 collected by the RETRO team of researchers (Schultz et al., 2007a).

[30] While RETRO uses existing ambient air quality monitors as inputs, the resulting emissions of the modeled database differ from ambient monitors. Ambient air quality monitors give important, quantitative information about concentrations and deposition, but they can only describe air quality at specific locations and times, without giving clear guidance on the identification of the causes of the air quality problem (they contain no information on the sources - point, non-point, economic sector, etc - of pollution). In contrast, modeled emissions can give a more complete deterministic description of the air quality problem, including an analysis of factors and causes, and some guidance on the implementation of mitigation measures (Daly and Zannetti, 2007).

[31] For example, when compared to the Emission Database for Global Atmospheric Research version 3.2, O_3 precursor and CO emissions in RETRO are about 8% lower globally on average (Schultz et al., 2007c).

[32] The International Emergency Disasters Database confirms the lack of large, unanticipated environmental shocks in the Philippines during the years 1982-1986 (EM-DAT, 2014).

[33] Note that these measures are in nanograms per meter squared per second ($ng/m^2/s$) and that they describe an emissions/exposure mix. In this study exposure is defined not as ambient concentrations but as the level of emissions in the individual's micro-environment during the period between conception and the outcome (or age 2).This distinction is required by the data and the interpretation of the results should emphasize emissions.

[34] Table A1 displays the correlation matrix of CO, NO_x and $VOCs$ and demonstrates that CO is uncorrelated with others but NO_x and $VOCs$ are highly correlated. Factor analysis confirms that NO_x and VOC measures should be combined. Additionally, as mentioned in the previous discussion regarding the conversion from NO_x and $VOCs$ to O_3, cloud cover and height statistics in Figure A1 for the area of Metro Cebu indicate that the vast majority of NO_x and $VOCs$ emitted are converted to O_3.

population density on the island and within the RETRO $0.5x0.5$ latitude-longitude grid, the sources of pollution within Metro Cebu are assumed to characterize the complete set of sources.

Point sources are single identifiable sources including immobile structures like power and manufacturing plants, and non-point sources emit from more diffuse areas like agricultural land or roads. The main data used to locate and describe the industries and sectors of Metro Cebu point sources existing during the years 1982-1986 are telephone directories from the Directories Philippines Corporation (DPC). Telephone directories provide information regarding the existence, location and industry of Metro Cebu firms. Polluting firms are identified by the 1999-2012 pollution permits database from the Environmental Management Bureau (EMB). Industries requiring permits during the 1999-2012 period are assumed to require them during the 1982-1986 period. The remaining point sources for the years 1982-1986 are mines, for which the types, locations and dates of operation are obtained from the Provincial Mining Office (PMO) and the Provincial Planning and Development Office (PPDO). 21 large and small scale mines existed during the early 1980s in Metro Cebu; 12 of the 21 mines were copper mines, 5 were coal mines, and others were clay, gold and silver mines. Figure 4 shows the locations of point sources by industry and sector. Figure 5 maps the non-point sources of pollution - agricultural, commercial, residential, and transportation - within Metro Cebu during the years 1982-1986. Land use (top left), zoning (top right) and road network (bottom) GIS maps are generated from data collected from the PPDO (land use and road)[35] and the archives of the planning and development offices of each city and municipality in Metro Cebu (zoning).

3.1.4 Instrumental Variables

The instrumental variables must satisfy the exclusion restriction for both unobserved heterogeneity and measurement error. The climate literature suggests an array of instruments including temperature, humidity, wind and precipitation due to their influences on production and resulting emissions.[36] Extremes and differences from seasonal averages in weather are chosen as instruments because standard measures such as mean and variance are more predictable they are more likely correlated with individual behavioral responses and less likely to meet the exclusion criteria. Extreme weather observations are identified as less than 10% or greater than 90% of the distribution during the exposure window of the CLHNS respondent, and the difference from seasonal averages is calculated by identifying the average seasonal dates in the data, differencing each observation from the average and totaling the absolute value for the relevant seasons during the exposure window of the CLHNS respondent.

Table 3 presents annual frequencies depicting the distributions of precipitation, temperature, wind speed and humidity by year and by season and Figure 6 displays daily measures of total precipitation, maximum wind speed, maximum and minimum temperature and maximum relative humidity between 1978 and 1987. Daily rainfall data was obtained for 5 observation stations throughout Metro Cebu from the Water Resources Center (WRC) of the University of San Carlos, Cebu. Hourly observations of temperature, wind speed and relative humidity are obtained from the National Climatic Data Center (NCDC). Weather patterns in Cebu are heavily influenced by the Amihan (dry season from September/October to May/June) and Habagat (wet season). Table 3 and Figure 6 depict significant differences across seasons and variation in extremes before and during the study.

As an example of the variation isolated by the instrumental variable identification strategy, consider the changes in the emissions induced by the seasonal average precipitation, extreme wind speeds, and deviations from seasonal

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[35] Mobile sources of air pollution in Cebu range from motorcycles to cars and taxis to jeepneys - retrofitted US military jeeps - each powered by leaded diesel fuel (EMB, 2010). The road network is limited to roads in existence during the 1982-1986 period.

[36] Bennett and McMichael (2010); Dell et al. (2011, 2013); Hassan and Barker (1999); Hsiang (2010); Hsiang and Jina (2014); Sudarshan and Tewari (2013)

average temperature and humidity during the highlighted time period in Figure 6. For simplification, assume that only production in the agricultural and the chemical/solvent manufacturing sectors are impacted by the weather during the highlighted period. In the agricultural sector, the extreme temperature and humidity cause increase activity and accompanying CO emissions. In the chemical/solvent manufacturing sector, the damages caused by extreme wind speeds increase production of replacement materials and accompanying O_3 precursor emissions. In micro-environments with farms and/or chemical/solvent manufacturing plants, the early-life exposure to CO and/or O_3 of children/fetuses less than age 2 increase relative to older and not yet conceived children (within micro-environment, temporal variation). Early-life exposure to CO increases in rural areas with farms relative to rural areas without farms, and early-life exposure to O_3 increases in urban areas near chemical/solvent manufacturing sources relative to urban areas proximate to sources of other sectors (within urban/rural areas, spatial variation). This simplified example illustrates the identifying temporal and spatial variation used by the identification strategy. The main threat to this instrumental variables identification strategy is that human capital is affected by weather beyond the effect through emissions and this is assessed in section 4.

3.2 Econometric Specification

A standard linear functional form is adopted for the human capital production function, simplifying interpretation and avoiding the specification pitfalls of instrumental variable estimation (Angrist and Krueger, 2001). Health and human capital outcomes are examined at the ends of periods p: birth ($p = 0$), age 1 ($p = 1$), age 2 ($p = 2$), ages 10-12 ($p = 3$) and ages 21-23 ($p = 4$). Let Y_{ip} denote the health and human capital outcomes, namely height, cognition and labor market outcomes including labor sector, hours and earnings, of individual i at the end of period p. Equation (1) shows the relationship between the health and human capital outcomes and early-life inputs:

$$Y_{ip} = \sum_j \beta_j \sigma^*_{imjp} + \delta_1 \boldsymbol{X}_i + \delta_2 \boldsymbol{W}_{ip} + \mu_i + \epsilon_{ip} \tag{1}$$

j denotes the pollutant type (CO, O_3) and $\sigma^*_{imjp} = \{\sigma^*_{i,m,CO,p}, \sigma^*_{i,m,O_3,p}\}$ describes the true exposure of individual i in the micro-environment m to pollutant j during period p. For instance, when considering height at age 2 ($p = 2$), as the outcome of interest, p denotes the entire period from conception until age 2. Let $\boldsymbol{X}_i$ denote a set of observable demographic, socioeconomic and environmental determinants of human capital. The set of observable control variables include child gender and season of birth[37], mother's education, height, consumption of pre-natal vitamins, and smoking behavior of the mother during pregnancy, as well as household per capita income, sanitary conditions, and solid-fuel use during pregnancy. Let $\boldsymbol{W}_{ip}$ denote a set of unobserved determinants of human capital including preferences. Finally, let μ_i capture urban/rural fixed effects.[38]

As $\boldsymbol{W}_{ip}$ is unobserved it enters as part of the error term in the final estimating equation and correlation between the variables of interest and $\boldsymbol{W}_{ip}$ produces omitted variable bias. This is the first type of bias that the instrumental variables are designed to correct.

$$Y_{ip} = \sum_j \beta_j \sigma^*_{imjp} + \delta_1 \boldsymbol{X}_i + \mu_i + \eta_{ip} \tag{2}$$

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[37] The distribution of births across the year in the sample as well as the regional vital statistics give no indication of fertility timing (HIS, 1985). Table A.3 compares observable parent and household characteristics across season and quarter of birth, giving little indication of birth timing.

