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RESEARCH ARTICLE

Early-life environment and human capital: evidence from the Philippines

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Abstract

This study examines how human capital develops in response to early-life weather and pollution exposures in the Philippines. Both pollution and weather are examined in relation to short- and long-term human capital outcomes. We combine a three-decade longitudinal survey measuring human capital development, a database of historical weather, and multiple databases characterizing carbon monoxide and ozone in the Philippines during the 1980s. We find evidence that extreme precipitation and temperature affect short-term anthropometric outcomes, but long-term outcomes appear unaffected. For long-term cognitive outcomes, we find that early-life pollution exposures negatively affect test scores and schooling. These long-term responses to early-life pollution exposures extend to the labor market with reduced hours worked and earnings. The implication is that a 25 per cent reduction in early-life ozone exposure would increase per person discounted lifetime earnings by $1,367, which would scale to $2.05 billion at the national level (or 2 per cent of 2005 GDP).

Keywords: development; environment; weather; pollution; human capital

JEL classification: O13; O15; Q51; Q53; Q54; Q56

1. Introduction

Human capital is the set of skills and resources that contribute to individual productivity, income and macroeconomic growth, making it critical to understand the factors that influence the development of human capital. Among the potential factors are weather and pollution exposure. Temperature and precipitation can affect human capital development through income and health (Maccini and Yang, 2009; Graff Zivin *et al.*, 2018); pollution may also disrupt other bodily systems related to human capital (Altshuler *et al.*, 2003). And in early-life, small changes to the environment can influence long-term developmental trajectories (Waterland and Michels, 2007). Existing cost-benefit analyses of environmental regulations exclusively count the costs of mortality and short-term morbidity; however, if the environment's effects extend to long-term human capital, the results may imply that environmental regulations, traditionally viewed as taxes, may be investments that fuel economic growth (Graff Zivin and Neidell, 2013).

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Extensive evidence links weather and pollution to health outcomes (Deschênes *et al.*, 2009), and recent studies link pollution (Allen *et al.*, 2017), temperature (Graff Zivin *et al.*, 2018) and precipitation (Maccini and Yang, 2009) to cognition and schooling. The effects of temperature and precipitation on labor market outcomes have been extensively examined (Dell *et al.*, 2014), and there is also evidence that pollution impacts labor market outcomes (Kim *et al.*, 2017). While the long-term human capital effects of weather have been explored (Graff Zivin and Neidell, 2013), few studies have examined the long-term human capital effects of early-life pollution exposure (Currie *et al.*, 2014), with fewer making the link to labor market outcomes (Kim *et al.*, 2017).

This study addresses the following research questions: what are the long-term human capital impacts of the early-life environment – both weather and pollution – and how do these impacts translate to the labor market? We examine the effects of temperature and precipitation, as well as the effects of carbon monoxide (CO) and ozone (O_3) exposures. Temperature and precipitation have been previously linked to human capital (Maccini and Yang, 2009) and CO and O_3 are common emissions with biological pathways to potentially impact human capital development (Block and Calderon-Garciduenas, 2009). While previous studies have examined either weather or pollution, we examine both because of their close relationship. And we look at both human capital and labor market outcomes because of the extensive evidence linking human capital to labor market outcomes (Strauss and Thomas, 1998), and the limited evidence of how environmental factors affect each (Kim *et al.*, 2017).

To do this, we combine a longitudinal birth cohort survey conducted in the Philippines with a unique combination of data characterizing weather and pollution during early-life. For each measure of human capital (anthropometrics including birth weight and length/height, as well as cognitive measures such as test scores and years of schooling) and labor market outcomes (earnings and hours worked), we first estimate the direct effects of temperature and precipitation while controlling for pollution exposure as well as social, demographic and economic factors. Then, for outcomes not directly affected by weather, we use weather as instruments for non-random pollution exposures. We define the early-life exposure window as conception up to the time when the outcome is observed (e.g., birth weight), or age 2 for long-term outcomes.

Data limitations have limited the analysis of the long-term effects of early-life environmental exposures, particularly in developing countries like the Philippines. To circumvent the data limitations, we combine multiple unique data sources. First, we use the Cebu Longitudinal Health and Nutrition Survey (CLHNS) which documents frequent anthropometric, cognitive and labor market measures of a cohort born in the Cebu Metropolitan area of the Philippines between 1983–1984. The CLHNS is combined with National Climatic Data Center and Water Resources Center of the University of San Carlos weather data, pollution emissions data from the REanalysis of the TROpospheric chemical composition over the past 40 years (1960–2000) (RETRO) database (Schultz *et al.*, 2007), and historical emission source data including archived telephone directories, pollution permits, land use, zoning and road network maps. RETRO and the emission source data are combined and matched to the early-life exposure window of each CLHNS birth cohort member.

The results of this study provide evidence from a developing country context of weather's short-term effects and pollution's long-term effects on human capital. Extreme precipitation and temperature demonstrate significant effects on short-term anthropometric measures of human capital observed between birth and age 2. These effects align with previous results like the effects of extreme temperatures on birth weight in

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Deschênes *et al.* (2009) and the birth weight effects of extreme precipitation in Grace *et al.* (2015). However, weather does not demonstrate significant effects on long-term outcomes like test scores, schooling, labor hours and earnings. This is similar to the results of Graff Zivin *et al.* (2018) which demonstrate significant contemporaneous effects of temperature on human capital but no long-term effects. In contrast, early-life CO and O_3 exposure demonstrate long-term effects on test scores and schooling. While previous studies have shown long-term cognitive effects of lead exposure and environmental disasters (Almond *et al.*, 2009; Black *et al.*, 2019), our results suggest that early-life exposures to more common environmental toxins also exert long-term human capital and labor market effects. Similar evidence has been found in few other studies (Sanders, 2012; Bharadwaj *et al.*, 2017; Isen *et al.*, 2017). In sum, the labor market results suggest that if early-life pollution exposure was reduced by 25 per cent, cumulative discounted lifetime earnings would increase by \$1,367 per person, \$44.5 million in the province, and \$2.05 billion at the national level (or 2 per cent of 2005 GDP).

The paper proceeds as follows. Section 2 describes background information on weather, air pollutants, the early-life origins of human capital, and the study's context. Section 3 describes the identification strategies, data and specifications. Section 4 describes the results, and Section 5 discusses the results. Section 6 concludes the study.

2. Background

There are multiple plausible short- and long-term mechanisms through which temperature and precipitation may affect human capital. First, temperature and precipitation are both related to income (Levine and Yang, 2014) which affects nutrition (Maccini and Yang, 2009). Temperature and precipitation may also affect human capital via disease. Temperature and precipitation are closely related to the incidence of infectious diseases, both vector-borne and water-borne, and consequently may impact school attendance and short-term human capital development. Alternatively, evidence suggests that early-life illnesses may affect long-term human capital development (Baird *et al.*, 2016). In the short-term, elevated environmental temperatures reduce the flow of cool blood to the brain and temporarily raise brain temperature (Kiyatkin, 2007). This diminishes attention, memory, information retention and the performance of psycho-perceptual tasks (Hocking *et al.*, 2001). However, even if the mechanism is initially short-term, the effects on human capital can accumulate over time (Graff Zivin *et al.*, 2018).

