Power Plants and Child Mortality in Nigeria

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Abstract: Quantitative evidence of negative externalities associated with power plant operations and their impact on infant and child mortality is rare in many developing countries. We fill this gap by assessing the consequences of power plant operations on infant and child mortality using four rounds of the Nigeria Demographic and Health Surveys (NDHS) and comprehensive information on power plant operations. We find that infants born within a 5-25 km radius of active power plants experience approximately 0.027 more deaths during their first month than those born before power plants became operational or near non-operational power plants. Pollutants generated by non-renewables are likely the cause as the mortality rates are more significant by 0.010 for those near power plants fueled by non-renewable energy sources. In contrast, the impact of renewable energy-fueled power plants is insignificant. These results further justify electricity generation by renewable energy sources in addressing Nigeria and other developing countries' pressing energy deficits with health and carbon-related benefits.

Keywords: Power Plants, Infant and Child Mortality, Renewable and Non-Renewable Energy

JEL Classifications: Q01, Q4, Q5

Introduction

Consistent and inexpensive electricity generation is vital in promoting people's wealth and well-being as everyone requires electricity in all facets of life (food processing, health care, agriculture, heating and cooling, communication, transportation, etc.). However, electricity generation and use have resulted in ambient air pollution, a global and local concern because it threatens the environment and human health. Combustion of fossil fuels such as coal, oil, and gas employed in energy production can release various pollutants into the air, including particulate matter, sulfur dioxide, nitrogen oxides, and mercury (Oberschelp et al., 2019). Exposure to these pollutants is linked to many adverse health outcomes, including respiratory and cardiovascular diseases, cancer, and adverse reproductive and developmental outcomes, including infant mortality (Currie et al., 2009; Gutierrez, 2015; Lewtas, 2007; Zhang & Mu, 2018). These adverse health outcomes of electricity generation by power plants on infant health can be especially pronounced in developing countries with fewer institutional capacities for pollution control and a lack of health care resources.

The approaches to mitigate pollution differ based on the country's resources, priorities, technological capabilities, policy frameworks, environmental awareness, and stage of development. Many developed countries are adopting policies to transition to cleaner energy sources, such as renewable energy, to reduce emissions from existing power plants through pollution controls and other measures. For example, the United States Environmental Protection Agency (US EPA) confirmed that over the last twenty years, the power sector in the U.S. has significantly reduced emissions (US EPA, 2021). Developed nations often provide financial incentives and subsidies to promote renewable energy deployment (DeShazo et al., 2017). This encourages the growth of clean energy sources and reduces the overall environmental impact of their energy systems. Additionally, efforts are being made to improve access to prenatal care and other health services for vulnerable populations around coal-fired power plants with mortality risk. However, developing nations may have fewer resources and technical capabilities to implement stringent pollution control measures.

In this paper, we explore the relationship between childhood mortality outcomes, including neonatal, post-neonatal, infant, and under-five mortality rates, and exposure to power plant operations between 2003 and 2018. We use Nigeria, Africa's largest and most populous economy, as a case study. Air pollution may impact children more than adults due to various factors such as their developmental stage, time spent outdoors, and their activities that increase their breathing rates (Bateson & Schwartz, 2007). These factors make children more susceptible to the adverse effects of air pollution. As such, the relationship between power plants and health, particularly infants, has been a research topic and concern for many years. In order to explore this relationship, we combine the most comprehensive spatially explicit power plant data from African Energy (Live Data) and micro-level information on infant mortality and other demographic/socioeconomic variables from the last four rounds of Nigeria Demographic and Health Surveys (NDHS). By spatially linking power plants to households' clusters and focusing on children within 5 - 25 km of power plants, we compare infants born after power plants commenced operations with those born before the operations using ordinary least square regressions and fixed effects at various levels. We investigate heterogeneous impacts and potential causal mechanisms and conduct sensitivity analysis to check the consistency of our results.

We find significant adverse outcomes of increased neonatal mortality rate associated with children residing within 5-25 km of an operational power plant. Infants born within 5 km of active power plants have about 0.027 more deaths in their first month than infants born before power plants became operational or those around non-operational power plants. Evidence shows that power plants with non-renewable fuel sources significantly increase infant/child mortality rates more than those with renewable fuel sources. The effects increase to 0.037 when we focus on power plants fueled by non-renewable energy, while we observe no significant impact from power plants fueled by renewable energy sources. Despite some regions exhibiting higher neonatal mortality rates, our analysis revealed no significant heterogeneity of impact by socioeconomic and demographic factors driving higher mortality rates. The initial findings regarding the mechanism being a higher level of PM 2.5 show some evidence of an increase in PM 2.5 during the 11th-16th year of power plants' operation. Our sensitivity analysis using different distance thresholds defining the households affected by power plants shows consistent results.

This paper makes two main contributions to existing literature. First, we provide evidence of the relationship between power plant development and infant mortality rates in Nigeria, a country located in Sub-Saharan Africa (SSA), with one of the highest child mortality rates globally, where quantitative evidence is rare. This is the first study to investigate the relationship between power plant operations and infant health in Nigeria. One of the United Nations' Sustainable Development Goals (SDGs) is to substantially reduce under-five mortality to at least 25 per 1,000 live births (0.025) by 2030. The quantitative estimates of the negative externality in increasing infant/child mortality rates could be informative in considering options for policy interventions for sustainable development in Nigeria and other SSA countries. Second, our results can help achieve the third SDG, which aims at healthy living and well-being for all by 2030, as many of these nations face energy poverty challenges. Many SSA and other developing countries require considerable investments in power infrastructures to achieve reliable power supply. However, when the share of power plants fueled by non-renewable energy sources is high, negative externality, such as increased mortality rates, could be a significant concern. In Nigeria, policies support coal-fired power projects even though such power plants have health-related damages (Cameron, 2020). Our study adds to evidence that power plants fueled by fossil fuel/non-renewable energy sources can adversely affect the health of life exposed to it, including human beings, animals, and crops for agricultural production (Jha & Muller, 2018; Yang & Chou, 2018).