[38] Table A.3 of compares observables across urban/rural residence.

$$\eta_{ip} = \epsilon_{ip} + \delta_2 \boldsymbol{W}_{ip}$$

3.2.1 Scaling Factors and Micro Environment Emissions

While equation (1) describes the relationship between the true exposure, σ^*_{imjp}, and human capital outcomes, a measure of the true exposure is unavailable. First, let E_{jsk} describe total emissions in the macro-environment of each pollutant j by month k and sector s. Let each source be denoted N_{mjsq} where m denotes the micro-environment and q the quarter of the year. The missing link is the level of contribution of each source to the total emissions of each pollutant. Let α_{jsq} denote the scaling factor converting the number or area density of pollution sources into total sectorized, s, emissions of pollutants j in quarter q. The functional relationship between the macro- and micro-environmental emissions is given as:

$$E_{jsk} = g\left(\sum_m N_{mjsq}, \boldsymbol{q}; \alpha_{jsq} \right) \tag{3}$$

$g(\cdot)$ is a function taking as inputs the total number (point sources) or total area (non-point sources) of polluters from sector s at time t, and $\boldsymbol{q}$, a vector of quarter-of-the-year indicators.[39] Therefore, the estimates of micro-environmental $m$emissions of pollutant j from sector s during q are:

$$\hat{E}_{mjq} = \sum_s \hat{\alpha}_{jsq} N_{mjsq} \tag{4}$$

Figures 7 and 8 display $\hat{E}_{mjq}$, the resulting levels of CO emissions and O_3 precursor emissions for each micro-environment by quarter of a selected year. Estimated emissions levels vary spatially across micro-environments according to the locations of sources, as well as temporally according to aggregate emissions levels within RETRO.

The final step required to produce an estimate of the true exposure is to align the timing of the exposure window to the individual i. Recall that for the true exposure denoted σ^*_{imjp}, p describes the period beginning at conception until the outcome is observed. Let $q = \{1, 2, ..., Q\}$ denote the timing of intra-annual estimates of emissions within period p. Therefore, for period p between conception and the observation of the human capital outcome, estimated exposure is given as:

$$\hat{\sigma}_{imjp} = \frac{1}{Q} \sum_{q \in p} \hat{E}_{mjq} = \frac{1}{Q} \sum_{q \in p} \sum_s \hat{\alpha}_{jsq} N_{mjsq}$$

An underlying assumption involved in the generation of $\hat{E}_{mjq}$ and ultimately $\hat{\sigma}_{imjp}$ is that within sectors the emissions of each pollutant by source are equal. The assumption that all sources within the industrial combustion sector emit the same amount of CO and O_3 is unlikely to be true and the differences across sources may be systematically correlated with the error term η_{it} in equation (2). Therefore, the relationship between the true exposure, σ^*_{imjp}, and the estimated exposure, $\hat{\sigma}_{imjp}$, measured with error, u_{imjp}, is given as follows:

$$\hat{\sigma}_{imjp} = \sigma^*_{imjp} + u_{imjp} \tag{5}$$

Systematic correlation between the measurement error, u_{imjp}, and the error term, η_{ip}, must be corrected in order to

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[39] α_{jsq} are estimated by adopting a linear functional form to $g(\cdot)$ with $\sum_m N_{mjsq}$ interacted with quarter of the year indicators (see Table A4). Standard errors of each scaling factors for quarters 2-4 are corrected using the delta method.

produce unbiased estimates of the causal impact of early-life CO and O_3 exposures on human capital. The instrumental variable procedure described in the following section is designed to correct the measurement error bias as well as the omitted variable bias previously described.

3.2.2 Instrumental Variable Regression

Substituting the true exposure σ^*_{imjp} in equation (2) with the estimated exposures measured with error as depicted in equation (5) yields the following:

$$Y_{ip} = \sum_j \beta_j(\hat{\sigma}_{imjp} - u_{imjp}) + \delta_1 \boldsymbol{X}_i + \mu_i + \eta_{ip} \tag{6}$$

Combining the measurement error u_{imjp} into the error term produces the following model:

$$Y_{ip} = \sum_j \beta_j \hat{\sigma}_{imjp} + \delta_1 \boldsymbol{X}_i + \mu_i + \nu_{ip} \tag{7}$$

$$\nu_{ip} = \epsilon_{ip} + \delta_2 \boldsymbol{W}_{ip} - \sum_j \beta_j u_{imjp}$$

Estimating equation (7) without correction yields coefficients $\hat{\beta}_j$ biased by the correlation between $\hat{\sigma}_{imjp}$, $\boldsymbol{W}_{ip}$ and u_{imjp}. The bias is corrected by the set of instrumental variables $\boldsymbol{Z}_{ip}$. The first condition of the IV estimation strategy is that $Cov(\boldsymbol{Z}_{ip}, \hat{\sigma}_{imjp}) \neq 0$. This condition is validated by the first of the two stage instrumental variable regression procedure. The second condition, that $Cov(\boldsymbol{Z}_{ip}, \nu_{ip}) = 0$, is complicated by the form of the error term ν_{ip}. Because ν_{ip} combines ϵ_{ip}, $\boldsymbol{W}_{ip}$ and u_{imjp} a zero covariance must be assumed between Z and each of the components of ν_{ip}:

$$\begin{aligned} Cov(\boldsymbol{Z}_{ip}, \nu_{ip}) &= Cov(\boldsymbol{Z}_{ip}, \epsilon_{ip} + \delta_2 \boldsymbol{W}_{ip} - \sum_j \beta_j u_{mjp}) \\ &= Cov(\boldsymbol{Z}_{ip}, \epsilon_{ip}) + Cov(\boldsymbol{Z}_{ip}, \delta_2 \boldsymbol{W}_{ip}) - Cov(\boldsymbol{Z}_{ip}, \sum_j \beta_j u_{mjp}) \end{aligned}$$

The assumption of equal emissions within sectors which links the macro- and micro-environmental databases implies that the estimated exposure may be correlated with the measurement error and preferences driving residential sorting.[40] Weather extremes and deviations from seasonal averages provides the instrumental variables for this study due to their impact on economic activities and the plausible lack of association with the measurement error and unobservable determinants of human capital. In the current context of Metro Cebu, households of higher income and socioeconomic status residentially sort into areas of substantial economic activity and high emissions.[41] This sorting pattern produces a correlation between exposure and unobserved preferences that positively biases the estimated effects of CO and O_3 towards zero.

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[40] Generated regressors, as the measures of exposure are, do not generally bias the estimates but yield incorrect standard errors. However, instrumenting the estimated exposures in the two stage regression procedure produces correct standard errors.

[41] Tables A.3 show differences in parental education, household income, wealth and solid-fuel use with respect to residential sorting.

4 Results

The main results are displayed in Tables 4-8 beginning with the first stage results of the following equation:

$$\hat{\sigma}_{imjp} = \gamma_1 \boldsymbol{Z}_{ip} + \gamma_2 \boldsymbol{X}_i + \mu_i + \xi_{ip} \tag{8}$$

In Table 4 the first column gives the first stage results for pollutant $j = CO$ during period $p = pregnancy$. The following column gives the first stage results for pollutant $j = O_3$ during period $p = pregnancy$, and the remaining columns repeat this pattern for exposures up to age 1 and up to age 2. The F-statistics typically exceed 40 (the minimum being 29 and the maximum 76).[42] The signs of the coefficients are generally predictable based on previous research and the magnitudes of the coefficients are often large because the instruments and exposures are different scales.[43] The instruments are assumed to meet the exclusion restriction after conditioning on covariates, $\boldsymbol{X}_i$ (Angrist and Pischke, 2009).

4.1 Main Results

Subsequent Tables 5-8 show the main results by outcome type from early-life to late of equation (7).

$$Y_{ip} = \sum_j \beta_j \hat{\sigma}_{imjp} + \delta_1 \boldsymbol{X}_i + \mu_i + \nu_{ip} \tag{7}$$

Table 5 provides the two-stage least squares instrumental variables estimates for anthropometric outcomes throughout life. Recall that z-scores express the anthropometric value as a number of standard deviations or z-scores below or above the age and sex specific international reference mean (WHO, 2014). Table 6 contains cognitive outcomes measured in adolescence and achieved schooling in adulthood. Table 7 illustrates pollution's impact on labor sector, hours worked and earnings. Table 8 assesses the effects of early-life exposure on hours and earnings by labor sector. In order to assist in the interpretation of the coefficients, the following discussion of results will convert the estimated effect sizes into familiar units describing a hypothetical policy of reducing emissions exposures by 10% of the sample averages. Note that each regression in the following tables employ standard errors clustered at the smallest administrative district of the Philippines, namely the barangay.

4.1.1 Anthropometrics

Examining the effects of early-life exposure to CO and O_3 on anthropometrics the first observation from Table 5 is that the non-instrumented, OLS estimates are generally insignificant and close to 0. Measurement error and contextual residential sorting locating high SES households with greater unobserved preferences for and investments in human capital near high economic activity areas would account for these estimates.[44] For the instrumental variable regressions, the first outcome to consider is low birth weight. The estimated coefficient of CO is small but highly significant at -.0006. A 10% reduction in emissions would imply a .3% reduction in the incidence of low birth weight. The estimated coefficient of O_3 is not significantly different from 0. Next, consider the instrumented effects of CO and O_3 on birth length z-score. Again, the estimated coefficient of CO is significant and O_3 is insignificant. A 10% reduction

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[42] The F-statistics displayed in Table 4 are partial F-statistics describing the explanatory power of the instruments alone.

[43] The consistency of the relationship between the instruments and the endogenous regressors is irrelevant to the effectiveness of the instruments (Angrist and Krueger, 2001).