In addition to directly affecting human capital, weather (including temperature and precipitation as well as humidity and wind) has been shown to impact agricultural and industrial output, which results in pollutant emissions (Hassan and Barker, 1999; Bennett and McMichael, 2010; Hsiang, 2010; Dell *et al.*, 2012, 2014; Hsiang and Jina, 2014). If the indirect effects can be isolated from the direct effects, this relationship makes weather potential instruments for non-random pollution exposure. Among the pollutants affected by weather are CO and O_3. CO and O_3 are among the most common air pollutants. Both are odorless, colorless gases; CO is primarily emitted from combustion processes and O_3 is formed by chemical reactions in the sunlight with its precursors: nitrogen oxides (NO_x) and volatile organic compounds (VOCs). CO bonds with hemoglobin more easily than oxygen, reducing the body's ability to deliver oxygen to organs and the fetus (Meter, 2000). Because oxygen is needed for proper growth and development, CO exposure has demonstrated consistent associations with low birth weight and early-life height/length (Currie *et al.*, 2014), while a minority of studies demonstrate an association to diminished cognitive function (Lavy *et al.*, 2014). The

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bonding of CO with hemoglobin and the impaired delivery of oxygen throughout the body is a potential short-term mechanism of pollution's effects on human capital. O_3 and its precursors[1] are neurotoxins that also cause increased inflammation and oxidative stress (Block and Calderon-Garciduenas, 2009). While O_3 does not typically pass through the placenta (Salam *et al.*, 2005), a large body of literature describes the impact that O_3 has on cognition (Allen *et al.*, 2017). These human capital implications of O_3 exposure indicate potential long-term mechanisms.

Extensive human epidemiologic and animal research indicate that during critical periods of prenatal and postnatal development, environmental exposures can influence developmental trajectories of lifetime health (Waterland and Michels, 2007). The developmental origins of health outcomes are commonly assessed in both epidemiology and economics, and although the economics literature has included assessments of human capital and labor market outcomes, these are much less common (Currie *et al.*, 2014). However, rapid cell division, epigenetic programming, and the development of diverse bodily systems during early-life magnify the potential impacts of environmental influences on the development of human capital (Altshuler *et al.*, 2003). The development of physical human capital may be impeded by perturbations or reductions to the flow of nutrients (Stieb *et al.*, 2012). And the development of cognitive human capital may be impacted by nutrient flow or inflammation, oxidative stress and neurotoxicity (Waterland and Michels, 2007).

Most studies of human capital's early-life origins are set in developed countries because of the scarcity of environmental data in developing economies. Metropolitan Cebu is located on the island of Cebu in the Central Visayas region of the Philippines. In 1983–1984 Metro Cebu consisted of ten cities or 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. Figure A1 in the online appendix shows the daily rainfall and temperatures in Metropolitan Cebu between 1978 and 1987. Metropolitan Cebu emissions compares to cities of similar population size in both the developing and developed world such as Kanpur, India and San Diego, United States, or even some larger cities in the developing world like Rio de Janiero, Brazil (table A2, online appendix).

3. Methods

The effects of early-life extreme temperature and precipitation on human capital and labor market outcomes are estimated using ordinary least squares (OLS) including a rich set of controls for other weather variables (wind speed and humidity extremes, as well as deviations from seasonal averages), CO and O_3 exposures, urban/rural residence, gender, season of birth, and household and parental risk factors such as per capita household income, maternal smoking and others (see table 1). The measures of extreme temperature and precipitation that we use are based on their distributions during a 10 year window, 1978 to 1987. As commonly used in the literature (Strand *et al.*, 2011),

[1] While this study refers to O_3 exposure, the measure of O_3 is derived via principal component analysis of NO_x and VOCs. This is done because NO_x and VOCs share similar mechanisms to affect human capital (Black *et al.*, 2019), are highly correlated (see online appendix, table A1), and convert to O_3 in the presence of sunlight which is highly abundant in Metro Cebu where over 90 per cent of the hourly weather observations describe the cloud cover as less than 20 per cent.

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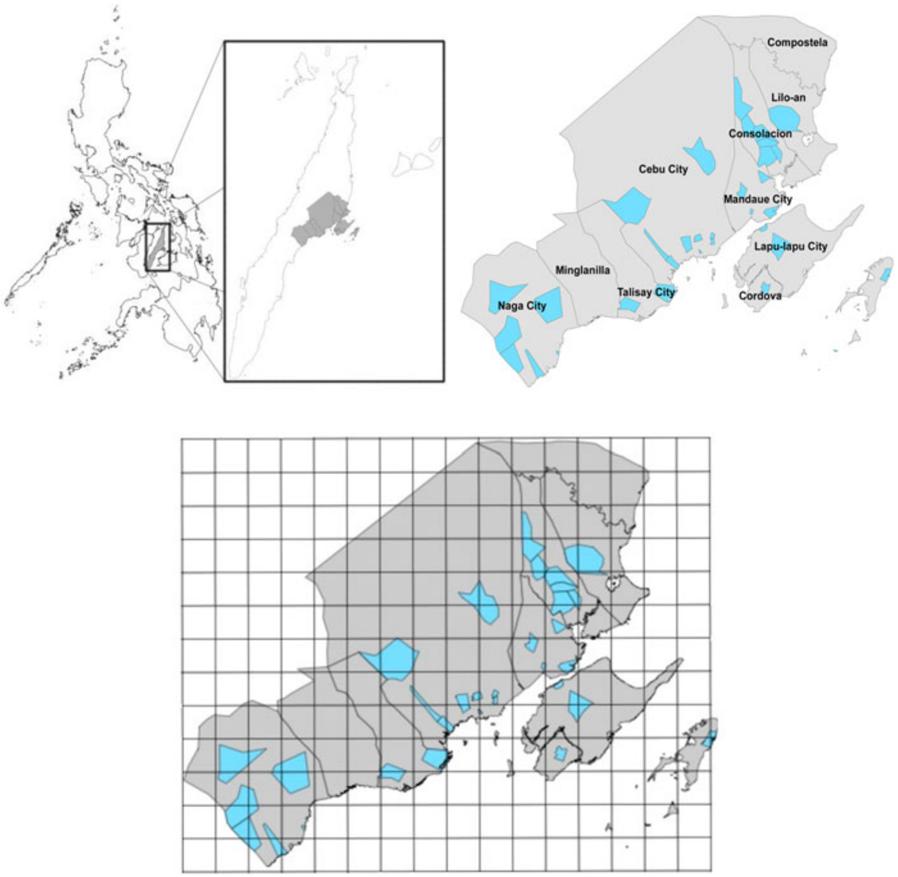

Figure 1. Maps of the study area: Philippines with Cebu Province and Metro Cebu highlighted (top left); cities and municipalities of Metro Cebu with barangay highlighted (top right); map of 0.5 $\times$ 0.5 degree RETRO grid divided into 400 micro-environments at 0.025 $\times$ 0.025 degrees (bottom).

extremes are measured as the number of days above the 90th and below the 10th percentile of the distributions. Focusing on the extremes of precipitation and temperature avoids the potential problem of compensatory responses to predictable weather.

The effects of early-life CO and O_3 exposure on human capital and labor market outcomes are estimated with the limited-information-maximum-likelihood (LIML) estimator which is consistent in the presence of many instrumental variables. In addition to the precipitation and temperature extremes, we also include extreme wind speed and humidity, as well as deviations from seasonal averages as instruments. Each of the weather instruments are interacted with location specific concentrations of pollution sources. The exclusion restriction is the key issue with this identification strategy. If weather directly affects human capital outcomes, the instrumental variable exclusion restriction is violated. However, if there are no direct effects of weather, the weather instruments may be used to estimate the effects of pollution exposure.

We examine whether our instruments exert direct effects in two ways. First, we use the previously described OLS estimates of the effects of temperature and precipitation.