The remainder of the paper is structured as follows. We first present a brief overview of the literature on power plants' impacts on livelihood, including their positive and negative externalities. We later briefly discuss infant mortality, and after that, we present the data and the empirical strategies, followed by the results and investigation of possible mechanisms. We conclude with a summary and discussion of the results.

Impacts of Power Plant Operations

The empirical literature on the impacts of power plants on local livelihoods has provided mixed outcomes at its best, as there has yet to be a consensus as to whether it yields net positive effects on the affected households or communities.

Several studies have explored the impacts of power plants on air pollution, a negative externality, causing increased mortality rates and other health issues, including mental health and respiratory disease in the U.S. (Levy et al., 2009; Martenies et al., 2019; Yang & Chou, 2018). Martenies et al. (2019) reported that the closure of two coal-fired power plants in Colorado prevented two premature fatalities. This is especially beneficial for areas with lower levels of education and weaker economic indicators. The costs associated with health damage varied between different coal-fired facilities in the United States. For instance, the costs per ton of PM2.5 ranged from $30,000 to $500,000, while those for SO_2 ranged from $6,000 to $50,000 per ton. Costs per ton of NO_x ranged from $500 to $15,000, and $0.02 to $1.57 per kilowatt-hour of electricity generated (Levy et al., 2009). Furthermore, Yang and Chou (2018) estimated that coal-fired power plants in New Jersey caused a 15% increase in low birth weight and a 28% increase in preterm birth.

Other studies have found that exposure to air pollution from power plants during pregnancy can increase the risk of preterm birth, low birth weight, and infant mortality. In a study conducted in Pennsylvania and New Jersey from the 1990s to 2000s, Yang et al. (2017) provided causal estimates of the impact of prenatal exposure to Pennsylvania coal-fired power plant emissions. They concluded that singleton births from New Jersey mothers as far as 32 to 48 km downwind of the power plant had more significant risks of low and very low birth weights. They argued that air pollutants (SO_2) from the transboundary power plant emissions have led to air quality standards violations. The US EPA's independent investigation confirmed this power plant as the sole pollution source. Another study investigating the impacts of fossil fuel power plants on local housing values and rents in the U.S. found statistically significant decreases in housing values (3-7%), mean household income, educational attainment, and the proportion of owner-occupied households (2-5%) within 3.2 km of the power plants (Davis, 2011). An exception is Mauritzen (2020), who found a significant positive effect of wind power investment on local wages (2%) in U.S. rural counties.

Similar to the studies in the U.S., many studies outside the U.S. investigate the impacts of power plants using fossil fuels, especially coal-fired power plants, on children's health (Amster

& Lew Levy, 2019). In Croatia, a positive correlation was found between methemoglobin levels (a biomarker of oxidative stress among pregnant women) and SO_2 concentrations when the studied power plant was operational. A follow-up study revealed lower frequencies of stillbirth and miscarriage at 60% for pregnant women in the "control" period when the power plant was not operational (Mohorovic, 2003). Only a few studies have quantified power plants' impacts in developing countries despite significantly impacting local livelihoods and the environment (Gutierrez, 2015). Air quality and infant mortality have been exploited in Mexico. Using the sharp changes in pollution resulting from small-scale power plants, Gutierrez (2015) estimated the elasticity of changes in infant mortality due to respiratory diseases. The estimates range from 0.58 to 0.84, suggesting that small-scale power plant installation led to increased infant mortality. Similarly, a quantitative study examining the socioeconomic impacts of multiple hydropower development on local livelihoods over extended periods in Brazil found short-term economic growth (39%). At the same time, socio-indicators are not statistically different from the control communities (de Faria et al., 2017). In India, polyaromatic hydrocarbon concentrations (PAHs) in residential soils around major coal-fired power plants were assessed to determine children's incremental lifetime cancer risk, assuming that PAHs result from coal combustion (Kumar et al., 2014).

Studies examining air pollution or power plant effects on health are scant in SSA (Bruederle & Hodler, 2019). Previous studies in the African context have primarily been qualitative in nature, providing valuable insights into the impacts of power plant development on various aspects. For instance, a qualitative study conducted in Kenya highlighted the positive effects of developing a large-scale renewable geothermal power plant on living standards. However, this study also uncovered a direct conflict between geothermal development and wildlife conservation, emphasizing the complexities involved (Mariita, 2002). Terrapon-Pfaff et al. (2019) focused on the social impacts of large-scale solar thermal power plants in Morocco. Their findings indicated that while solar power plants could contribute to meeting energy demands, they were less likely to promote sustainable development, particularly for local communities residing close to these facilities.

Although several studies have explored the effects of power plants on local livelihoods in both developed and developing countries, such investigations remain limited in SSA, particularly in quantitative research. This scarcity can be attributed to the absence of reliable and accurate datasets on power plant operations and pollution (Avila et al., 2017; Wichmann, 2016). Marais et al. (2019) quantitatively assessed the health impacts of electricity generation from fossil fuels and transport in Africa and calculated emissions from power plants based on factors such as generating capacity, thermal efficiency, and stack gas volume, as emission data was not readily available. Avoidable deaths from the attendant air pollution are estimated at 48000 in Africa, with 10400 in South Africa, 7500 in Nigeria, and 2400 in Malawi. Mortality rates from power plants are three times higher than from transport (Marais et al., 2019).

Infant and Child Mortality in Nigeria

Infant and child mortality are crucial indicators of development outcomes and reflect the health and well-being of families (Bruederle & Hodler, 2019; Fagbamigbe et al., 2021; Kotsadam et al., 2018). While global studies have shown a decline in infant and child mortality rates, the decreasing rates remain low in SSA and Southeast Asia (Fotso et al., 2007). In 2019, India and Nigeria accounted for a significant proportion of global child mortality (IGME UN, 2020). Nigeria faces one of the highest child mortality rates globally. Therefore, energy production from non-renewable sources must not exacerbate Nigeria's current child mortality rate.