[44] See Tables A.3.

in emissions would increase birth length by .05 cm on average. The effects on length/height grow over time. At age 1 the point estimate grows to -.006, increasing height by .1 cm with a 10% reduction, and at age 2 the point estimate is -.009, increasing height by .25 cm with a 10% reduction. At age 2 exposure to O_3 begins to exert a statistically significant effect - a 10% reduction in O_3 precursor emissions by 10% increases height by .25 cm. At ages 10-12 early-life exposure to emissions of both CO and O_3 are statistically significant producing an increase of .73 and .7 cm with a 10% decrease in emissions exposure. Finally, a 10% reduction in early-life exposure to CO emissions increases adult height by .5 cm, and a similar change to early-life O_3 precursor emissions exposure increases adult height by .34 cm. Additionally, note throughout these regressions that gender, mother's education, mother's height, consumption of prenatal vitamins, and household solid fuel use are consistently significant determinants of height.

4.1.2 Cognition

The results in Table 6 demonstrate the effects of early-life pollution exposure on the following cognitive outcomes: non-verbal, math and language test scores and achieved education. Again, OLS estimates are generally insignificant and close to 0 due to measurement error and the sorting of high SES households to high emissions areas. When instrumented, early-life exposure to CO emissions demonstrates a significant, negative effect on each test score. A 10% reduction in CO emissions yields an increase of approximately one additional question answered correctly on the non-verbal test, or 1.5% of the sample average. Similarly, the number of correct answers by 1% of the math test average and by less than 1% of the language test average. Early-life exposure to O_3 precursor emissions does not demonstrate significant effects to non-verbal test scores, but a 10% reduction in emissions would add 1.18 additional correct math test answers (2% of average) and .56 additional correct language test answers (1% of average). Surprisingly, impacts to achieved years of schooling are not observed perhaps because of cultural norms, institutional structures, or because years of schooling is a less continuous measure of cognition.

4.1.3 Labor Market

Table 7 shows the full sample and gender specific effects of early-life CO and O_3 exposures on labor sector participation, weekly hours worked and the log of hourly earnings, and Table 8 shows the hours and earnings effects by labor sector. OLS estimates are, with few exceptions, indistinguishable from 0.[45] However, IV estimates indicate that increased early-life CO and O_3 exposures increase the likelihood of employment in the non-physical labor sector, CO decreases hours worked and O_3 decreases earnings. Reducing CO exposures by 10% would decrease the likelihood of working in the non-physical labor sector by 4%, and a 10% reduction in O_3 exposure would decrease the likelihood of working in the non-physical sector by 6%. The impacts of early-life exposure also varies by gender; the effects on hours worked are mainly for females. A 10% reduction in CO exposure increases hours worked by 1 per week for the full sample and over 2 per week for females. The effects of early-life pollution exposure on human capital throughout life culminate in earnings. A 10% reduction in exposure to O_3 precursor emissions would increase earnings by 6.2%. The effect is slightly larger for females than males but only statistically significant for males. By labor sector, the effect of CO on hours is mainly borne by the physical labor sector. Contrastingly for earnings, the effect of O_3 is borne by the non-physical labor sector. While the impact of early-life exposure to CO emissions on hours in the physical sector is slightly larger than the full sample, the magnitude of O_3's impact on earnings in the non-physical sector is double the full sample estimate. Despite reduced precision due to smaller sample sizes, these estimates imply that the choice

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[45] CO and O_3 effects on weekly hours worked are negative and significantl and the CO effect on earnings is positive and significant.

of labor sector may exacerbate the effects of early-life exposures.

4.2 Analysis of the Exclusion Restriction

While the estimated effects of CO and O_3 on birth weight and height throughout life are consistent, they may simply reflect the established relationship between weather, early-life morbidity and human capital development. The validity of the exclusion restriction is first addressed by placebo tests of acute morbidity and medical expenditures. Next, subsample analyses address whether households or individuals that are more susceptible to weather are driving the results rather than the exogenous variation in exposure to pollutant emissions produced by the weather. Finally, the overidentification tests exclude precipitation from the set of instruments and compare the two-stage results to the main results because, of all the instruments, early-life precipitation has demonstrated associations to long-term human capital and labor market outcomes.

4.2.1 Placebo Tests

Table 9 gives the effects of pollution on diarrheal incidence, respiratory illness and the log of medical expenditures between ages 0 and 2. If the weather instruments are affecting human capital accumulation through morbidity then pollution exposure would affect all measures of acute morbidity, even those which lack a biological mechanism. However, if the weather instruments are isolating exogenous variation in pollution exposure through their impact on emissions, then only the measures of morbidity for which plausible biological mechanisms exist will show significant effects. Exposure to CO and O_3 air pollution demonstrate biological mechanisms to impact the incidence of acute respiratory illness and subsequently medical expenditures (Kelly and Fussell, 2011; Patel and Miller, 2009; Schlenker and Walker, 2011), but there is no mechanism through which air pollution leads to diarrheal incidence. The results show that instrumented exposures to CO and O_3 produce no statistically significant effect on diarrheal incidence. In contrast, CO and O_3 exposure increase the incidence of acute respiratory illness when instrumented. Monetizing these effects, CO and O_3 exposure increase medical expenditures - a 10% CO reduction would reduce medical expenditures by approximately 6% and a similar reduction in O_3 would reduce expenses by 10%.

4.2.2 Subsample Analyses

Previous studies have found associations between weather and health outcomes such as birth weight and mortality (Bantje and Niemeyer, 2008; Deschenes and Moretti, 2009), and others have included weather as a control in estimating the impact of pollution (Sanders, 2012). The subsample analysis of the exclusion restriction repeats the previous estimations while including interaction terms indicating whether or not the respondent belongs to a subsample whose income, health and behaviors are plausibly less susceptible to the weather. The tests of the exclusion restriction are one-sided: interaction term coefficients of the selected subsamples would invalidate the exclusion restriction if positive.

The following subsamples are analyzed with the results summarized in Table 10:[46] non-farm households (i), high income households (ii), good quality housing material (iii), mothers who spend less than the average amount of time outdoors (iv), children with good dietary diversity (v), and children with less than average diarrheal incidence (vi). The income of non-farm households is less dependent on the weather than farm households implying that if the weather

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[46] Full results are given inTables A.5-A.8.

instruments do not meet the exclusion criteria and directly impact human capital the coefficients of the exposure-subsample interaction terms will be positive and significantly different from 0. Similarly, high income households are more insulated from the income, nutrition, health and other effects of weather so if the interaction term coefficient is positive and significant the results are being driven by low-income households. Many homes in Cebu are constructed of poor quality materials - 43% constructed of palm tree - and respondents in improved quality homes - wood, cement or iron - are likely insulated from weather similar to high income households. Weather may also affect access to nutrition and children with good nutritional quality are less susceptible to the fluctuations. Dietary diversity, as defined by the Daniels et al. (2009) index, is used to determine nutritional quality.[47] A positive and significant interaction term would indicate that the results may not be driven by exposure but by the impact of weather on nutritional access. Heterogeneity in avoidance behaviors may also drive the results. With information concerning employment and daily activities in the CLHNS, the amount of time that mothers spend outdoors is derived. Positive exposure-subsample interaction terms would indicate that the results are driven by children whose mothers spend more time outdoors and whose behaviors are more susceptible to weather variation.[48]

Overall, the subsample analysis gives little evidence that the exclusion restriction is violated. Table 10 shows the the total number of tests performed (16 outcomes, 2 exposures, and 6 subsamples each except the diarrheal incidence outcome produce 190 tests), and the number of one-sided rejections at the 5% level. Given the number of tests (190), it is likely that some will exhibit significant estimates. Consequently, corrections are required to interpret the overall pattern of results. By employing the Bonferroni correction which guarantees a error rate less than or equal to .05 for the set of 190 one-sided tests, the threshold for significance moves from 1.645 to 3.476 (Miller, 1981). None of the estimated interaction term coefficients give t-statistics greater than or equal to 3.476. Therefore, there is insufficient evidence to conclude that subsamples plausibly less susceptible to the impacts of weather are driving the results and invalidating the instrumental variable strategy.

4.2.3 Overidentification Tests

Among the instruments, precipitation during early-life has demonstrated effects on human capital and labor market outcomes outside of the mechanism of emissions. Maccini and Yang (2009) estimate a significant impact of early-life rainfall on adult health, education and socioeconomic outcomes in rural Indonesia. If the results of Maccini and Yang (2009) translate to Metro Cebu and seasonal deviations and extremes in precipitation have a direct impact on human capital and labor market outcomes, then the precipitation instruments would not meet the exclusion restriction. Therefore, overidentification tests by reestimating the first and second stages while excluding the precipitation instruments are performed.

As summarized in Table 11, the non-precipitation IV estimates are not identical to the estimates using the full set of weather instruments - occasionally larger or smaller, occasionally more or less significant - but the inclusion or exclusion of precipitation as an instrumental variable does not substantially alter the results.[49] Hausman-Wu tests comparing the two models do not reveal any consistent, statistically significant differences. One reason why the

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[47] Dietary diversity scores are valuable, predictive indicators of nutrient adequacy (Daniels et al., 2009). The authors use a dietary diversity score of 4 as the threshold for good nutrition, the same convention is adopted for the current analysis.

[48] Given that research of fetal vulnerability to environmental insults was just beginning in the late 1970s (Almond and Currie, 2011), the Philippine climatic context (average temperature 29°C (85°F)), the lack of monitoring in Cebu until the mid-1990s, the typical home construction material in Cebu (43% nipa, or palm tree), and the small size of the pollutants enabling travel through small passageways (Branis et al., 2005), heterogeneous effects by time spent outdoors in this context are not expected a priori and would suggest an alternative driver of the results.