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Second, we use a test introduced by the many invalid instrumental variables method of Kolesár *et al.* (2015). Kolesár *et al.* (2015) introduced the modified-bias-two-stage-least-squares (MBTSLS) which produces consistent estimates with invalid instruments if the instruments' direct effects are independent of their indirect effects. If we were confident in the assumption that the direct and indirect effects of the weather instruments are independent, we could use MBTSLS to estimate pollution's indirect effects even if the weather instruments directly affect the outcomes. However, we cannot verify that assumption, so the MBTSLS estimates do not comprise our main results. Instead, we only use the MBTSLS estimates as part of our second test for whether our instruments exert direct effects. We test whether the LIML and MBTSLS estimates differ. LIML produces consistent estimates with many instrumental variables, but inconsistent estimates if the instruments are invalid. A significant difference between the LIML and MBTSLS estimates indicates the presence of the instruments' direct effects. So, if the OLS estimates of the weather variables' effects are null and the LIML-MBTSLS test is null, we have multiple pieces of evidence that the instruments do not directly affect the outcomes and are valid. Where both these tests are null, the effects of early-life CO and O_3 exposure are identified using the LIML estimator.

3.1. Data

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

The years of life documented and the human capital and labor market outcomes measured in the CLHNS provides the unique opportunity to assess the effects of the early-life environment 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 Philippines. The 33 sampled barangays contained in total roughly 28,000 households in 1982, all of which were canvassed in search of pregnant women. Women from the selected barangays who gave birth between 1 May 1983, and 30 April 1984 are included in the baseline sample that took place during the 6th or 7th month of pregnancy. In total, 3,327 women were surveyed at baseline and 3,122 were resurveyed at childbirth. Following the child's birth, 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 (followed by limited tracking surveys).

Table 1 provides summary statistics of mothers, fathers, household characteristics, residence, migration, attrition, and children's health and human capital at birth,

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Table 1. Summary statistics of individual and household characteristics, environmental exposures, and outcomes

	Percent or Mean	Std. Dev.		Percent or Mean	Std. Dev.
Child, Parental, and Household Characteristics $(n = 3327)$			***Emissions Exposure Prior to Age 2 in*** $\mathrm{ng/m^2/s}$ $(n = 3122)$		
Child: Birth in amihan season (Sept-May)	59%		CO: monthly average exposure prior to birth	48.12	27.9
Child: Male %	53%		Ozone: monthly average exposure prior to birth	11.84	8.83
Mother: Elementary school or less education %	54%		CO: monthly average exposure prior to age 2	75.94	40.79
Mother: Smoked during pregnancy %	14%		Ozone: monthly average exposure prior to age 2	18.89	14.08
Mother: Drank alcohol during pregnancy %	8%				
Mother: Consumes pre-natal vitamines %	58%		***Short-term Anthropometric Outcomes***		
Mother: Number of previous pregnancies	2.52	2.43	Low birth weight (2500 grams) %	13%	0.34
Mother: Height in cm	150.64	5.1	Birth length in cm	49.25	2.14
Mother: Age in years	26.04	5.98	Height in cm at age 2	78.79	3.9
Father: Present in household %	94%				
Father: Elementary school or less education %	47%		***Cognitive and Schooling Outcomes***		
Father: Age in years	28.82	6.56	Non-verbal intelligence scores (scale 0+) in 1994	67.01	11.16
Household: Per capita monthly income in 1983–1984 (PhP)	255.37	309.62	Math test scores (scale 0+) in 1994	51.23	13.16
Household: Uses solid fuels	83%		Language (Cebuano and English) test scores (scale 0+) in 1994	56.72	9.26
Household: No piped water	72%		Achieved years of schooling by 2009	12.5	4.38
Household: Urban residence	77%				

(continued)

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Table 1. Continued

	Percent or Mean	Std. Dev.		Percent or Mean	Std. Dev.
			Labor Market Outcomes		
Migration and Attrition ($n = 3327$)			Male hours worked per week in 2005	40.5	18.06
Ever temporarily attrit throughout all waves %	17%		Female hours worked per week in 2005	42.8	21.16
Ever permanently attrit throughout all waves %	24%		Male individual monthly income in 2005 (PhP)	7614.35	37405.35
			Female individual monthly income in 2005 (PhP)	5793.23	10934.12
Extreme Weather Exposures Prior to Age 2 ($n = 3122$)					
Temperature (>90% of distribution)	22%	0.05	***Short-term Morbidity Outcomes***		
Temperature (<10% of distribution)	12%	0.04	Number of reported diarrheal incidences	3.44	3.89
Precipitation (>90% of distribution)	8%	0.01	Number of reported acute respiratory infections	4.47	2.41
Precipitation (<10% of distribution)	3%	0.04	Medical expenditures (pesos) during first two years	193.73	266.6

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 per cent with primary or less education). Fifty-three per cent 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 cm tall) and are, on average, 26 years old at the time of the birth of the CLHNS cohort member. Just under 50 per cent of the sample reside in Cebu City at birth and over three-quarters of the sample reside in urban barangays. Furthermore, 24 per cent of the sample permanently attrit from the three-decade long survey, while 17 per cent temporarily attrit for a period of time and are observed in later periods. Thirteen per cent of children are low birth weight (less than 2,500 g). 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. Between birth and ages 1 and 2, mean 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 per cent of pregnancies in the sample, and infant mortality within the first year is 4 per cent.[2]

Hourly observations of wind direction and wind speed from the NCDC provide high frequency observations of temperature, wind speed and humidity. WRC data provides daily precipitation measures from five observation stations throughout Metro Cebu. Table 1 provides summary statistics of early-life exposures to extreme temperature and precipitation. Generally, the cohort experienced greater exposure to extreme temperatures than to extreme precipitation during their exposure window between conception and age 2. Weather patterns in Cebu are influenced by the seasons: the dry season, or Amihan, from September/October to May/June, and the wet season, or Habagat. Online appendix figure A1 shows trends and variation in daily precipitation and maximum and minimum temperatures across the seasons before, during and after the early-life period of the CLHNS cohort (1978 to 1987).

The RETRO database of historical emissions describes the temporal variation in CO and O_3 precursors for Metro Cebu during the first two years of the lives of CLHNS birth cohort members. RETRO contains global monthly emissions by sectors for the years 1960–2000 at a 0.5×0.5 latitude-longitude degree of spatial resolution.[3] 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.*, 2007). Figure A2 in the online appendix shows examples of the RETRO database for CO and O_3 precursor emissions for a randomly selected month and an example sector (residential/commercial). We focus solely on the single 0.5×0.5 grid located at the 10.25 degrees North and 123.75 degrees East latitude-longitude which covers Metro Cebu. This 0.5×0.5 degree, 55 km × 55 km grid is shown as the outer border in the bottom panel of figure 1. The RETRO database is particularly relevant for the current study because the 0.5×0.5 grid covering Metro Cebu does not cover any other land mass or population hub that could contribute to emissions.

[2]The low number of miscarriages, stillbirths and infant deaths indicate an oversampling of healthy pregnancies.

[3]While concentrations in weight per cubic meter, or m^3, are most common, RETRO uses nanograms per square meter per second ($ng/m^2/s$).

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Available monitored emissions as well as descriptions of economic activity (energy and solvent usage, and biomass burning), technology, behavior (legislation, economic and industrial policies), population, and meteorology form inputs to the atmospheric transport and chemistry models yielding monthly emissions by pollutant and sector for each 0.5×0.5 latitude-longitude grid (Schultz *et al.*, 2007). 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.*, 2007).[4] Where deviations from existing databases exist, the RETRO estimated emissions are generally conservative (Schultz *et al.*, 2007).