Nigeria's infant and under-five mortality rates stand at 71 and 111 per 1,000 live births, respectively, surpassing the average rates for the African continent as of 2021 (IGME UN, 2023; World Bank Group, 2023). Moreover, considerable geographical disparities exist depending on the region where households reside (Kotsadam et al., 2018). This raises the question of whether power plants could contribute to the child mortality rate in Nigeria. While two related studies on infant mortality have been conducted in Nigeria, these studies focused on the effects of oil spills and official development aid (ODA) on infant mortality (Bruederle & Hodler, 2019; Kotsadam et al., 2018). The study on oil spill effects identified a causal relationship by comparing children born to the same mother before and after a nearby oil spill, revealing an increase in neonatal mortality of 38.3 deaths per 1,000 live births (Bruederle & Hodler, 2019). Conversely, ODA reduced infant mortality, particularly among disadvantaged groups such as children living in rural, Muslim-dominated areas and born to Muslim women (Kotsadam et al., 2018).

In Nigeria, the government has initiated plans to bridge the gap between electricity demand and supply, aiming to provide energy access to 90% of the population by 2030, with a renewable energy target accounting for over 10% of the generation mix (Ugwoke et al., 2020). However, the low ratio of renewable energy in the mix implies a heavy reliance on non-renewable sources to meet energy needs. The demand for electricity in Nigeria far surpasses the current supply due to inadequate operational power infrastructure (Avila et al., 2017). Consequently, a significant portion of the population has limited access to electricity, hindering their access to modern energy. Many communities remain off-grid, meaning they are not connected to the national grid, while those connected to the grid often face electricity shortages.

A sustainable nation must ensure a reliable and sufficient energy supply, particularly in the form of electricity. However, addressing the adverse health and environmental concerns associated with energy production is important.

Data

To quantify the impacts of power plants in Nigeria, we purchased commercial data from Live Data, provided by African Energy. Data collection and analysis are central to African Energy's work, and Live Data provides detailed information on more than 6,700 power generation plants across 54 African countries. Available information includes plant name, installed capacity, fuel, geocoordinates, location, connection type, operating status, ownership type, and, where available, the start of construction, commercial operations, and retirement dates. According to Alova et al. (2021), Live Data is a trustworthy and comprehensive source of information on Africa's power-generation assets, enabling predictions about the continent's electricity mix. It contains information on most African power plants, including operating, retired, and planned power plants. The authors have pointed out that some small off-grid projects might have been excluded, specifically the unsuccessful ones. In the empirical design section, children born after the power plant became operational and lived nearby are considered the treatment group. Thus, small off-grid projects' exclusion should not bias the outcome results. Live Data's power projects are geocoded with point coordinates, enabling us to link them with the demographic data from NDHS. Over half of the projects have exact geocoordinates. To accurately evaluate the impact of active power plants on infant mortality, we retain operational power plants with commercial operation dates and all non-operational power plants in our data sample. This approach allows us to analyze the effects on children born before and after the power plants start operation.

We establish a robust linkage between the power plants and the children data obtained from the Nigeria Demographic Health Surveys (NDHS) using the geocoordinates available in both datasets. Our study focuses on children born before and after the initiation of power plant operations, allowing us to examine the potential impact of these plants on child-related outcomes. To gather demographic information and valuable insights into child-related variables and outcomes, we utilize the most recent four rounds of NDHS conducted in 2003, 2008, 2013, and 2018. These surveys provide comprehensive national representation, covering women respondents aged 15-49 from urban and rural areas across all regions and states of Nigeria. These interviews cover various mothers' social demographic factors, including ethnicity, religion, age, education, household assets, and characteristics related to their children's births. Additionally, questions about sexual and reproductive health are included in the survey. We also collect PM 2.5 data from the reputable Atmospheric Composition Analysis Group (Van Donkelaar et al., 2019) for all available points across Nigeria from 1998 to 2020. We provide variables' information in Appendix A1, including descriptive statistics for three distance thresholds.

Empirical Strategy

Outcome indicators

The unit of the analysis for all empirical strategies is the children born by the women interviewed in NDHS; therefore, we analyze the children's data, including the various mother and child characteristics. We focus on children's survival rates within the first five years of life, using five mortality rates: neonatal, post-neonatal, infant, ages one-to-four, and under-five. Infant mortality is a crucial indicator of development and overall population health, as it measures the death of a child within the first year of life. Other common indicators are neonatal and under-five mortality, and we include two others to determine the prevailing mortality rates using the five different outcomes.

The neonatal mortality rate equals 1 if an infant *i* died within its first month of life, and the post-neonatal mortality rate equals 1 if an infant *i* survived the first month but died within its first year. At the same time, infant mortality rate combines the neonatal and post-neonatal rates. It is equal to 1 if an infant *i* died within the first year of life and zero otherwise. In addition, one-to-four if the infant *i* dies after one year and before five years, while the under-five mortality rate equals one if the infant *i* dies before the fifth-year birthday. Our study focuses explicitly on the neonatal period to examine its potential impact on infant and under-five mortality rates. By analyzing the mortality rates for infants aged one to four, we aim to understand whether neonatal mortality significantly drives the overall under-five mortality rates. This approach allows us to shed light on the contribution of early-life factors to the broader pattern of child mortality. Table A1 in the appendix presents summary statistics for the different sample sizes according to the children's proximity to power plants. Infant and neonatal mortality rates are 0.060 and 0.039, about 60 and 39 deaths in 1,000 live births for the sample of children with 5 km of power plants which are similar to the 60.27 and 37.08 deaths, respectively, as reported by Bruederle & Hodler (2019) in their sample representing children conceived within 10 km of an oil spill. The sample of children within 10km of power plants in our data is 0.068 and 0.043 for the same indicators.