[49] Tables A.10 and A.11 of the appendix give the detailed first and second stage results for each of anthropometric, cognitive, labor market, and morbidity outcomes.

current results contrast to those of Maccini and Yang (2009) is that they isolate their study to residents of rural areas where daily activities and employment are plausibly more influenced by precipitation than the mostly urban residents of Metro Cebu. Additionally, the amount of precipitation in Indonesia is substantially larger than Metropolitan Cebu - the wet season in Indonesia is defined by at least 200 mm of rain per month (Maccini and Yang, 2009) while less than 50% of the wet season (Habagat) months between 1983-1986 in Metro Cebu exceeded 200 mm of rainfall. The larger amount and increased variation in precipitation may have resulted in larger effects attributable to rainfall in Indonesia.

4.2.4 Additional Threats To Identification

In order to address concerns of model misspecification, alternative models are estimated and the results for a subsample of outcomes are displayed in Table A.9 of the appendix. The impacts of CO are separately estimated from the effects of O_3 (and vice versa) in order to compare to the jointly estimated effects.[50] No separately estimated effects of exposure to CO and O_3 differ in terms of sign from the jointly estimated effects, neither do most levels of significance. Furthermore, the magnitudes of the estimates are generally similar.

Beyond the instruments, attrition is an additional threat to identification. If people with greater education, income and socioeconomic status respond to pollution by migrating out of Metro Cebu those left to provide data will be of lower socioeconomic status and the estimated effects of pollution on human capital will be biased downwards. Only approximately 60% of the original mother-child pair remain in the survey in 2005. There are two types of attritors in the CLHNS: temporary (unobserved for at least 1 wave) and permanent. Because the human capital and labor market outcomes of many temporary attritors are observed, permanent attrition is the largest threat to the results. Summary statistics demonstrate that permanent attritors from the CLHNS are higher socioeconomic status and urban respondents (Feranil et al., 2008). The results presented in Table A.12 compare the full sample estimated effects of early-life pollution exposure to the effects estimated on the sample of non-permanent attritors for each outcome. If there are significant differences between the estimates, selective attrition is not sufficiently controlled. Overall, the estimates do not differ substantially suggesting that non-random attrition is not driving the main results.

5 Discussion

In summary, the results indicate that human capital and labor market outcomes are negatively affected by increased early-life exposure to carbon monoxide and ozone precursor emissions. Early-life exposure to CO emissions exhibits consistent negative effects throughout life to anthropometric measures and measures of cognition. The impact of early-life exposure to O_3 precursor emissions on height grows over time and cognition is particularly damaged. In the labor market, the consistent negative effects of early-life exposure to CO emissions on anthropometric measures manifest via reduced hours of work and the damage to cognition produced by early-life exposure to O_3 precursor emissions reduces earnings.

While early-life exposure to CO emissions and O_3 precursor emissions damage human capital, CO mainly affects the physical dimension and O_3 mainly affects the cognitive dimension of human capital. Regarding birth weight, the moderate but significant impact of CO and insignificant impact of O_3 aligns with previous research (Currie et al., 2013; Shah and Balkhair, 2011; Stieb et al., 2012). Furthermore, the results confirm previous studies which demonstrated di-

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[50] The analysis does not include a comparison of the results excluding covariates. The inclusion of the covariates is assumed to be required for the conditional independence assumption of the instrumental variable strategy (Angrist and Pischke, 2009). Moreover, the inclusion of covariates generally produces more precisely estimated effects (Angrist and Pischke, 2009).

minished early growth as a consequence of CO exposure (Ghosh et al., 2011; Kyu et al., 2009; Mishra and Retherford, 2007). While previous studies have been unable to show a persistence of the growth effects into adulthood, the results indicate that early-life exposure to CO and O_3 precursor emissions impacts adult height. Concerning cognition, while previous studies demonstrate that increased CO exposure diminishes cognition, the literature lacks a specific mechanism (Lavy et al., 2012). The current study confirms the previous results but suggests that the impact of CO on cognition is less than the impact of O_3. Animal studies support at least three specific mechanisms through which O_3 impairs cognitive development: inflammation, oxidative stress and neurotoxicity (Block and Calderon-Garciduenas, 2009; Genc et al., 2012; Gonzalez-Flecha, 2004; Dorado-Martinez et al., 2001; Rivas-Arancibia et al., 1998; Sirivelu et al., 2006; Sorace et al., 2001). The results of this study confirm these mechanisms and demonstrate that early-life exposure to O_3 precursor emissions produces the largest, negative effects to cognition which persist into the labor market. Moreover, examining the effects by labor sector, the results indicate that the negative impact of O_3 is much larger in the non-physical labor sector where the non-physical dimensions of human capital are more highly rewarded.

The working hours and earnings impact of early-life exposure to O_3 precursor emissions implied by our estimates contextualizes and monetizes the magnitude of the impacts, summarized in Table 10.[51] The inputs to this calculation are the mean sample earnings in annual US dollars (88,335 in Philippine pesos converted to \$1,478 USD with the average 2005 exchange rate of 55 pesos to \$1) and the following assumptions: 1). the impact of O_3 estimated on earnings in 2005 when respondents were 21-23 years old remains constant over the life-cycle, 2). the impact of CO and O_3 exposure on hours worked in 2005 when respondents were 21-23 years old remains constant over the life-cycle, 3). earnings are discounted at 3% real rate (5% discount rate with 2% wage growth) back to age zero.[52] Given these inputs and assumptions, the mean present value of lifetime earnings at age zero in Metropolitan Cebu is approximately \$39,927. The financial value of a hypothetical policy reducing the amount of emissions by 10% and subsequently increasing earnings by 6.2% and weekly hours worked by 1 are combined, monetized and discounted to present value terms totaling \$3,434 per person.

Generalizing outside the sample requires assuming that the mean earnings of the CLHNS cohort and the estimated impacts of early-life exposures have external validity (Angrist and Pischke, 2009). External validity is assessed by subsample analysis and contextual facts. Heterogeneous effects of early-life exposures observed in the subsample analysis would indicate that a variety of local average treatment effects (LATEs) could be estimated by different instruments inducing different variation in exposures to emissions and responses. A lack of heterogeneous effects would provide evidence that the estimated parameters are average treatment effects (ATEs) conditional on covariates and can be generalized outside the sample (Heckman and Vytlacil, 2005).[53] Evidence from two-sided subsample interaction tests are summarized in Table 10. Because only one of the estimated interaction term coefficients give t-statistics exceeding 3.476 (the Bonferroni correction threshold) in absolute value, the evidence suggests that the effects are not heterogeneous.[54] However, because there are a number of unexamined subsamples, the analysis provides incomplete evidence that the estimates are ATEs. Estimation of ATEs requires that agents not select into exposure on the basis of an idiosyncratic (and unobserved) component of their exposure response, an assumption which implies the ignorance of agents (Heckman, 1997). Stylized, contextual facts provide evidence of agent ignorance. As previously

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[51] The monetization of the benefits to a 10% emissions reduction is performed similar to Chetty et al. (2011) and Isen et al. (2014).

[52] Estimates are conservative because annual earnings at ages 21-23 are likely underestimates of earnings throughout life.

[53] Additionally, the ATE assumes full compliance and ignores general equilibrium effects.

[54] Tables A.5-A.8 display the full one and two-sided test results for each outcome. Note that 2 symbols are used to identify statistically significant estimates: asterisk (*) indicates significance at the 5% level for the one-sided, positive t-test of the exclusion restriction (values greater than 1.645), and the cross (†) indicates significance at the 10% level for negative t-statistics (therefore, both the asterisk (*) and the cross (†) indicate t-statistics significant at the 10% level for the two-sided test).

mentioned, the pollution monitors did not exist in Metro Cebu during the early 1980s and because CO and O_3 are colorless, odorless gases it is likely that individuals were uninformed and unaware of their exposures. Additionally, lacking any environmental disasters during the period, the exposures are typical and unlikely to illicit responses. Furthermore, during the time period research had not progressed beyond the assumption that the fetal part of the early-life exposure window was protected from nutritional, environmental and other damage (Susser and Stein, 1994; Almond and Currie, 2011).

Given this evidence from subsample analysis and the stylized contextual facts, the estimates are assumed ATEs with external validity. Consequently, the estimates are applied to the province and national level. The size of the Cebu province birth cohort in 1983-84 was approximately 34,000 and the size of the 1983-84 Philippine birth cohort was approximately 1.5 million (HIS, 1985). Given a \$3,434 benefit per person, the province-level annual benefit to earnings and hours worked by reducing emissions by 10% is approximately \$116.76 million (in 2005 dollars). Furthermore, the benefits to a national 10% reduction in emissions total \$5.15 billion (in 2005 dollars) annually. The total gross domestic product of the Philippines in 2005 was approximately \$90 billion, making the value of the national 10% CO and O_3 precursor emissions reduction 5.7% of Philippine GDP in 2005 (The World Bank, 2014).