Table 1 also provides summary statistics of early-life monthly average exposures.[5] 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. CO is the most commonly emitted pollutant by non-point sources, the majority emitted by residential and commercial sources.

While the RETRO emissions database provides temporal variation in total emissions of CO and O_3 precursors for Metro Cebu, the database contains no spatial variation to determine individual CLHNS birth cohort member 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 population density on the island and within the RETRO 0.5×0.5 latitude-longitude grid, the sources of pollution within Metro Cebu are assumed to characterize the complete set of sources that contribute to the emissions described in RETRO.

Point sources are single, identifiable sources including immobile structures like power and manufacturing plants, while non-point sources emit from more diffuse areas like agricultural land or roads. Online appendix figure A3 shows the locations of point sources by industry and sector (top row) and non-point sources of pollution (middle and bottom rows). Telephone directories from the Directories Philippines Corporation locate and describe the point sources that existed during the years 1982–1986. Telephone directories provide information regarding the existence, location and industry of Metro Cebu firms. Sources that belong to industries that required pollution permits during the 1999–2012 period are assumed to require them during the 1982–1986 period and are included as point sources for the years 1982–1986. The remaining point sources included in the data come from the Provincial Mining Office (PMO) and the Provincial Planning and Development Office (PPDO) and describe large and small scale mines. Only mines that existed between 1982–1986 are included (per PMO and PPDO data). In total, 21 large and small scale mines existed during the early 1980s in Metro Cebu; 12 of the 21 mines were copper mines, five were coal mines, and others were clay, gold and silver mines. To describe non-point sources within Metro Cebu during the years 1982–1986, we use maps describing land use (from the PPDO), zoning (each municipality planning and development offices), and the road network (PPDO) generated from

[4] While RETRO uses existing ambient air quality monitors as inputs, the resulting emissions are modeled to give a more complete description of air quality (Daly and Zannetti, 2007).

[5] Table A3 in the online appendix provides annual means and standard deviations of monthly emissions of CO and O_3 precursors by source type (point and non-point) and sector.

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data collected from the PPDO. Land use and zoning maps describe agricultural and commercial/residential pollution sources. The road network is limited to roads in existence during the 1982–1986 period. Traffic flows are estimated using a standard gravity model incorporating relative populations of barangays from the 1980s census collected from the National Statistics Office and supplemented with 1980–1985 zoning information from the Information Services Offices of the various municipalities of Metro Cebu in order to describe commuting flows between each barangay (Fernandez and Santos, 2014).

Data on the point and non-point sources of pollution in Metro Cebu enables the overall pollution levels described by RETRO to be disaggregated spatially. In the next section we will describe how this disaggregation is performed in order to generate more refined measures of exposure. Additionally, the counts of point sources and the area of non-point sources will be interacted with the weather instruments as part of the set of many, invalid instrumental variables. These instruments and their use will be further described in the following section.

3.2. Econometric specification

A standard linear functional form is adopted for the human capital production function, simplifying interpretation and avoiding specification pitfalls, 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_{ibp} denote the human capital outcomes, namely height, cognition and labor market outcomes including labor sector, hours and earnings, of individual i residing in barangay b. The outcome is observed at the end of period p. Equation (1) shows the relationship between the human capital outcomes and early-life environmental factors:

$$Y_{ibp} = \alpha + \sum_{l} \beta_l^W \boldsymbol{W}_{iblt} + \sum_{j} \beta_j^{\sigma} \sigma_{ibjt} + \delta \boldsymbol{X}_{ibt} + \mu_g + \epsilon_{ibp}. \tag{1}$$

Here $\boldsymbol{W}_{iblt}$ denotes the exposure of individual i to extreme weather and b denotes individual i's barangay of residence. Let l denote the type of extreme weather exposure and let t denote the time period of exposure. Let j denote the pollutant type such that $\sigma_{ibjt} = \{\sigma_{i,b,CO,t}, \sigma_{i,b,O_3,t}\}$ describes the exposure of individual i to pollutant j during time t. For early-life outcomes observed at birth, age 1, or age 2, t and p are equal (i.e., for birth outcomes the period of exposure is from the estimated date of conception until birth, and at age 1 the period of exposure is from estimated conception until age 1). For later life outcomes, t and p are not equal. For these outcomes, t describes the early-life time of exposure (prenatal up to age 2), while p describes the period when the outcome is observed (age 10–12 or 21–23). Furthermore, let $\boldsymbol{X}_{ibt}$ denote a rich set of observable control variables. The set of observable control variables includes child gender and season of birth,[6] indicators for household environmental quality (solid fuel use, sanitary conditions and access to piped water), as well as maternal, paternal and household risk factors including per capita income, mother's education, mother's smoking, mother's alcohol consumption, mother's consumption of prenatal vitamins, the number of the mother's previous pregnancies, mother's height, mother's age, father's presence in the

[6]The distribution of births across the year in the sample as well as the regional vital statistics gives no indication of fertility timing. Table A4 in the online appendix compares observable parent and household characteristics across season and quarter of birth, giving little indication of birth timing.

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household, father's education and father's age. For test score outcomes, month of year when the tests were taken is also included in order to control for contemporaneous exposures. Finally, let μ_g capture urban/rural fixed effects within the broader urban/rural geographic category denoted g.

When the coefficients of interest are β_l^W, the estimation of equation (1) should yield unbiased estimates because the unpredictable extremes of temperature and precipitation denoted by $\boldsymbol{W}_{iblt}$ are unlikely to be correlated with the error term ϵ_{ibp}. For β_j^σ, the situation is more complicated. The first problem is that pollution exposures are non-random. In the context of Metro Cebu, households of higher income and socioeconomic status live in areas of greater economic activity and high emissions (see online appendix table A4). This suggests that unobserved determinants of human capital (denoted as $\boldsymbol{V}_{ibt}$) in the error term could be correlated with σ_{ijp} producing positive omitted variable bias. The second problem is that measures of true exposures to (CO, O_3) are unavailable. To address this, we estimate σ_{ibjt} by combining the emissions described in RETRO, the locations of point and non-point sources of pollution in Metro Cebu, and the early-life exposure window of CLHNS birth cohort members. Intuitively, we do this by dividing the total emissions measured by RETRO across Metro Cebu according to the locations of pollution sources, and then relating the timing of the exposures to the early-life exposure windows of the CLHNS birth cohort members. The first step is to divide the 0.5×0.5 degree RETRO grid into 400 0.025×0.025 degree grids.[7] These smaller grids are matched to CLHNS birth cohort members' barangay of residence. Assuming equal emissions for each pollution source within a particular sector, we estimate the emissions of pollutant j during quarter of the year q for the 0.025×0.025 grid m, denoted as $\hat{E}_{mjq}$.[8] Figure A4 in the online appendix displays $\hat{E}_{mjq}$ for CO and O_3 in each 0.025×0.025 grid of Metro Cebu for a selected year. Estimated emissions levels vary spatially according to the locations of sources, and temporally according to aggregate emissions levels described in RETRO. Finally, the estimated exposure of the CLHNS birth cohort member, or $\hat{\sigma}_{ibjt}$, is the average of $\hat{E}_{mjq}$ across the quarters q of the years corresponding to the individual's exposure window t. An underlying assumption in the process of generating $\hat{\sigma}_{ibjt}$ is that within sectors the emissions of each pollutant source are equal. This assumption is unlikely to be true. In other words, $\hat{\sigma}_{ibjt}$ may have measurement error (denoted as u_{ibjt}) that may be systematically correlated with the error term. The bias caused by measurement error is also likely to be positive because of the residential sorting patterns in Metro Cebu.