Definition of children affected by power plants

We categorize power plants into two groups: operational and non-operational. Operational power plants are currently generating energy, while non-operational ones include those that have never been active or are still in the planning or construction phase. We exclude any power plants that were previously active to avoid introducing bias. We compare mortality rates of children living near operational and non-operational power plants to address potential bias from site selection. We assume that the biophysical and socioeconomic characteristics around these plants are similar, making them suitable for power plant establishment. We consider children born after the active power plant's commencement as the treatment group, while children born around non-operational power plants or those born before power plants start operations are the control group. We set the distance threshold that defines whether a household belongs to the treatment group as 5 km. The treatment variable, *operational*, is equal to one if infant *i* was conceived after power plants became operational within 5 km of the mother's reported cluster location and zero if infant *i* was conceived and born near non-operational power plants or before power plants within 5 km started operations. Our initial analysis involves examining all power plants and comparing the mortality rates among children within a 5 km radius of operational and non-operational power plants. However, we conduct the sensitivity analysis to check how the results change using different thresholds, as specified in the robustness check section. This comparative approach allows us to examine the potential impact of power plant operations on child mortality outcomes, considering the proximity of their residential locations to these facilities.

Empirical model

We utilize Ordinary Least Squares (OLS) regression models with and without birth year fixed effects to estimate the difference in mortality rates and examine the relationship between power plants and mortality. This approach allows us to account for possible time-invariant factors influencing mortality outcomes. Our preferred specification is OLS, or Linear Probability Model (LPM), over the logistic regression, which we also use as a robustness check. The estimates from OLS can be readily interpretable and are more comparable to the existing literature on infant mortality, where rates are expressed as the number of deaths per thousand. The mortality rates are easily interpretable as the change in the probability of an infant or child dying if the cluster is located near operational power plants. For models where we employ sub-samples, LPM provides more precise estimates. The LPM is commonly used over logit or probit models in the literature for reasons ranging from a more straightforward interpretation of estimated marginal effects than logit or probit and OLS having similar outcomes (e.g., Betts & Fairlie, 2001; Currie & Gruber, 1996; Klaassen & Magnus, 2001; McGarry, 2000).

Our analysis incorporates a comprehensive set of covariates to control for potential confounding variables. The selection of covariates follows prior literature, drawing on studies conducted by Bruederle and Hodler (2019) and Kotsadam et al. (2018). These covariates capture various birth characteristics, including the mother's age at infant birth, birth spacing, whether the birth was a single birth, the infant's sex, wealth status, education level of the mother, birth year, birth order, and whether the birth took place in a hospital. Additionally, we include location qualities such as urban residence to account for potential spatial variations. We estimate the following equation.

$$Y_{ivt} = \alpha + \beta_1 . operational_t \ + \lambda X_{it} + \delta_t + \varepsilon_{ivt}, \quad (1)$$

where Y_{ivp} is the outcome variable of interest (infant, neonatal, post-neonatal, one-four, or under-five mortality rates) of infant i in DHS cluster v at time period t. $operational_t$ is a dummy of whether the infant i lives within the chosen distance of an operating power plant at time period t. Other variables (X_{it} Regressors) are birth order, sex, birth year, birth spacing, rich, education, hospital, mother's age at the infant's birth, urban, and single birth as defined in the appendix Table A1. δ_t refers to survey year fixed effects that capture unobservable survey year fixed factors. We cluster the standard errors at the power plants group level to control for the power plants heterogeneity and heteroscedasticity (Stock & Watson, 2008). We run equation (1) using household observations around all types of power plants, capturing both renewable and non-renewable power plants.

Next, we run the same equation (1) but additionally control for the birth year fixed effects and region-specific characteristics. The birth year fixed effects capture unobserved birth-year-specific features that can vary with the different birth years of children and allow us to compare power plants' effects on children while still including the use of rich covariates. An example of such a feature is health infrastructure or health care access, which can vary or improve with the years due to technological advancement and increased health care providers/population ratios. Nigeria has six geopolitical zones, and administrative decisions and cultures can vary among these regions. We control for the unobserved region-specific characteristics by adding region-fixed effects to equation (1). As an alternative specification, we employ logistic regression in contrast to the OLS in the main regression. Logistic regression estimates how changes in the independent variables affect the probability or likelihood of observing the mortality outcomes. The dependent variables take two values, i.e., survived (=0) or died (=1). We present results in the odds ratio of the binary mortality outcomes.

Mechanism Analysis and Robustness Check

To delve deeper into the potential health impacts of power plants, we conduct additional estimations by focusing on subsamples of children residing near non-renewable energy-fueled power plants. Our rationale for this analysis stems from the hypothesis that the health effects associated with power plants would be more significant for households situated around non-renewable energy-fueled facilities. This is primarily attributed to the higher levels of pollutants emitted by such power plants, which have been found to exhibit stronger associations with mortality rates. Furthermore, we extend our investigation by examining the effects of power plants on changes in pollutant levels, specifically focusing on PM 2.5. By incorporating this aspect into our analysis, we aim to shed light on the potential mechanisms through which power plants may impact health outcomes. Fine particulate matter such as PM 2.5 has been identified as a particularly concerning pollutant due to its ability to penetrate deep into the respiratory system, posing significant health risks. Through these estimations, we seek to provide a more nuanced understanding of the relationship between power plants and health outcomes. By investigating changes in PM 2.5 levels using event study specification, we aim to elucidate the potential health risks associated with these power plants and their emissions of pollutants.

We estimate the following equation:

$$Y_{it} = \alpha + \gamma_v + \delta_t + + \sum_{y=-20}^{-2} \theta_y D_i(t - T^* = y) + \sum_{y=0}^{20} \rho_y D_i(t - T^* = y) + \varepsilon_{it}\,, \qquad (2)$$

where the outcome Y_{it} is the PM 2.5 a point i in a year $t.$ γ_v and δ_t are time dummies and region time trends controlling for policies or events specific to each region and period, respectively. D_i is a dummy variable equal to 1 if a point's closest power plant is operational and zero otherwise. T^* refers to a power plant operation's commencement period and $t - T^* = y$ are the leads and lags' periods, indicating the number of periods before and after power plants became operational. We use $y = -1$ as the baseline period, which refers to a period before power plants became operational. ε_{it} is the error term. We cluster standard errors at the power plant level, assuming that the outcome variables are likely to be correlated at the power plant level. The coefficient of interest is ρ_y, which measures the effects of power plants on the PM 2.5 of treatment points compared to the PM 2.5 of control points relative to the baseline period.