Lacking costs as well as ecosystem, productivity, and other benefits, this analysis is incomplete. However, observed child medical expenditures provide insight to short-term health benefits and their comparison to the aforementioned long-term benefits. Using estimates from Table 9, scaling to reduce exposure to emissions by 10%, and assuming equivalent annual expenditures, the combined annual benefit via medical expenditures of reducing both CO and O_3 by 10% is approximately \$1 per person, \$34,000 for the Cebu province, and \$1.5 million for the nation (2005 USD).[55] The short-term impacts to medical expenditures are dramatically less than the long-term impacts to earnings partially because of impact persistence and accumulation. The persistence of early-life exposure on long-term human capital means that the annual effects to earnings are accumulated over the length of the working life and discounted, whereas the respiratory illnesses and resulting medical expenditures are acute. Lacking persistence and accumulation, the impacts to short-term outcomes are generally outweighed by long-term impacts and analysis based on short-term outcomes underestimate the total impact.[56]

Up to this point, the small set of research concerning the long-term human capital and labor market outcomes of early-life pollution exposure takes place in developed economies. The paucity of environmental quality data in developing nations limits potential studies where pollution is least regulated and individuals potentially most vulnerable. Furthermore, given different institutions and labor markets the results from developed economies are not directly applicable to developing nations. While not directly applicable to other developing nations, the results suggest that the benefits for pollution control policies in developing nations differ from previous developed country estimates (Greenstone et al., 2012; Isen et al., 2014; Walker, 2012). The estimated impacts of pollution on human capital in the developing economy context of the Philippines examined in this study imply that environmental regulations are investments yielding long-term individual benefits and potentially fueling economic growth and development (Graff Zivin and Neidell, 2013; Nelson and Phelps, 1966; Schultz, 1990).

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[55] Previous estimates from the World Bank imply that air pollution costs approximately \$23 per person in acute morbidity costs annually throughout the 4 largest metropolitan areas in the Philippines, namely Manila, Davao, Bagiuo and Cebu.The difference in the estimates are potentially due varying pollution levels, under- or inaccurate reporting of costs, and the sample, however replacing the mean with the maximum only increases the estimate to \$19 per person (2005 USD).

[56] Even assuming that early-life pollution exposures produced a persistent, constant level of medical expenditures throughout life, the present value of lifetime medical expenditures of a 10% emissions reduction would still be dramatically less than the value of similar human capital/labor market effects.

6 Conclusion

This paper provides the first quasi-experimental evidence of the human capital and labor market impacts of early-life exposure to carbon monoxide and ozone. Utilizing a unique methodology combination of longitudinal survey and macro- and micro-environmental data, the human capital effects are traced over time and translated into labor market effects in a developing economy context where recourses are limited and marginal returns to human capital higher. Evidence indicates that early-life pollution exposure contribute to long-term human capital development. *In vivo* and *in vitro* studies of CO and O_3 demonstrate biological pathways to human capital development and this is one of the first studies to observe these effects in humans. The effects are observed via an instrumental variable strategy leveraging the link between weather and emissions in order to correct measurement error and unobserved heterogeneity bias.

The results provide evidence of large, long-term benefits to pollution reduction often ignored by policy makers. Specifically, I show that a hypothetical policy reduction in fetal CO emissions produces a small decrease in the incidence of low birth weight, and increases birth length. The effects of a 10% reduction in both fetal and early-life exposure to CO emissions generally grow over time; height at age 1 increases by .1 cm, .25 cm at age 2, .73 cm at ages 10-12, and .5 cm in adulthood. A similar policy reduction in O_3 emissions does not exhibit any short-term effects to birth weight, birth length or age 1 height. However, by age 2 a 10% reduction in O_3 exposure increases height by .25 cm, followed by .7 cm at ages 10-12, and .34 cm in adulthood. A 10% reduction in early-life CO emissions increases non-verbal, math and language test scores by between .5 and 1.5% and a similar reduction in O_3 emissions increases test scores by between 1-2%. A culmination of the effects to the various physical and cognitive dimensions of human capital takes place in the labor market. The policy reduction in CO emissions significantly increases hours worked (particularly for women and physical labor sector workers) and raises hourly earnings by 6.2% (particularly for non-physical sector laborers). The results indicate (and coincide with previous research) that CO exposure mainly impacts the physical dimensions of human capital while O_3 exposure primarily impacts the cognitive dimensions.

The results demonstrate that a relatively small reduction in emissions could produce significant long-term benefits to various dimensions of human capital and culminate in increased lifetime earnings however significant questions remain. Restricting the application of the results to the province of Cebu would produce an increase to lifetime earnings of approximately \$116.76 million annually. And at the country level, reducing emissions by 10% would produce \$5.15 billion of benefits, or 5.7% of Philippine 2005 GDP. Moreover, the gains to human capital and earnings in the developing economy context of the Philippines could fuel economic growth and development. Despite these gains, there is a wide array of related questions that remain unanswered. First, are the estimated labor market effects observed at 21-23 years old an over or under estimate, and do the effects change over time? What are the general equilibrium costs and benefits of pollution reduction and are they context specific? What, if any, intergenerational effects can be observed in health and economic outcomes? While the current study demonstrates that the full sample results do not substantially differ from the sample of individuals that never attrit, what role does pollution exposure play in migration? Additionally, with the growing amount of pollutants, which pollutants affect which dimensions of human capital and which generate the largest benefits to reduction? The growing amount of longitudinal data capturing human capital development and the increasing measurement of pollutants will allow future research to address these and other questions.

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7 Figures

Figures not included in this submission because of file size. Please contact for full paper including figures

8 Tables

Table 1: Summary Statistics of CLHNS Respondents

	Percent or Mean	Std. Dev.		Percent or Mean	Std. Dev.
Mother, Father and Household Statistics (n=3327)			***Outcomes at Birth (n=3122)***		
Mother: Elementary school or less education %	54%		Birth in Amihan Season (Sept-May)	59%	
Mother: Smoked during pregnancy %	14%		Male %	53%	
Mother: Drank alcohol during pregnancy %	8%		Stillbirth/miscarriage/died within 7 days %	2%	
Mother: Consumes pre-natal vitamines %	58%		Low birth weight (<2500 grams) %	12%	
Mother: Number of previous pregnancies	2.52	2.43	Birth weight in kg	3.01	0.48
Mother: Height in cm	150.64	5.1	Birth length z-score	-0.32	0.87
Mother: Age in years	26.04	5.98	Birth length in cm	49.25	2.14
Father: Present in household %	94%				
Father: Elementary school or less education %	47%		***Outcomes in First Two Years***		
Father: Age in years	28.82	6.56	Died within first year %	4%	
Per capita household monthly income in 1983-84 (PhP)	255.37	309.62	Number of reported diarrheal incidences	3.44	3.89
			Number of reported acute respiratory infections	4.47	2.41
Household Baseline Residence (n=3327)			Medical expenditures (pesos) during first two years	193.73	266.6
Cebu City	47%		Height z-score at age 1	-1.43	1.06
Consolacion/Lilo-an	12%		Height in cm at age 1	70.48	3.2
Lapu-Lapu/Cordova	10%		Height z-score at age 2	-2.11	1.04
Mandaue	14%		Height in cm at age 2	78.79	3.9
Naga	9%				
Talisay	7%		***Anthropometrics in Adolescence and Adulthood***		
Urban population in all cities/municipalities	77%		Height in cm at ages 10-12	133.04	8.19
			Height z-score at ages 10-12	-1.83	1.02
Migration and Attrition (n=3327)			Height in cm at ages 21-23 cm	157.16	8.8
During 1983-86 migrate from urban to rural area %	2%		Body Mass Index at ages 21-23	20.71	3.29
During 1983-86 migrate from rural to urban area %	1%				
Ever temporarily attrit throughout all waves %	17%		***Cognitive and Labor Market Outcomes***		
Ever permanently attrit throughout all waves %	24%		Non-verbal test scores (scale 0-100) in 1994	66.78	11.36
			Math test scores (scale 0-100) in 1994	57.15	13.17
Emissions Exposure Prior to Age 2 in $ng/m^2/s$			Language test scores (scale 0-100) in 1994	65.72	9.26
CO: monthly average exposure prior to birth	48.12	27.9	Achieved years of schooling by 2009	12.5	4.38
Ozone: monthly average exposure prior to birth	11.84	8.83	Non-physical labor sector participation in 2005 %	54%	
CO: monthly average exposure prior to age 2	75.94	40.79	Hours worked per week in 2005	41.5	19.59
Ozone: monthly average exposure prior to age 2	18.89	14.08	Individual monthly income in 2005 (PhP)	6777.92	26306.02