Denoting ν_{ibp} as the combination of the previous error term, ϵ_{ibp}, with the unobserved determinants, $\boldsymbol{V}_{ibt}$, and the measurement error, u_{ibjt}, equation (1) becomes:

$$Y_{ibp} = \alpha + \sum_l \beta_l^W \boldsymbol{W}_{iblt} + \sum_j \beta_j^\sigma \hat{\sigma_{ibjt}} + \delta \boldsymbol{X}_{ibt} + \mu_g + \nu_{ibp}. \tag{2}$$

[7] These smaller grids are 2.75 km long on each side. The 0.025×0.025 latitude-longitude grids were chosen due to correspondence with average area of Metro Cebu barangay. Robustness checks of differently sized grids have been performed.

[8] The relationship between the total emissions and the density of sector-specific sources in each 0.025×0.025 grid is specified as: $E_{jsk} = g\big(\sum_m N_{mjsq}, \boldsymbol{q}; \alpha_{jsq}\big)$, where E_{jsk} denotes the total emissions in Metro Cebu of pollutant j from sector s in month k; N_{mjsq} denotes the pollutant source density in the small grids during quarter of the year q; and $\boldsymbol{q}$ denotes quarter of the year indicators. The scaling factor α_{jsq} is estimated which is used to scale the density of pollution sources into estimated emissions, or $\hat{E}_{mjq}$. These scaling factors are reported in online appendix table A5.

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Instrumental variables can address the omitted variable and measurement error biases. As discussed, we use weather instruments to estimate the effects of early-life pollution exposure. The obvious problem is that weather, $\boldsymbol{W}_{iblt}$, is included in equation (2) and may directly affect Y_{ibp}. Estimating β_l^W using equation (2) provides our first test of whether weather instruments can be used. For the outcomes where the estimates of β_l^W indicate that weather does not directly affect the outcomes, the empirical specification becomes:

$$\hat{\sigma}_{ibjt} = \gamma_1 \boldsymbol{Z}_{ibt} + \gamma_2 \boldsymbol{X}_{ibt} + \mu_g + \xi_{ibjt}, \tag{3}$$

$$Y_{ibp} = \alpha + \sum_j \beta_j^\sigma \hat{\sigma}_{ibjt} + \delta \boldsymbol{X}_{ibt} + \mu_g + \nu_{ibp}. \tag{4}$$

$\boldsymbol{Z}_{ibt}$ denotes the set of many instrumental variables, including extreme weather, deviations from seasonal averages, and the interactions of each with location-specific concentrations of pollution sources (counts of point pollution sources and area of non-point pollution sources). Equations (3) and (4) are estimated with LIML and MBTSLS. Comparing the LIML and MBTSLS estimates provides the second test of the direct effects of weather. For the human capital outcomes where weather does not demonstrate direct effects either in equation (2) or by comparing the LIML and MBTSLS estimators, we use the weather instruments to estimate β_j^σ.

4. Results

Tables 2–4 show the main results, the effects of the early-life environment on short-term anthropometric, and long-term cognitive and labor market outcomes. In table 2, only the OLS estimates of weather's effects are shown, while tables 3 and 4 show the effects of weather (panel A) and pollution (panel B). Table 2 omits estimates of β_j^σ and shows that weather directly affects short-term anthropometric outcomes. In contrast, estimates of β_l^W in tables 3 and 4 show no direct effects of weather on long-term cognitive and labor market outcomes. Consequently, β_j^σ is estimated. Sargan tests of the differences between the LIML and MBTSLS estimates are given for each of the cognitive outcomes (table 3) and labor market outcomes (table 4). For outcomes where weather does not exhibit any direct effects, our main results are the LIML estimates. In tables 3 and 4 we also show Sargan test p-values that have been adjusted for multiple hypothesis tests (Benjamini and Hochberg, 1995).

The anthropometric outcomes in table 2 are low birth weight, birth length and age 2 height. Birth length and age 2 height are expressed in z-scores which convert the measures to the number of standard deviations or z-scores below or above the age and sex specific international reference mean (WHO, 2014). The cognitive outcomes in table 3 are the standardized scores on non-verbal, math and language tests administered when the respondents were 10–12 years old. The labor market outcomes in table 4 are hours worked per week and log of hourly earnings in 2005 when the respondents were 21–23 years old.

In order to assist in the interpretation of the coefficients, each of the exposure measures have been standardized. Each OLS regression employs robust standard errors, each LIML regression employs Bekker standard errors robust to many instruments and many exogenous regressors, and each MBTSLS regression employs Kolesár *et al.* (2015) standard errors that are robust to the presence of independent direct effects.

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Table 2. Short-term anthropometric outcomes

	Low Birth Weight ($n = 3059$)	Birth Length *Z*-Score ($n = 3059$)	Age 2 Height *Z*-Score ($n = 2663$)
Panel A: Weather			
Temperature (>90% of distribution)	0.024**	−0.017*	−0.020
	(0.012)	(0.010)	(0.020)
Temperature (<10% of distribution)	0.032	−0.022*	−0.023
	(0.028)	(0.013)	(0.015)
Precipitation (>90% of distribution)	0.005	−0.003	−0.009
	(0.004)	(0.004)	(0.010)
Precipitation (<10% of distribution)	0.012*	−0.029***	−0.014**
	(0.007)	(0.008)	(0.006)

Notes: Control variables included in each regression are: CO and O3 exposure, gender, birth season, mother's education, mother smoked during pregnancy, mother drank alcohol during pregnancy, mother's consumption of prenatal vitamins, number of previous pregnancies, mother's height, mother's age, father present, father's education, father's age, per capita household income, household uses solid fuels, non-piped water, and urban residence. OLS standard errors are robust. Significance levels are indicated by *** 1%, ** 5%, *10%.

4.1. Short-term anthropometrics

Table 2 shows the estimated effects of extreme precipitation and temperature on short-term anthropometric measures. Because extreme temperature and precipitation demonstrate significant direct effects on these measures, we do not estimate the effects of CO and O_3 exposure.

The results indicate that extremely high temperature and low precipitation during gestation significantly increase the likelihood of low birth weight. A 1 standard deviation increase in the incidence of temperatures greater than the 90th percentile of the distribution during gestation increases the likelihood of low birth weight by 2.4 per cent, and a 1 standard deviation increase in the incidence of precipitation below the 10th percentile of the distribution during gestation increases the likelihood of low birth weight by 1.2 per cent. Extreme weather also has significant, negative effects on birth length. A 1 standard deviation increase in exposures to extreme high and low temperatures reduces birth length by .017 and .022 z-score standard deviations, respectively. Low precipitation exhibits the largest effect. A 1 standard deviation increase in exposures to low precipitation reduces birth length by .029 z-score standard deviations. While the signs and magnitudes of the estimated effects of high and low temperature remain the same, only low precipitation exerts a significant effect on height at age 2. A 1 standard deviation increase in exposures to low precipitation reduces age 2 height by .014 z-score standard deviations.