We perform robustness checks to test the model's sensitivity to a different specification and assess the reliability and validity of the primary results. We examine the sensitivity of our results by expanding the distance threshold from power plants, which defines whether a household is affected by power plant operations. We extend the distance from 5 km up to 25 km away from the power plants. By doing so, we aim to explore the potential variation in outcomes for children residing in different proximity to non-renewable energy-fueled power plants, specifically focusing on neonatal mortality rates. By implementing this robustness check, we can assess the consistency of our primary findings. It allows us to analyze whether the observed associations between power plants and neonatal mortality rates hold across varying distances, providing valuable insights into the spatial effects of power plant operations on health outcomes. This approach strengthens the validity of our research by considering a range of distances and evaluating the impacts of non-renewable energy-fueled power plants on neonatal mortality rates in a more comprehensive manner. Through these robustness checks, we aim to enhance the reliability and robustness of our analysis, further contributing to the understanding of the relationship between power plants and health outcomes in the context of Nigeria.

Results

Overall Mortality Rates and by Power Plants Fuel Source

In Table 1, we present the outcomes of the impacts of all types of power plants on children's health with and without birth year and regional fixed effects. The results from panel A show that children residing within 5 km of active power plants exhibit higher neonatal mortality rates ($p<0.05$). The average increase in neonatal mortality rate is estimated to be 0.024, associated with proximity to operational power plants. However, the mortality rates for the post-neonatal, infant, one-to-four, and under-five age groups do not show significant differences between children around operational and non-operational power plants. To further examine the impact of power plants while accounting for birth year effects, we include birth year fixed effects in Panel B. The findings in this panel remain consistent with those in Panel A, where the neonatal mortality rate remains significant but with a slightly reduced magnitude, estimated at 0.022. As in the previous panel, the outcomes for post-neonatal, infant, one-to-four, and under-five mortality rates do not exhibit significant differences between children residing near operational and non-operational power plants.

In Panel C of Table 1, we extend the analysis by incorporating additional control variables, including birth year fixed effects and regional fixed effects for the six geopolitical zones. The results obtained in this panel align with the previous findings, with only the neonatal mortality rate demonstrating statistical significance. Specifically, the estimated neonatal mortality rate is 0.027 near power plants. We consistently find no significant differences in other health outcomes: including post-neonatal, infant, one-to-four, and under-five mortality rates, between children residing around operational and non-operational power plants across all three specifications. These results provide valuable insights into the association between power plants and children's health outcomes, particularly concerning neonatal mortality rates.

Next, we investigate the effects of active power plants on different mortality rates by examining two distinct subsamples: power plants fueled by non-renewable energy and those fueled by renewable energy sources. The estimation results are presented in Table 2. When focusing solely on the impacts of non-renewable power plants, we find that neonatal, infant, and under-five mortality rates are significantly higher when children are born around active power plants than non-operational power plants. This suggests a stronger association between non-renewable fuel-fired power plants and adverse health outcomes for children. Specifically, the neonatal mortality rate is estimated to be 0.037, approximately 1.4 times higher than the earlier estimate of 0.027 when considering all power plants.

Table 1: Estimation Results for All Power Plants

Variables	Neonatal	Post-neonatal	Infant	One-to-Four	Under-Five
		Without Birth Year Fixed effects			
Treatment	0.024**	-0.005	0.019	-0.001	0.018
	(0.011)	(0.007)	(0.013)	(0.004)	(0.013)
Observations	2,576	2,484	2,576	2,429	2,576
R-squared	0.027	0.014	0.026	0.045	0.043
		With Birth Year Fixed effects			
Treatment	0.022**	-0.004	0.018	0.000	0.018
	(0.011)	(0.007)	(0.012)	(0.005)	(0.013)
Observations	2,576	2,484	2,576	2,429	2,576
R-squared	0.035	0.020	0.034	0.057	0.051
		With Birth Year and Region Fixed Effects			
Treatment	0.027***	-0.008	0.020	-0.003	0.017
	(0.010)	(0.009)	(0.014)	(0.006)	(0.016)
Observations	2,576	2,576	2,484	2,429	2,576
R-squared	0.039	0.021	0.035	0.060	0.052

Notes: Each column reports results from a separate regression, where the dependent variable is one of the defined outcome mortality rates earlier described. All regression specifications include birth order fixed-effects, DHS years fixed-effects, mother age, birth spacing, single birth (0/1), sex (0/1), education (0/1), urban (0/1), hospital (0/1) and rich (0/1). Standard errors are clustered at the project level.
Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.10

The current finding is comparable to estimates by Bruederle and Hodler (2019), where authors reported an increase in neonatal mortality rates of 0.038 in areas near oil spills compared with 0.037 in children near non-renewable power plants. Moreover, infant and under-five mortality rates become higher and more significant, with estimates of 0.041 and 0.043., respectively, compared to 0.020 and 0.017 when analyzing all power plants. In contrast, the results for the subsample of power plants fueled by renewable energy sources (Panel B) do not yield any statistical significance. It comes as no surprise that renewable energy sources are typically linked to decreased emissions and fewer negative health effects, as this is in line with our anticipated outcomes.