Table 2: RETRO emissions by source type and sector

	Mean and Standard Deviation of monthly average emissions in ng/m^2/s				
	1982	**1983**	**1984**	**1985**	**1986**
Point Sources:					
Carbon Monoxide (CO):					
Industrial Combustion	7.58	10.09	9.31	9.20	8.39
	(0.32)	(0.43)	(0.39)	(0.39)	(0.35)
Power Generation	5.79	6.25	5.56	5.34	4.45
	(0.51)	(0.55)	(0.49)	(0.47)	(0.39)
Ozone (O3):					
Industrial Combustion	48.38	55.97	47.75	44.27	42.90
	(2.05)	(2.37)	(2.02)	(1.87)	(1.81)
Power Generation	144.95	153.73	136.32	130.53	116.82
	(12.79)	(13.57)	(12.03)	(11.52)	(10.31)
Manufacturing with Solvents/Chemicals	130.63	134.19	127.09	126.30	132.35
	(3.53)	(3.63)	(3.44)	(3.41)	(3.58)
Fossil Fuel Extraction and Distribution	2.11	2.06	1.78	1.58	1.74
	(0.30)	(0.29)	(0.25)	(0.23)	(0.25)
Non-Point Sources:					
Carbon Monoxide (CO):					
Agricultural	626.19	626.19	626.19	626.19	626.19
	(134.17)	(134.17)	(134.17)	(134.17)	(134.17)
Residential and Commercial	3410.20	3473.62	2690.85	2742.77	2783.86
	(3,784.55)	(3,854.92)	(3,441.97)	(3,508.38)	(3,560.94)
Shipping	0.05	0.05	0.05	0.05	0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Road and Other Land Transportation	1433.70	1428.80	1346.07	1313.06	1421.12
	(58.87)	(58.67)	(55.27)	(53.91)	(58.35)
Ozone (O3):					
Agricultural	114.50	114.50	114.50	114.50	114.50
	(25.01)	(25.01)	(25.01)	(25.01)	(25.01)
Residential and Commercial	384.85	391.94	372.49	363.57	372.28
	(136.35)	(138.86)	(131.97)	(128.81)	(131.90)
Shipping	0.59	0.54	0.53	0.54	0.57
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Road and Other Land Transportation	181.72	179.96	167.20	160.59	167.98
	(7.46)	(7.39)	(6.86)	(6.59)	(6.90)
Waste Disposal	50.54	51.67	49.97	58.16	63.46
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total Emissions:					
Carbon Monoxide	5483.52	5544.99	4678.03	4696.61	4844.06
	(3,811.65)	(3,881.72)	(3,521.69)	(3,587.23)	(3,642.61)
Ozone	1058.27	1084.57	1017.63	1000.05	1012.60
	(134.63)	(138.09)	(130.07)	(126.58)	(128.10)

Notes: Monthly emissions come from the .5x.5 latititude-longitude grid of RETRO emissions dataset covering the province of Cebu

Table 3: Precipitation, Wind Speed, Temperature, Humidity - Percent of Annual Observations

	1982		1983		1984		1985		1986	
	Amihan	**Habagat**	**Amihan**	**Habagat**	**Amihan**	**Habagat**	**Amihan**	**Habagat**	**Amihan**	**Habagat**
Precipitation (daily)										
0 mm	35%	7%	45%	4%	25%	6%	37%	6%	35%	6%
0 - 1 mm	13%	6%	9%	3%	14%	3%	10%	4%	12%	4%
1 - 3 mm	14%	5%	7%	4%	11%	6%	11%	4%	11%	5%
3 - 5 mm	5%	1%	4%	2%	5%	3%	5%	1%	5%	2%
5 - 10 mm	5%	2%	7%	3%	6%	3%	5%	3%	6%	3%
Over 10 mm	3%	4%	5%	8%	13%	4%	7%	7%	7%	6%
Wind Speed (km/hour)										
0 - 3 kph	28%	51%	21%	47%	25%	40%	24%	40%	18%	33%
3 - 6 kph	10%	8%	15%	11%	11%	16%	14%	17%	16%	21%
6 - 8 kph	1%	0%	3%	1%	2%	3%	2%	2%	4%	4%
>8 kph	0%	0%	1%	1%	1%	2%	1%	1%	2%	2%
Temperature (Fahrenheit)										
<70 degrees	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
70 - 80 degrees	20%	8%	23%	8%	31%	9%	28%	11%	28%	11%
80 - 90 degrees	51%	16%	47%	16%	41%	15%	46%	14%	46%	14%
>90 degrees	3%	1%	5%	1%	2%	1%	2%	0%	2%	0%
Relative Humidity (%)										
<60	1%	0%	2%	0%	1%	0%	0%	0%	1%	0%
60 - 70	18%	4%	18%	3%	10%	4%	12%	4%	11%	4%
70 - 80	20%	7%	20%	7%	19%	7%	22%	6%	22%	6%
80 - 90	26%	10%	25%	10%	29%	10%	30%	9%	29%	9%
>90	10%	4%	10%	5%	16%	5%	12%	7%	11%	6%

Notes: Hourly observations of wind direction, temperature and humidity are obtained from the NCDC. Rainfall is obtained from the WRC.

Table 4: Instrumental Variable First Stage

	Pregnancy		**Pregnancy and Year 1**		**Pregnancy and Years 1-2**	
	Carbon Monoxide (CO)	**Ozone (O3)**	**Carbon Monoxide (CO)**	**Ozone (O3)**	**Carbon Monoxide (CO)**	**Ozone (O3)**
Extreme Values						
Precipitation (>90% of distribution)	513.582***	236.768***	1,986.510***	-238.475***	1,285.603***	229.176***
	(34.050)	(81.709)	(116.592)	(36.281)	(236.223)	(85.365)
Wind Speed (>90% of distribution)	273.243***	41.113	803.334***	34.215	386.981***	35.717
	(34.018)	(34.895)	(75.047)	(136.378)	(109.543)	(39.586)
Temperature (<10% or >90% of distribution)	-106.747	-340.038**	-580.253***	-209.182	-2,222.899***	-408.536*
	(124.236)	(159.654)	(149.412)	(210.267)	(616.513)	(222.793)
Humidity (<10% or >90% of distribution)	247.355*	7.409***	602.069***	10.083***	5,317.428***	10.968***
	(144.705)	(0.655)	(190.818)	(0.889)	(507.070)	(1.077)
Difference from Seasonal Averages						
Precipitation	85.027***	78.559*	1,357.423	73.923*	11,331.786***	363.200**
	(28.751)	(44.895)	(1,352.588)	(44.655)	(748.295)	(183.242)
Wind Speed	70.883***	-102.347	117.339**	-266.895	243.206***	-232.063
	(20.324)	(137.136)	(58.585)	(206.832)	(75.089)	(270.415)
Temperature	-147.135***	-31.144***	-283.945***	-45.235**	131.917	-47.043*
	(12.006)	(11.406)	(54.593)	(18.179)	(166.009)	(27.135)
Humidity	36.954***	7.036***	157.818	9.695***	519.866***	11.305***
	(10.023)	(0.388)	(170.268)	(0.563)	(123.981)	(0.658)
Additional Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Observations:	3,061	3,061	3,061	3,061	3,061	3,061
Partial F-Statistic:	76.590	41.530	48.888	43.162	29.628	43.752

Notes: Significance levels are indicated by *** 1%, ** 5%, *10%. As part of the first stage, regressions also include full set of control variables as seen in tables 5-9

Table 5: Anthropometric Outcomes Throughout Life

	Low Birth Weight		**Birth Length Z-Score**		**Age 1 Height Z-Score**		**Age 2 Height Z-Score**		**Age 10-12 Height Z-Score**		**Adult Height (in cm)**	
	(i)	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
Fetal and Early Life Exposures:												
CO (monthly average)	0.000	0.006***	-0.000	-0.004***	0.000	-0.006***	-0.000	-0.009***	0.001*	-0.013***	0.002	-0.069***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)	(0.026)
O3 (monthly average)	0.000	-0.057	0.002	-0.017	-0.001	-0.013	-0.001	-0.040**	0.002	-0.053**	-0.015*	-0.182*
	(0.001)	(0.098)	(0.002)	(0.054)	(0.002)	(0.026)	(0.002)	(0.019)	(0.002)	(0.026)	(0.008)	(0.099)
Additional Controls:												
Male	-0.004	-0.006	-0.065**	-0.069**	-0.265***	-0.274***	-0.031	-0.024	-0.359***	-0.360***	11.629***	11.696***
	(0.010)	(0.022)	(0.027)	(0.031)	(0.033)	(0.040)	(0.035)	(0.045)	(0.037)	(0.053)	(0.273)	(0.232)
Mother's Education	-0.003	0.008	0.030**	0.045***	0.078***	0.096***	0.111***	0.143***	0.086***	0.127***	0.352***	0.474***
	(0.003)	(0.026)	(0.013)	(0.017)	(0.012)	(0.017)	(0.014)	(0.018)	(0.013)	(0.022)	(0.078)	(0.118)
Mother's Height	-0.010***	0.000	0.032***	0.000	0.053***	-0.005***	0.053***	-0.009***	0.061***	-0.002	0.482***	0.484***
	(0.001)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)	(0.023)	(0.027)
Mother consumes pre-natal vitamins	-0.008	-0.014	0.134***	0.163***	0.225***	0.291***	0.269***	0.401***	0.177***	0.399***	0.627**	1.823***
	(0.013)	(0.039)	(0.042)	(0.041)	(0.045)	(0.046)	(0.042)	(0.055)	(0.050)	(0.069)	(0.292)	(0.542)
Mother smokes during pregnancy	0.024	0.023	-0.075*	-0.117**	-0.159***	-0.223***	-0.145**	-0.242***	-0.076	-0.225***	-0.077	-0.765
	(0.016)	(0.046)	(0.043)	(0.050)	(0.060)	(0.058)	(0.065)	(0.064)	(0.057)	(0.080)	(0.387)	(0.485)
Per Capita Household Income	-0.000*	0.000	0.000	0.000	0.000***	0.000***	0.000***	0.000***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sanitary Conditions	-0.030	0.498	-0.110	-0.118	0.129	-0.042	0.593***	0.682***	0.196**	0.382	-0.153	-0.445
	(0.029)	(0.738)	(0.087)	(0.407)	(0.101)	(0.295)	(0.168)	(0.258)	(0.092)	(0.373)	(0.440)	(0.666)
Household Solid-fuel use	0.003	-0.161	-0.122***	-0.214	-0.123**	-0.244**	-0.218***	-0.447***	-0.242***	-0.494***	-0.510	-0.999*
	(0.022)	(0.273)	(0.038)	(0.154)	(0.048)	(0.114)	(0.049)	(0.104)	(0.058)	(0.115)	(0.317)	(0.515)
Urban Household	-0.004	0.421	0.144***	0.227	-0.040	-0.013	0.039	0.398*	0.075*	0.597**	-0.112	0.268
	(0.020)	(0.694)	(0.044)	(0.385)	(0.054)	(0.253)	(0.092)	(0.229)	(0.045)	(0.297)	(0.234)	(1.200)
Birth in Amihan Season	-0.007	0.028	-0.056*	-0.073*	-0.068	-0.094**	0.018	0.015	0.001	-0.000	-0.397**	-0.392*
	(0.012)	(0.043)	(0.031)	(0.038)	(0.042)	(0.044)	(0.031)	(0.046)	(0.038)	(0.057)	(0.197)	(0.202)
Observations (N):	3,059	3,059	3,059	3,059	2,816	2,816	2,663	2,663	2,280	2,280	2,129	2,129
R-squared:	0.029		0.085		0.156		0.221		0.220		0.623	