4.2. Long-term cognition

In contrast, estimates of extreme precipitation's and temperature's long-term effects on cognition are not statistically significant (table 3). None of the measures of extreme weather during early-life – high or low temperature, high or low precipitation – show significant effects on non-verbal test scores, math test scores, language test scores, or

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Table 3. Long-term cognitive outcomes

	Std. Non-Verbal Test Score ($n = 2180$)	Std. Math Test Score ($n = 2167$)	Std. Language Test Score ($n = 2165$)	Achieved Years of Schooling ($n = 2006$)
Panel A: Weather				
Temperature (>90% of distribution)	−0.004	−0.006	0.002	−0.006
	(0.009)	(0.009)	(0.011)	(0.008)
Temperature (<10% of distribution)	0.002	0.006	0.001	0.002
	(0.003)	(0.009)	(0.010)	(0.004)
Precipitation (>90% of distribution)	0.002	0.007	0.008	0.009
	(0.012)	(0.019)	(0.009)	(0.009)
Precipitation (<10% of distribution)	0.001	−0.003	−0.005	0.002
	(0.033)	(0.034)	(0.036)	(0.036)
Panel B: Pollution				
LIML:				
CO (std.)	−0.027*	−0.038	−0.042**	−0.309
	(0.015)	(0.024)	(0.021)	(0.197)
O3 (std.)	−0.050**	−0.041*	−0.070***	−0.498**
	(0.020)	(0.022)	(0.024)	(0.238)
MBTSLS:				
CO (std.)	−0.027	−0.038	−0.042	−0.307
	(0.027)	(0.028)	(0.031)	(0.261)
O3 (std.)	−0.050**	−0.041*	−0.070***	−0.498*
	(0.025)	(0.025)	(0.025)	(0.266)
Sargan Tests:				
CO: *P*-Value	0.649	0.148	0.356	0.134
CO: Adjusted *P*-Value	0.822	0.822	0.822	0.822
O3: *P*-Value	0.328	0.153	0.275	0.367
O3: Adjusted *P*-Value	0.822	0.822	0.822	0.822

Notes: Panel A regressions include controls for CO and O3 exposure. Additional control variables included in each Panel A and B regression are: gender, birth season, mother's education, mother smoked during pregnancy, mother drank alcohol during pregnancy, mother's consumption of prenatal vitamins, number of previous pregnancies, mother's height, mother's age, father present, father's education, father's age, per capita household income, household uses solid fuels, non-piped water, and urban residence. Test score outcomes also include indicators of the month the test was administered. OLS standard errors are robust. For pollution, first stage regressions employ extreme weather & deviations from seasonal means and interactions with local prevalence of polluters as instruments. LIML standard errors are Bekker and robust to many instruments and many exogenous regressors, and MBTSLS standard errors are robust to the presence of direct effects of the instrument on the outcome. Sargan test *p*-values for each coefficient and outcome are adjusted for multiple hypothesis tests using the Benjamini-Hochberg method. Significance levels are indicated by *** 1%, ** 5%, *10%.

years of schooling. With this first test of weather's direct effects exhibiting null results, we estimate the effects of CO and O_3 exposure using the LIML and MBTSLS estimators.[9]

[9] A representative example of the first stage is displayed in online appendix table A6. The results of the first stage show that the many instruments including extreme weather, deviations from seasonal averages, and

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Table 4. Long-term labor market outcomes

	Weekly Hours Worked			Log of Hourly Earnings		
	Full Sample ($n = 1942$)	Females ($n = 951$)	Informal ($n = 1398$)	Full Sample ($n = 1792$)	Females ($n = 878$)	Informal ($n = 1342$)
Panel A: Weather						
Temperature (>90% of distribution)	0.065	−0.051	−0.024	−0.026	−0.017	−0.006
	(0.063)	(0.126)	(0.105)	(0.033)	(0.014)	(0.004)
Temperature (<10% of distribution)	0.129	0.106	−0.031	0.024	0.030	−0.003
	(0.096)	(0.157)	(0.125)	(0.025)	(0.042)	(0.031)
Precipitation (>90% of distribution)	0.209	0.501	0.341	0.026	0.032	0.014
	(0.214)	(0.416)	(0.295)	(0.023)	(0.030)	(0.027)
Precipitation (<10% of distribution)	−0.082	−0.098	0.137	−0.003	0.002	−0.001
	(0.124)	(0.216)	(0.143)	(0.033)	(0.041)	(0.035)
Panel B: Pollution						
LIML:						
CO (std.)	0.287	−0.144	0.143	−0.042	−0.011	−0.004
	(0.606)	(0.277)	(0.229)	(0.037)	(0.014)	(0.004)
O3 (std.)	−1.335***	−0.825	−1.394**	−0.082**	−0.123**	−0.089**
	(0.506)	(0.544)	(0.552)	(0.041)	(0.049)	(0.041)
MBTSLS:						
CO (std.)	0.286	−0.147	0.147	−0.042	−0.011	−0.004
	(0.606)	(0.279)	(0.275)	(0.053)	(0.017)	(0.004)
O3 (std.)	−1.335***	−0.824	−1.398**	−0.084*	−0.125**	−0.089**
	(0.506)	(0.545)	(0.662)	(0.049)	(0.052)	(0.041)
Sargan Tests:						
CO: *P*-Value	0.783			0.102		
CO: Adjusted *P*-Value	0.822			0.822		
O3: *P*-Value	0.822			0.132		
O3: Adjusted *P*-Value	0.822			0.822		

Notes: Panel A regressions include controls for CO and O3 exposure. Additional control variables included in each Panel A and B regression are: gender, birth season, mother's education, mother smoked during pregnancy, mother drank alcohol during pregnancy, mother's consumption of prenatal vitamins, number of previous pregnancies, mother's height, mother's age, father present, father's education, father's age, per capita household income, household uses solid fuels, non-piped water, and urban residence. OLS standard errors are robust. For pollution, first stage regressions employ extreme weather & deviations from seasonal means and interactions with local prevalence of polluters as instruments. LIML standard errors are Bekker and robust to many instruments and many exogenous regressors, and MBTSLS standard errors are robust to the presence of direct effects of the instrument on the outcome. Sargan test *p*-values for each coefficient and outcome are adjusted for multiple hypothesis tests using the Benjamini-Hochberg method. Significance levels are indicated by *** 1%, ** 5%, *10%.

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First note that, for each outcome, the LIML and MBTSLS estimates in table 3 are nearly identical and not significantly different according to the Sargan tests. This provides the second piece of evidence that weather does not directly affect long-term cognitive outcomes. Focusing on the LIML estimates which are consistent and efficient for many instrumental variables, the evidence suggests that early-life CO exposure significantly reduces non-verbal and language test scores, and early-life O_3 exposure significantly reduces non-verbal, math, and language test scores. A 1 standard deviation increase in early-life CO emissions exposure corresponds to a 0.027 standard deviation decrease in non-verbal test scores, and a 0.042 standard deviation in language test scores. The effect of early-life O_3 exposure is larger: non-verbal test scores are reduced by 0.05 standard deviations, math test scores are reduced by 0.041 standard deviations, and language test scores are reduced by 0.07 standard deviations. The results also indicate that early-life O_3 negatively affects achieved years of schooling: a 1 standard deviation increase in early-life O_3 exposure corresponds to 0.5 fewer years of schooling.

4.3. Long-term labor market

Similar to the cognitive outcomes, the estimated effects of extreme precipitation and temperature on long-term labor market outcomes in table 4 do not indicate any significant direct effects. None of the measures of extreme weather show significant effects on weekly hours worked or the log of hourly earnings in the full sample or among females or informal sector employees. Consequently, we estimate the effects of CO and O_3 exposure using the LIML and MBTSLS estimators.