Table 2: Estimation Results by Power Plants Fuel Source

Variables	Neonatal	Post-neonatal	Infant	One-to-Four	Under-Five
			Non-renewable		
Treatment	0.037***	0.005	0.041***	0.003	0.043***
	(0.012)	(0.006)	(0.013)	(0.007)	(0.012)
Observations	2,027	1,948	2,027	1,904	2,027
R-squared	0.049	0.034	0.052	0.051	0.067
			Renewable		
Treatment	-0.002	-0.048	-0.05	-0.007	-0.056
	(0.010)	(0.040)	(0.040)	(0.015)	(0.051)
Observations	549	536	549	525	549
R-squared	0.101	0.112	0.098	0.200	0.127

Notes: Each column reports results from a separate regression, where the dependent variable is one of the defined outcome mortality rates earlier described. All regression specifications include birth order fixed-effects, DHS years fixed-effects, region fixed-effects, mother age, birth spacing, single birth (0/1), sex (0/1), education (0/1), urban (0/1), hospital (0/1) and rich (0/1). Standard errors are clustered at the project level.
Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.10

The findings are consistent with previous research indicating that power plants using non-renewable energy sources produce harmful emissions that add to air pollution and negatively affect the general public's health (Currie et al., 2009; Yang & Chou, 2018). The higher neonatal mortality rates observed around non-renewable power plants likely drive the significant differences observed in infant and under-five mortality rates. Since infant mortality encompasses both deaths within the first month of life and those occurring before the child's first birthday, the pronounced effect on neonatal mortality is a crucial factor contributing to significant infant mortality. Notably, our findings also indicate that post-neonatal mortality rates are generally insignificant. This observation supports a previous study conducted in Nigeria, where the authors confirmed that increased infant mortality primarily stems from higher mortality rates in the first month of life (Bruederle & Hodler, 2019). These findings highlight significant and negative health impacts associated with power plant operations and emphasize the importance of considering the negative externalities associated with power plants fueled by non-renewable energy sources.

Alternative Specification and Robustness Checks

Table 3 presents the logistic regression (odds ratio) results, further validating the findings obtained through our primary empirical strategy. The outcomes are consistent, reaffirm our previous analyses, and provide additional insights into the relationship between power plants and mortality rates. When considering all power plants (Panel A), the logistic regression results indicate that only the neonatal mortality rate exhibits a significant likelihood of increasing with exposure to power plants. This finding suggests that residing near operational power plants is associated with a higher probability of neonatal mortality. The odds of an infant dying within the first month of life increases by a factor of 2.692 when the infant lives near a power plant. However, the likelihood of mortality rates for other age groups, such as infants and children under five, does not show statistical significance and negative for post-neonatal and one-to-four.

In the case of non-renewable power plants (Panel B), the logistic regression results reveal a more pronounced effect, consistent with our previous findings. Specifically, we observe significant likelihood of high odd ratios for neonatal (4.545), infant (2.525), and under-five (2.277) mortality rates among children born around active non-renewable power plants. This finding emphasizes the adverse impact of non-renewable energy sources on child health outcomes, as the exposure to pollutants emitted by these power plants is associated with an increased probability of mortality in the early stages of life. These logistic regression results complement and reinforce the main empirical findings, providing additional robustness to our analysis. They highlight the consistent and significant relationship between power plants, particularly non-renewable ones, and the likelihood of elevated mortality rates among children.

Table 3: Estimation Results by Power Plants Fuel Source

Variables	Neonatal	Post-neonatal	Infant	One-to-Four	Under-Five
			All		
Treatment	2.692***	0.664	1.538	0.729	1.366
	(0.810)	(0.311)	(0.423)	(0.349)	(0.362)
Observations	2,376	2,371	2,526	1,597	2,526
			Non-renewable		
Treatment	4.545***	1.06	2.525***	1.631	2.277***
	(1.624)	(0.391)	(0.672)	(1.036)	(0.497)
Observations	1,849	1,856	1,965	1,230	1,984

Notes: Each column reports results from a separate regression, where the dependent variable is one of the defined outcome mortality rates earlier defined. All regression specifications include birth order fixed-effects, DHS years fixed-effects, region fixed-effects, mother age, birth spacing, single birth (0/1), sex (0/1), education (0/1), urban (0/1), hospital (0/1) and rich (0/1). Standard errors are clustered at the project level.

Using event study difference in difference, we exploit variation in the power plants' commencement year to estimate changes in PM 2.5, the alternate outcome variable. Figure 1 shows that PM 2.5 changes were insignificant before the power plants became operational, revealing a parallel trend. However, at the 11^{th} to 16^{th} years of power plant operation, PM 2.5 in points around operational power plants is significantly higher than non-operational power plants. The increasing PM 2.5 around operational power plants could contribute to the higher neonatal mortality rate observed. We observe similar trends with varying proximities to power plants (20, 40, 60, 80, and 100 km).

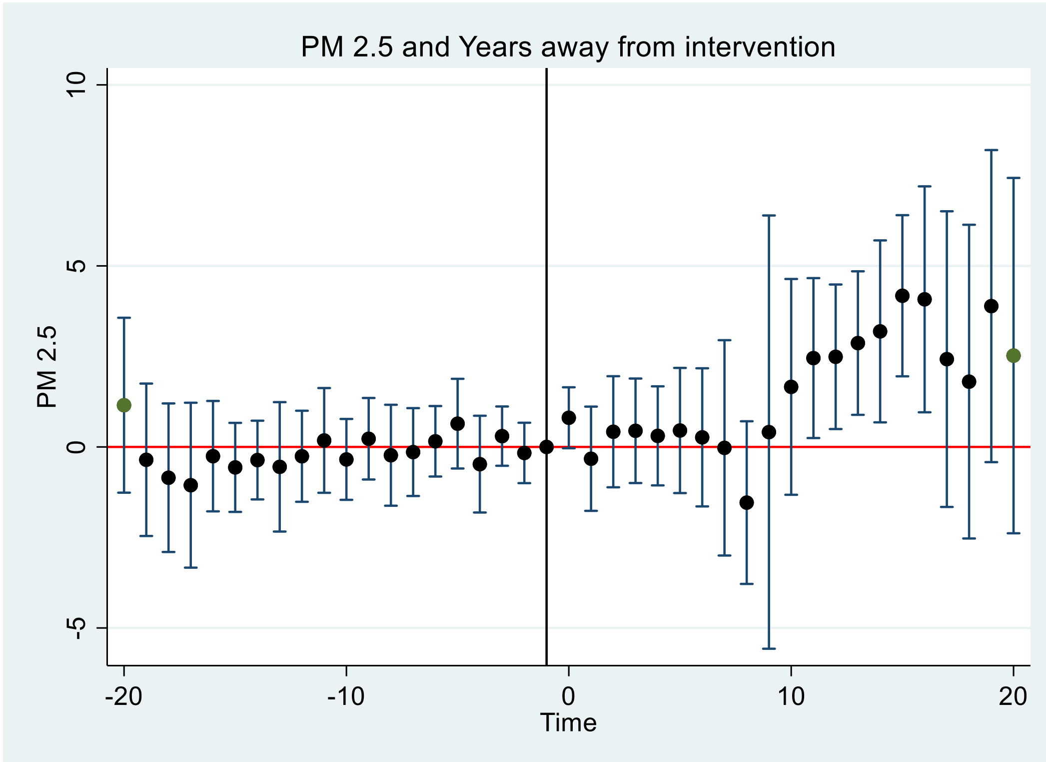

Figure 1. PM 2.5 changes with years before and after the intervention.