Notes: Columns are: (i) non-instrumental variable OLS estimates, (ii) two-stage least squares instrumental variable estimates. First stage regressions employ extreme weather and deviations from seasonal means as instruments. Standard errors are clustered at the barangay (smallest administrative district) level. Significance levels are indicated by *** 1%, ** 5%, *10%.

Table 6: Cognitive Outcomes

	Std. Non-Verbal Test Score		Std. Math Test Score		Std. Language Test Score		Achieved Years of Schooling	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Fetal and Early Life Exposures:								
CO (monthly average)	0.001	-0.010***	0.000	-0.006***	-0.000	-0.005**	0.005**	0.010
	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.009)
O3 (monthly average)	0.001	-0.016	-0.000	-0.047**	-0.001	-0.032*	0.008	0.061
	(0.004)	(0.014)	(0.003)	(0.022)	(0.003)	(0.019)	(0.006)	(0.069)
Additional Controls:								
Male	-0.114***	-0.109**	-0.327***	-0.315***	-0.406***	-0.399***	-1.251***	-1.260***
	(0.042)	(0.044)	(0.045)	(0.046)	(0.033)	(0.040)	(0.143)	(0.145)
Mother's Education	0.160***	0.175***	0.166***	0.188***	0.172***	0.188***	0.525***	0.501***
	(0.012)	(0.018)	(0.012)	(0.019)	(0.014)	(0.016)	(0.034)	(0.040)
Mother's Height	0.010**	0.006*	0.011***	0.006***	0.011***	0.004***	0.037***	0.036***
	(0.005)	(0.003)	(0.004)	(0.002)	(0.004)	(0.001)	(0.013)	(0.013)
Mother consumes pre-natal vitamins	0.171***	0.341***	0.209***	0.334***	0.216***	0.306***	0.911***	0.796***
	(0.052)	(0.082)	(0.041)	(0.062)	(0.040)	(0.053)	(0.192)	(0.172)
Mother smokes during pregnancy	-0.152**	-0.246***	-0.196***	-0.266***	-0.209***	-0.263***	-1.011***	-0.962***
	(0.067)	(0.072)	(0.059)	(0.070)	(0.052)	(0.060)	(0.176)	(0.174)
Per Capita Household Income	0.000	0.000	-0.000	-0.000	-0.000	-0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sanitary Conditions	-0.089	-0.271**	-0.343**	0.100	-0.269*	-0.001	-0.259	-0.822
	(0.215)	(0.127)	(0.143)	(0.321)	(0.142)	(0.277)	(0.316)	(1.104)
Household Solid-fuel use	-0.152***	-0.226***	-0.256***	-0.395***	-0.214***	-0.312***	-0.651***	-0.519*
	(0.059)	(0.087)	(0.054)	(0.100)	(0.066)	(0.086)	(0.198)	(0.311)
Urban Household	0.131	0.269	0.049	0.547**	0.133	0.458**	0.178	-0.428
	(0.111)	(0.212)	(0.085)	(0.246)	(0.085)	(0.212)	(0.223)	(0.869)
Birth in Amihan Season	0.017	0.011	-0.070**	-0.040	-0.042	-0.024	-0.091	-0.123
	(0.038)	(0.045)	(0.033)	(0.050)	(0.032)	(0.043)	(0.111)	(0.115)
Observations (N):	2,180	2,180	2,167	2,167	2,167	2,167	2,006	2,006
R-squared:	0.160		0.204		0.245		0.252	

Notes: Columns are: (i) non-instrumental variable OLS estimates, (ii) two-stage least squares instrumental variable estimates. First stage regressions employ extreme weather and deviations from seasonal means as instruments. Standard errors are clustered at the barangay (smallest administrative district) level. Significance levels are indicated by *** 1%, ** 5%, *10%.

Table 7: Labor Market Outcomes

	Non-Physical Labor Sector				**Weekly Hours Worked**				**Log of Hourly Earnings**			
	(i)	**(ii)**	**(iii)**	**(iv)**	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(i)**	**(ii)**	**(iii)**	**(iv)**
Fetal and Early Life Exposures:												
CO (monthly average)	0.000	0.005**	0.004	0.002	-0.031**	-0.126**	-0.008	-0.228*	0.001*	0.003	-0.001	-0.003
	(0.000)	(0.003)	(0.003)	(0.003)	(0.014)	(0.058)	(0.061)	(0.118)	(0.000)	(0.002)	(0.003)	(0.009)
O3 (monthly average)	0.000	0.030***	0.028**	0.019*	-0.090*	0.234	0.391	-0.239	-0.000	-0.031***	-0.033***	-0.038
	(0.001)	(0.010)	(0.012)	(0.011)	(0.051)	(0.535)	(0.515)	(0.444)	(0.001)	(0.009)	(0.010)	(0.031)
Additional Controls:												
Male	-0.343***	-0.356***			-6.558***	-6.438***			0.227***	0.278***		
	(0.023)	(0.029)			(1.254)	(1.998)			(0.063)	(0.070)		
Mother's Education	0.026***	-0.000	0.013	-0.000	-2.407***	-2.746***	-2.767***	-2.525***	0.053**	0.079***	0.045***	0.145***
	(0.010)	(0.013)	(0.015)	(0.017)	(0.347)	(0.618)	(0.334)	(0.806)	(0.025)	(0.014)	(0.009)	(0.049)
Mother's Height	-0.001	-0.001	-0.003	0.002	0.051	0.451***	0.362***	0.482***	-0.001	0.004*	0.006	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.107)	(0.051)	(0.047)	(0.085)	(0.005)	(0.002)	(0.005)	(0.005)
Mother consumes pre-natal vitamins	0.043*	-0.077	-0.019	-0.064	-3.878***	-3.036***	-2.034	-3.237***	0.129***	0.144***	0.130**	0.319*
	(0.022)	(0.057)	(0.061)	(0.079)	(1.238)	(0.928)	(1.530)	(1.194)	(0.048)	(0.045)	(0.058)	(0.170)
Mother smokes during pregnancy	-0.037	0.024	-0.004	0.015	2.954**	2.765*	3.881**	1.468	-0.072	-0.058	0.005	-0.209*
	(0.026)	(0.047)	(0.061)	(0.056)	(1.242)	(1.650)	(1.679)	(2.922)	(0.060)	(0.051)	(0.079)	(0.125)
Per Capita Household Income	0.000***	0.000	0.000	0.000	0.001	0.001	-0.000	0.003	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Sanitary Conditions	-0.012	-0.120	-0.131	-0.096	0.135	-5.028	-7.546	1.323	-0.037	0.292	0.344	-0.103
	(0.065)	(0.078)	(0.105)	(0.093)	(2.757)	(5.542)	(6.536)	(9.676)	(0.098)	(0.200)	(0.309)	(0.325)
Household Solid-fuel use	-0.078**	0.039	0.071	-0.033	1.728	3.925*	-0.144	8.350***	0.272***	0.088	0.177***	-0.059
	(0.039)	(0.056)	(0.080)	(0.059)	(1.583)	(2.200)	(2.489)	(2.284)	(0.074)	(0.070)	(0.051)	(0.100)
Urban Household	0.030	-0.130	-0.270	0.034	-4.130**	-6.717	-7.286	-2.247	0.039	0.256**	0.207*	0.199
	(0.033)	(0.130)	(0.196)	(0.130)	(1.763)	(5.564)	(5.903)	(5.274)	(0.052)	(0.108)	(0.121)	(0.241)
Birth in Amihan Season	-0.046***	-0.048*	-0.032	-0.071**	-1.211	-1.170	-2.441**	0.145	-0.027	-0.038*	-0.063***	-0.013
	(0.013)	(0.029)	(0.038)	(0.035)	(1.160)	(0.826)	(0.984)	(2.064)	(0.049)	(0.022)	(0.022)	(0.037)
Observations (N):	1,942	1,942	1,036	906	1,942	1,942	1,036	906	1,818	1,818	1,009	865
R-squared:	0.144				0.078				0.037			

Notes: Columns are: (i) non-instrumental variable OLS estimates on the full sample, (ii) two-stage least squares instrumental variable estimates on the full sample, (iii) two-stage least squares instrumental variable estimates on subsample of males, (iv) two-stage least square instrumental variable estimates on subsample of females. First stage regressions employ extreme weather and deviations from seasonal means as instruments. Standard errors are clustered at the barangay (smallest administrative district) level. Significance levels are indicated by *** 1%, ** 5%, *10%.