For both hours worked and earnings, the LIML and MBTSLS estimates in table 4 are nearly identical and not significantly different. This provides the second piece of evidence that weather does not directly affect long-term labor market outcomes. In the full sample, early-life O_3 exposures corresponds to fewer hours worked per week and lower hourly wage, while early-life CO exposures exhibit no significant effects on hours or earnings. Early-life O_3 exposures are shown to decrease the number of hours worked per week by approximately 1.34 and hourly earnings by 8.2 per cent. These effects on hours and earnings are large and likely reflect the compounding effects of O_3 exposure on multiple dimensions of cognition (non-verbal, math and language) and schooling. Interestingly, the effect on hours is concentrated among males, and the earnings effect is driven by females. A 1 standard deviation increase in early-life O_3 exposure does not significantly reduce female hours but is shown to reduce female earnings by 12.3 per cent. Additionally, the informal sector is driving both the hours effect and the earnings effect. In the informal sector, a 1 standard deviation increase in early-life O_3 exposure significantly reduces hours by 1.39 and earnings by 8.9 per cent.

4.4. Long-term effects by exposure time period

In table 5 the estimated effects of CO and O_3 exposure on cognitive and labor market outcomes are broken down by time period: pregnancy and birth to age 2. Overall the results for CO suggest that the effects of CO exposure may be more pronounced during pregnancy. This aligns with CO's likely mechanism, the more ready binding to hemoglobin

the interactions of each with location specific concentrations of pollution sources, are related to emission levels. The partial F-statistics are large and the signs of the base weather coefficients align with previous research (Dell *et al.*, 2012; Hsiang and Jina, 2014).

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than oxygen, and biological evidence that CO impedes the flow of oxygen to the fetus (Meter, 2000). For O_3, overall the results indicate that the effects of O_3 exposure may be more pronounced after birth. This would align with the neurotoxic effects of O_3 exposure as well as evidence that O_3 does not typically pass through the placenta (Salam *et al.*, 2005). However, these conclusions should be interpreted with caution. These patterns do not hold for every long-term outcome, and the time period estimates do not significantly differ from each other.

4.5. Attrition

Selective attrition is an important threat to identification in our analysis. The CLHNS includes respondents that never attrit, respondents that permanently attrit, and respondents that temporarily attrit from at least one wave of the survey. Given the negative long-term effects of early-life pollution exposures, the selective attrition of a high human capital subsample could be driving the results. In order to assess whether selective attrition is driving our main results, we leverage the presence in the data of temporary attritors (or those that attrit for one or more waves but reappear later). Comparing never attritors to temporary and permanent attritors, comparison of baseline observable characteristics shows that temporary and permanent attritors are similar, while both differ from those that never attrit (see online appendix table A4). Leveraging the similarity between temporary and permanent attritors, we can assess whether attrition is driving the results. Specifically, if we observe that the long-term effects are driven by temporary attritors, then we can conclude that selective attrition is likely driving the results. Table 6 shows estimates of an interactive model of early-life CO and O_3 exposure and a temporary attrition indicator. Negative and significant estimates would suggest that the main results in tables 3 and 4 are driven by selective attrition. However, the estimates show that among the temporary attritor subsample the differences are small and not statistically significant.

4.6. Corrections for multiple hypothesis tests

Because we estimate the effects of multiple early-life environmental exposures on multiple short- and long-term outcomes, the p-values should be adjusted to reflect the number of tests. Table 7 summarizes the p-values of all the statistically significant effects (for brevity, not all p-values are shown). Since there is little consensus on which correction procedure is most appropriate, the p-values are adjusted using the Simes (1986) method and the more restrictive Benjamini and Hochberg (1995) method. After adjustment, the following relationships remain significant (by at least one method): low precipitation's effect on birth length, O_3's effect on language test scores, O_3's effect on hours worked, O_3's effect on non-verbal test scores, low precipitation's effect on age 2 height, and O_3's effect on years of schooling.

5. Discussion

In summary, the results demonstrate that the early-life environment may affect multiple dimensions of short- and long-term human capital. However, the various environmental exposures exhibit different effects on different dimensions of human capital. The results show that extreme weather is detrimental to short-term anthropometric measures of human capital, and pollution exposure – particularly O_3 – is shown to negatively affect long-term cognitive and labor market outcomes.

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Table 5. Time period of exposure

		Std. Non-Verbal Test Score	Std. Math Test Score	Std. Language Test Score	Achieved Years of Schooling	Weekly Hours Worked	Log of Hourly Earnings
CO (std.)	Pregnancy	−0.031*	−0.041*	−0.036	0.043	−0.025	−0.046
		(0.017)	(0.022)	(0.026)	(0.222)	(0.509)	(0.040)
	Birth to Age 2	−0.025	−0.035	−0.044**	−0.375	0.219	−0.034
		(0.020)	(0.029)	(0.022)	(0.240)	(0.562)	(0.033)
O3 (std.)	Pregnancy	−0.041	−0.011	−0.068**	−0.401	−1.293*	−0.085*
		(0.026)	(0.018)	(0.035)	(0.272)	(0.692)	(0.049)
	Birth to Age 2	−0.052**	−0.045	−0.071*	−0.501**	−1.403***	−0.078
		(0.026)	(0.028)	(0.040)	(0.254)	(0.611)	(0.052)
Estimator:		LIML	LIML	LIML	LIML	LIML	LIML

Notes: Control variables included in each regression are: gender, birth season, mother's education, mother smoked during pregnancy, mother drank alcohol during pregnancy, mother's consumption of prenatal vitamins, number of previous pregnancies, mother's height, mother's age, father present, father's education, father's age, per capita household income, household uses solid fuels, non-piped water, and urban residence. LIML standard errors are Bekker and robust to many instruments and many exogenous regressors. Temporary attritors make up 17% of the full sample. Significance levels are indicated by *** 1%, ** 5%, *10%.

Table 6. Is attrition selective?

	Std. Non-Verbal Test Score	Std. Math Test Score	Std. Language Test Score	Achieved Years of Schooling	Weekly Hours Worked	Log of Hourly Earnings
Temporary Attrition	−0.011	0.601	0.214	−0.321	−0.103	−0.987
	(0.402)	(0.980)	(0.675)	(0.223)	(1.263)	(0.765)
CO (std.)*Temporary Attrition	−0.003	−0.001	−0.010	0.023	0.154	−0.003
	(0.022)	(0.003)	(0.016)	(0.053)	(0.452)	(0.031)
O3 (std.)* Temporary Attrition	−0.002	0.004	0.002	−0.004	−0.513	−0.051
	(0.005)	(0.005)	(0.004)	(0.025)	(0.459)	(0.061)
Estimator:	LIML	LIML	LIML	LIML	LIML	LIML
Temporary Attritor Observations:	490	484	482	327	339	302

Notes: Control variables included in each regression are: gender, birth season, mother's education, mother smoked during pregnancy, mother drank alcohol during pregnancy, mother's consumption of prenatal vitamins, number of previous pregnancies, mother's height, mother's age, father present, father's education, father's age, per capita household income, household uses solid fuels, non-piped water, and urban residence. LIML standard errors are Bekker and robust to many instruments and many exogenous regressors. Temporary attritors make up 17% of the full sample. Significance levels are indicated by *10%.