Note: All regression specifications include PM 2.5 points and year-fixed effects, including region time trends. The vertical lines represent 95% confidence intervals. Standard errors are clustered at the project level.

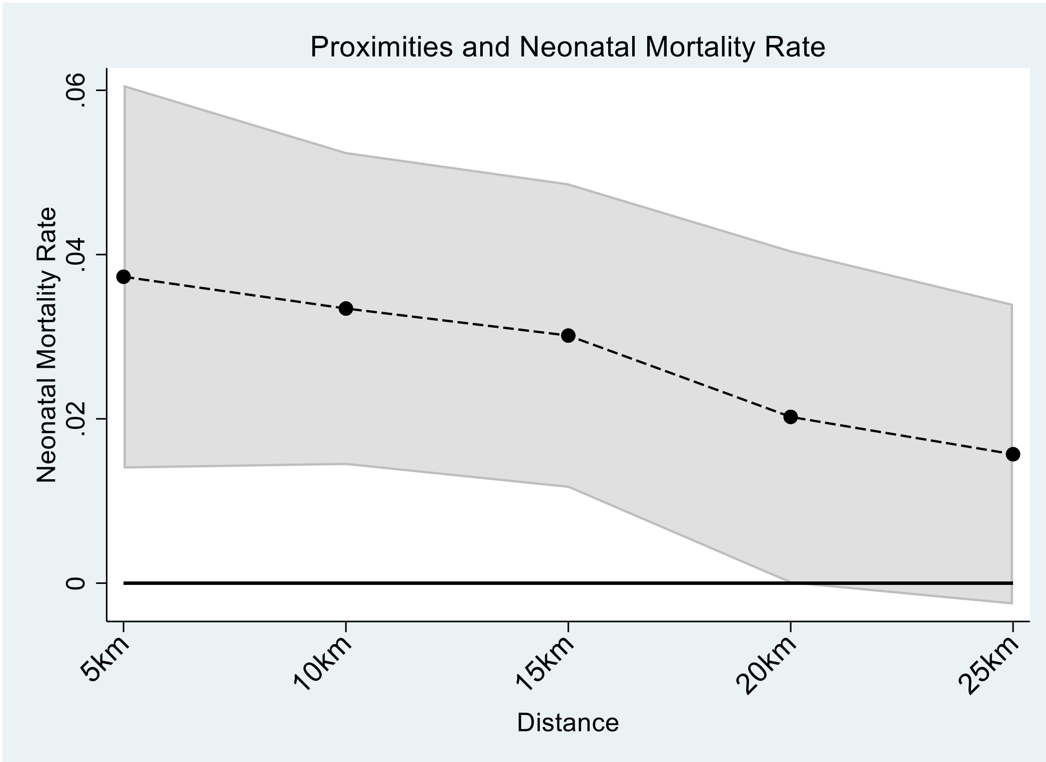

Figure 2. Treatment coefficients for neonatal mortality rates using different distance thresholds, ranging from 5 to 25 km.

Note: All regression specifications include birth order fixed-effects, DHS years fixed-effects, region fixed-effects, mother age, birth spacing, single birth (0/1), sex (0/1), education (0/1), urban (0/1), hospital (0/1) and rich (0/1). The vertical lines/point estimates' heights represent 95% confidence intervals. Standard errors are clustered at the project level.

We conduct robustness checks using different distance thresholds to define the treatment group and focus on the sub-sample of non-renewable energy-fired power plants. The results further prove the positive and significant relationship between active power plants and neonatal mortality rates (Figure 2). The findings indicate that the neonatal mortality rate within 5-25 km from active power plants is consistently higher than in areas surrounding inactive non-renewable power plants. The statistical significance is achieved at the level of 5% ($p<0.05$) for all distance thresholds, except for the 25 km distance threshold, where it remains significant at 10% ($p<0.10$). It is important to note that we observe a decreasing magnitude of the effect as the distance from the power plants increases. This finding aligns with our expectation, as emissions from power plants can disperse and impact health less at greater distances. These results are plausible, considering pollutants' ability to travel long distances. Supporting this notion, a previous study by Yang and Chou (2018) demonstrated that mothers residing as far as 32-48 km downwind from coal-fired power plants exhibited an increased likelihood of low birth weight and preterm infants, even in affluent regions. This evidence highlights the adverse health effects on infant well-being caused by pollutants emitted by power plants.

The robustness checks strengthen the validity and reliability of our findings, as they confirm the consistent association between active power plants and higher neonatal mortality rates across different distance thresholds. The decreasing magnitude with increasing distance highlights the importance of considering the dispersion patterns of pollutants and their potential impacts on infant health outcomes. These robustness checks support our main empirical findings, offering further insights into the relationship between active power plants and neonatal mortality rates. The evidence suggests that the proximity to active power plants, particularly those fueled by non-renewable energy sources, poses a significant risk to neonatal health.