Table 8: Labor Market Outcomes by Labor Sector
Instrumental Variables

	Weekly Hours Worked			**Log of Hourly Earnings**		
	(i)	**(ii)**	**(iii)**	**(i)**	**(ii)**	**(iii)**
Fetal and Early Life Exposures:						
CO (monthly average)	-0.126**	-0.080	-0.139*	0.003	-0.011	-0.005
	(0.058)	(0.070)	(0.076)	(0.002)	(0.007)	(0.005)
O3 (monthly average)	0.234	0.512	-0.124	-0.031***	-0.062**	-0.018
	(0.535)	(0.543)	(0.695)	(0.009)	(0.031)	(0.021)
Additional Controls:						
Male	-6.438***	-7.677***	-7.830***	0.278***	0.364***	0.424***
	(1.998)	(2.231)	(2.849)	(0.070)	(0.056)	(0.074)
Mother's Education	-2.746***	-2.932***	-1.902	0.079***	0.164***	0.081*
	(0.618)	(0.602)	(1.250)	(0.014)	(0.032)	(0.042)
Mother's Height	0.451***	0.404***	0.501***	0.004*	-0.003	0.005
	(0.051)	(0.060)	(0.062)	(0.002)	(0.007)	(0.007)
Mother consumes pre-natal vitamins	-3.036***	-4.529**	-2.063	0.144***	0.399**	0.207*
	(0.928)	(1.830)	(1.879)	(0.045)	(0.155)	(0.109)
Mother smokes during pregnancy	2.765*	6.024*	-0.453	-0.058	-0.311**	-0.005
	(1.650)	(3.423)	(1.197)	(0.051)	(0.140)	(0.110)
Per Capita Household Income	0.001	0.001	0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Sanitary Conditions	-5.028	-4.409	-4.686	0.292	-0.043	0.173
	(5.542)	(6.831)	(4.900)	(0.200)	(0.192)	(0.182)
Household Solid-fuel use	3.925*	5.857***	-0.437	0.088	-0.221*	0.002
	(2.200)	(1.998)	(2.617)	(0.070)	(0.126)	(0.167)
Urban Household	-6.717	-11.306*	-0.732	0.256**	0.147	-0.075
	(5.564)	(6.048)	(6.607)	(0.108)	(0.211)	(0.277)
Birth in Amihan Season	-1.170	-2.448*	-0.387	-0.038*	-0.018	-0.004
	(0.826)	(1.249)	(1.390)	(0.022)	(0.053)	(0.069)
Observations (N):	1,942	1,039	903	1,874	967	907

Notes: Columns are: (i) two-stage least squares instrumental variable estimates on the full sample, (ii) two-stage least squares instrumental variable estimates on subsample of non-physical labor sector workers, (iii) two-stage least square instrumental variable estimates on subsample of physical labor sector workers. First stage regressions employ extreme weather and deviations from seasonal means as instruments. Standard errors are clustered at the barangay (smallest administrative district) level. Significance levels are indicated by *** 1%, ** 5%, *10%.

Table 9: Acute Morbidity Outcomes

	Diarrheal Incidence		**Acute Respiratory Illness Incidence**		**Log of Medical Expenditures**	
	(i)	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
Fetal and Early Life Exposures:						
CO (monthly average)	0.004	0.029	0.002	0.014***	-0.000	0.008*
	(0.003)	(0.020)	(0.002)	(0.005)	(0.001)	(0.004)
O3 (monthly average)	0.006	0.047	-0.005*	-0.012	0.007***	0.050***
	(0.010)	(0.080)	(0.003)	(0.040)	(0.002)	(0.016)
Additional Controls:						
Male	0.363***	0.348***	0.104	0.099	0.049	0.034
	(0.102)	(0.083)	(0.081)	(0.089)	(0.040)	(0.053)
Mother's Education	-0.101**	-0.119**	-0.090**	-0.092***	0.106***	0.088***
	(0.044)	(0.059)	(0.038)	(0.034)	(0.018)	(0.020)
Mother's Height	-0.042***	-0.044***	0.007	0.021***	0.014**	0.018***
	(0.013)	(0.013)	(0.010)	(0.003)	(0.006)	(0.004)
Mother consumes pre-natal vitamins	-0.109	-0.405**	0.153*	0.017	0.327***	0.232***
	(0.154)	(0.182)	(0.085)	(0.110)	(0.059)	(0.077)
Mother smokes during pregnancy	0.207	0.315*	-0.156	-0.109	-0.112	-0.065
	(0.154)	(0.170)	(0.143)	(0.132)	(0.068)	(0.081)
Per Capita Household Income	-0.000	-0.000	-0.000	-0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sanitary Conditions	0.485	0.536	0.016	0.410	0.173	-0.134
	(0.799)	(1.522)	(0.319)	(0.520)	(0.203)	(0.149)
Household Solid-fuel use	0.414	0.443	0.183	0.103	-0.157**	-0.015
	(0.275)	(0.481)	(0.131)	(0.217)	(0.066)	(0.101)
Urban Household	0.559*	0.140	0.075	0.196	0.399***	0.409*
	(0.330)	(1.029)	(0.175)	(0.467)	(0.110)	(0.220)
Birth in Amihan Season	0.215	0.205	0.116	0.135	0.091*	0.075
	(0.177)	(0.186)	(0.104)	(0.094)	(0.051)	(0.054)
Observations (N):	3,061	3,061	3,061	3,061	2,669	2,669
R-squared:	0.021		0.009		0.132	

Notes:Columns are: (i) non-instrumental variable OLS estimates, (ii) two-stage least squares instrumental variable estimates. First stage regressions employ extreme weather and deviations from seasonal means as instruments. Standard errors are clustered at the barangay (smallest administrative district) level. Significance levels are indicated by *** 1%, ** 5%, *10%.

Table 10: Subsample Analyses Summary

Number of outcomes	16
Number of subsamples*	6
Number of exposures	2
Total number of interaction term tests	190
One-Sided Tests:	
One-sided test threshold at 5% level	1.645
Number of rejections (% of all tests)	5 (2.6%)
Bonferroni, multiple one-sided tests threshold**	3.476
Number of Bonferroni rejections (% of all tests)	0 (0%)
Two-Sided Tests:	
One-sided test threshold at 10% level	±1.645
Number of rejections (% of all tests)	11 (5.8%)
Bonferroni, multiple one-sided tests threshold**	±3.476
Number of Bonferroni rejections (% of all tests)	1 (<1%)

* - For one outcome, diarrheal incidence, there are only 5 subsamples

** - See Miller 1981

Table 11: Overidentification Tests Summary

	Hausman-Wu Test P-Value
Anthropometrics:	
Low Birth Weight	0.430
Birth Length Z-Score	1.000
Age 1 Height Z-Score	1.000
Age 2 Height Z-Score	1.000
Age 10-12 Height Z-Score	1.000
Adult Height (cm)	0.845
Cognition:	
Std. Non-Verbal Test Score	0.937
Std. Math Test Score	1.000
Std. Language Test Score	1.000
Achieved Years of Schooling	1.000
Labor Market:	
Labor Sector	0.936
Weekly Hours Worked	0.986
Log of Hourly Earnings	1.000
Morbidity:	
Diarrheal Incidence	0.996
Acute Respiratory Illness	0.946
Medical Expenditures	0.996

Table 12: Hypothetical 10% Emissions Reduction Policy and Birth Cohort Impacts

Short Term: Medical Expenditures		***Long Term: Labor Market Income***	
Mean annual expenditures years 0-2 (2005 USD)	$6.15	Mean annual labor market earnings (2005 USD)	$1,477.70
Annual policy impact, individual (2005 USD)	$0.99	Mean present value of lifetime earnings (2005 USD)	$39,927.25
Annual policy impact, province **(mil 2005 USD)**	$0.03	Annual policy impact, individual (2005 USD)	$2,475.49
Annual policy impact, country **(mil 2005 USD)**	$1.49	Annual policy impact, province **(mil 2005 USD)**	$84.17
		Annual policy impact, country **(mil 2005 USD)**	$3,713.23
Short Term: Medical Expenditures		***Long Term: Work Hours***	
Maximum annual expenditures years 0-2 (2005 USD)	$115.53	Mean hourly labor market earnings (2005 USD)	$0.69
Annual policy impact, individual (2005 USD)	$18.60	Annual policy impact, individual (2005 USD)	$958.25
Annual policy impact, province **(mil 2005 USD)**	$0.63	Annual policy impact, province **(mil 2005 USD)**	$32.58
Annual policy impact, country **(mil 2005 USD)**	$27.90	Annual policy impact, country **(mil 2005 USD)**	$1,437.38

Notes: Calculation of monetary benefits to the hypothetical policy is performed similar to Chetty et al. (2011) and Isen et al. (2014). Medical expenditures includes both the significant effects of CO and O3, while labor market income only includes the significant effects of O3. Work hours assumes 34.5 work weeks per year. Size of Cebu province 1983-84 birth cohort 34k. Size of Philippine 1983-84 birth cohort: 1.5m