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Table 7. Multiple hypothesis test adjustments

		P-Value	Benjamini-Hochberg Adjusted *P*-Values	Simes Adjusted *P*-Values
Short-Term Anthropometric Outcomes:				
Low Birth Weight	Temp (high)	0.046**	0.495	0.165
	Precip. (low)	0.087*	0.717	0.330
Birth Length	Temp (high)	0.089*	0.753	0.373
	Temp (low)	0.091*	0.792	0.413
	Precip. (low)	0.000***	0.045**	0.008***
Age 2 Height Z-Score	Precip. (low)	0.020**	0.285	0.051*
Long-Term Cognitive Outcomes:				
Std. Non-Verbal Test Score	CO (std)	0.070*	0.659	0.202
	O3 (std)	0.012**	0.260	0.043**
Std. Math Test Score	O3 (std)	0.061*	0.594	0.202
Std. Language Test Score	CO (std)	0.045**	0.489	0.156
	O3 (std)	0.003***	0.082*	0.019**
Achieved Years of Schooling	O3 (std)	0.037**	0.315	0.085*
Long-Term Labor Market Outcomes:				
Weekly Hours Worked	O3 (std)	0.008***	0.193	0.035**
Log of Hourly Earnings	O3 (std)	0.046**	0.495	0.165

Note: Only the *p*-values of statistically significant estimates are included here, though all estimates were included in the multiple hypothesis test adjustments. *P*-values for the short-term anthropometric outcomes are from OLS estimates. *P*-values for long-term cognitive and long-term labor market outcomes are from the LIML estimates. Significance levels are indicated by *** 1%, ** 5%, *10%.

First, the results show that high temperatures and low precipitation increase the incidence of low birth weight. Existing evidence suggests that both high and low temperature extremes increase the incidence of low birth weight (Deschênes *et al.*, 2009). While temperatures above the thresholds previously identified in the literature are relatively common in Cebu, the insignificance of low temperatures is likely because temperatures below the previously identified thresholds are uncommon in Cebu. Birth length is negatively affected by both high and low temperatures, and low precipitation. And the effects of low precipitation extend to age 2 height. Our results align with evidence that early-life exposures to longer dry seasons reduce height (Sohn, 2015). On the other hand, we do not observe any significant effects of high precipitation on any short-term anthropometric outcomes.[10] Additionally, the lack of direct effects of weather on long-term cognitive and labor market outcomes align with recent research on the relationship

[10]Relevant to this result is that the Philippines is vulnerable to typhoons and two typhoons hit Metro Cebu and the surrounding areas during the first two years of life of the CLHNS birth cohort members: typhoon Nitang on 2 September 1984 and typhoon Undang on 4 November 1984. Typhoons are characterized by high precipitation and high windspeeds, both of which do not show any effects in our results. However, this result is likely because the entire Metro Cebu area was affected and we have no temporal or spatial variation in exposures to identify the typhoon's effects.

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between temperature and human capital. Graff Zivin *et al.* (2018) show that short-term exposures to high temperatures negatively affect cognitive performance, but the effect diminishes in the long-term.

The results show that early-life exposures to both CO and O_3 are likely detrimental to test scores, and that these effects carry through to schooling attainment and labor market hours worked and earnings. The estimated effects of CO exposure on non-verbal and language test scores are similar to the trimester specific impact of CO exposure in Chile from Bharadwaj *et al.* (2017). Relatively speaking, the results suggest that CO's effects are smaller than the effects of O_3. And because O_3 is also shown to negatively affect math test scores, the results suggest that O_3 may negatively affect a wider range of cognitive abilities than CO. O_3's larger magnitude and breadth of cognitive impact aligns with documented biological mechanisms (Block and Calderon-Garciduenas, 2009). Ultimately, the evidence indicates that early-life O_3 exposure reduces schooling attainment, hours worked and earnings. While our results confirm previous estimates of pollution's long-term effect on hours (Kim *et al.*, 2017), the effect we estimate is larger. We also show that O_3's effects on hours are driven by males and the informal sector, and the effects on earnings are driven by females and the informal sector.

Up to this point, evidence of the long-term human capital and labor market outcomes of early-life pollution exposure comes from developed economies. For example, Isen *et al.* (2017) show that the Clean Air Act of 1970 increased long-term earnings for those less exposed in utero. However, the estimated effects in developed economies are not directly applicable to developing nations given the different levels of exposure, different institutions and different labor markets. Consequently, the cost-benefit analysis of environmental regulations are different. We provide the first evidence of the effects on long-term earnings of early-life pollution exposure.

While environmental regulations have demonstrated large monetary benefits in developed economies like the United States (Graff Zivin and Neidell, 2013), the argument that environmental regulations are heavy taxes on developing economies is popular (Dasgupta *et al.*, 2002). As a hypothetical exercise to describe the potential benefits of environmental regulations, consider a mandated 25 per cent reduction to emissions, which is a conservative estimate of the effects of the Philippine 1999 Clean Air Act which cost \$50 million annually (EMB, 2010). In order to perform this hypothetical exercise we generalize outside the sample and assume external validity,[11] in order to scale O_3's effects on hours and earnings. Under these assumptions, the long-term effect of a 25 per cent reduction in early-life exposure to O_3 precursor emissions is an increase in earnings by 2.8 per cent and an increase in hours worked by 0.45 per week. With a mean present value of lifetime earnings at age zero in Metropolitan Cebu of approximately \$39,927 and using

[11] Estimation of average treatment effects (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 in this context. As previously 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, the exposures were typical to other time periods in the area and therefore unlikely to illicit idiosyncratic responses. Furthermore, at the time 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. If these facts are assumed to hold and the estimates are assumed ATEs with external validity, the estimates can be extended to the province and national level.

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standard assumptions,[12] the discounted present value of reducing O_3 exposures by 25 per cent is \$1,367 per person. Scaling by the size of the provincial birth cohort and the national birth cohort, the 25 per cent reduction in O_3 precursor emissions translates to an annual provincial impact of approximately \$44.5 million (2005 USD) and an annual national impact of \$2.05 billion (2005 USD). \$2.05 billion is roughly 2 per cent of the \$90 billion Philippine GDP in 2005 (The World Bank, 2014). Comparing the \$2.05 billion in benefits to the \$50 million annual cost of the Philippine Clean Air Act of 1999 suggests that the long-term benefits of environmental regulations may outweigh the costs and may fuel economic growth in developing nations (Nelson and Phelps, 1966; Graff Zivin and Neidell, 2013).

6. Conclusion

By utilizing unique data and novel methods, we examine the short- and long-term effects of weather and pollution on multiple measures of human capital. The results add to the growing evidence of the wide ranging effects of the early-life environment. These long-term effects also translate to the labor market. The results imply that environmental policy should also consider the often ignored costs to long-term human capital. The long-term human capital gains from improvements to the early-life environment could provide fuel for economic growth and development.

While this study provides evidence of the short- and long-term human capital effects of the early-life environment, its limitations point to potential future research. While the data is unique in the developing country context, future studies should employ more detailed and accurate measures of weather and pollution exposures. Additionally, we assume a limited scope for pollution avoidance behaviors in this context due to the lack of monitoring and alerts, and limited, if any, difference between indoor and outdoor exposures. However, the limited scope for avoidance behaviors is an assumption that should be explored further. Furthermore, follow-up longitudinal data could uncover additional labor market effects over time as well as potential intergenerational effects. Future research should also address general equilibrium costs and benefits of efforts to improve environmental quality – both in terms of pollution as well as for climate change. Additionally, future research should aim to identify the interactive and cumulative effects of various early-life environmental exposures.

Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/S1355770X20000224

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[12]Similar to Isen *et al.* (2017), we calculate the discounted present value of the long-term effects using the mean present value of lifetime earnings at age zero, and: (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) earnings are discounted at 3 per cent real rate (5 per cent discount rate with 2 per cent wage growth) back to age zero. These assumptions are conservative because annual earnings at ages 21–23 are likely underestimates of earnings throughout life.

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