Lastly, we further examine the heterogeneity in the impacts of power plants on neonatal mortality by interacting the treatment variable with sex, education, household wealth, location, hospital, and region. The results, presented in Figure 3, indicate that the difference in coefficients between the paired interaction terms is generally not statistically significant at the 10% level when birth year fixed effects are included and evaluated at the 5 km treatment distance threshold. It is worth noting that while neonatal mortality rates tend to be higher in poor households, the estimate does not significantly differ from non-poor households. However, we do observe a significant difference in the case of geographical locations, specifically between the southern and northern regions. The analysis suggests that the marginal effect of nearby active power plants on neonatal mortality is not limited to a specific subset of the sample, except for children residing in the northern region. This finding aligns with a previous study conducted in Nigeria, which reported higher infant mortality levels in the northern areas (Kotsadam et al., 2018). Cultural and traditional practices differences may be responsible for the higher mortality rate observed in the northern region of Nigeria. Early marriage and limited autonomy for women may contribute to higher fertility rates and increased health risks during pregnancy and childbirth. These practices are more prevalent in some northern regions and may impact infant health outcomes.

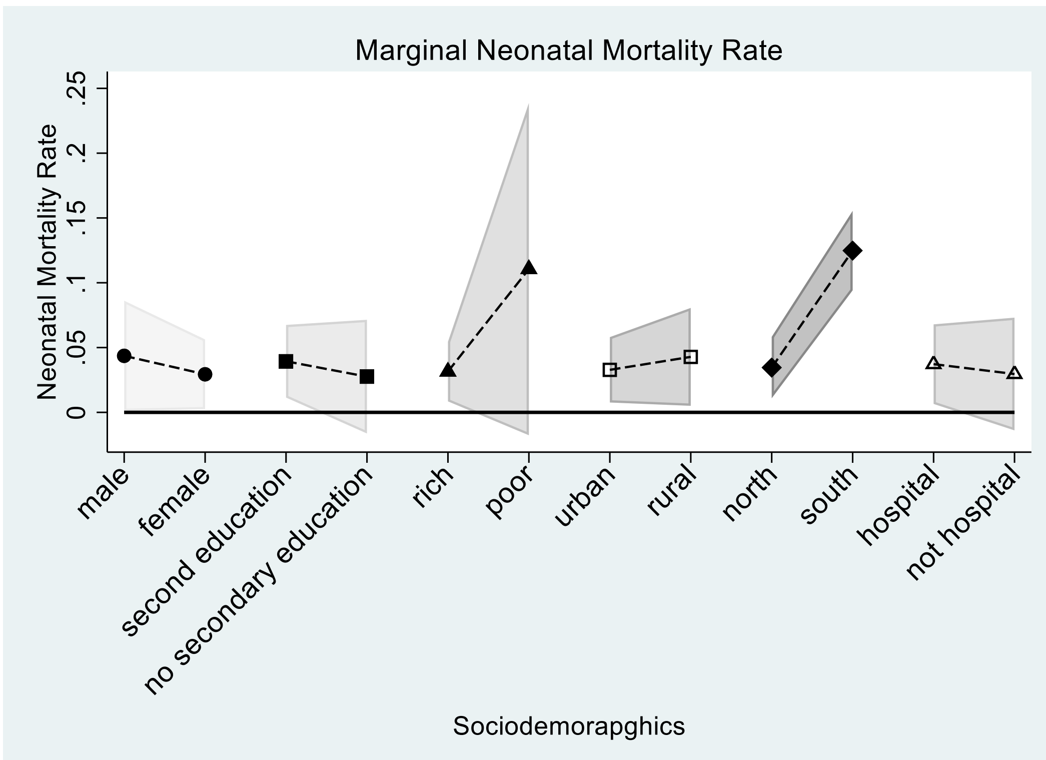

Figure 3. The coefficient estimates from six separate linear regressions of the neonatal mortality rate on the interaction term between treatment and each sociodemographic indicator.

Note: Each regression includes all the control variables, DHS survey years, and regional and birth year fixed effects. The vertical lines represent 95% confidence intervals. Standard errors are adjusted for clustering at the level of power plants level.

Figure 3 also shows whether mortality rates could be alleviated when children are born in hospitals, assuming wealthier households may opt for hospital births due to access to medical facilities. However, the results indicate no significant difference in neonatal mortality rates when children are born in hospitals for mothers residing near active power plants. In fact, the point coefficient estimate for hospital births is slightly higher. This finding is plausible if we consider that individuals with high-risk pregnancies may be more inclined to utilize hospitals for delivery. These results provide valuable insights into the heterogeneity of the impacts of power plants on neonatal mortality, highlighting the significant differences observed in geographical locations.

Conclusion

Energy production, particularly using non-renewable fuel sources, can have negative externalities in the form of higher mortality rates caused by increased air pollution. While previous studies have examined the impacts of power infrastructures on infant health in developed countries, research in Sub-Saharan Africa, including Nigeria, remains limited. Our paper sheds light on the relationship between power plants and infant health and mortality in Nigeria, the most populous country with one of Africa's top ten mortality rates. We combine publicly available NDHS data and georeferenced data on power plants to conduct a comprehensive analysis to assess the relationship between power plant operations and infant mortality rates.

Our findings indicate that neonates living within 5 km of active power plants experience higher mortality rates, with an increase of 0.027 compared to those living near inactive power plants or born before power plants started operations. This increased mortality effect is even more pronounced for children residing near non-renewable-fueled power plants, with about 1.4 times higher mortality rates. Our logistic regression analysis indicates that infants living near non-renewable energy-based power plants face a substantially elevated risk of neonatal mortality, with the odds ratio increasing by a factor of 4.545. It is alarming to note that even those infants living up to 25 km away from these facilities may still suffer from adverse health effects. Despite some regions exhibiting higher neonatal mortality rates, our analysis revealed no significant impact of other sociodemographic factors driving higher mortality rates. The initial findings regarding the alternative outcome of PM 2.5 show some significant and higher levels of PM 2.5 during the 11th-16th year of power plants' operation.

The knowledge generated from this study has important implications for policymakers and practitioners involved in energy planning and infrastructure development. It highlights the need to carefully consider the energy generation mix and invest in sustainable power infrastructure to meet the growing demand for electricity while mitigating the negative externalities associated with fossil fuel-based power plant operations. As developing countries strive to address their population's energy needs, it is crucial to incorporate measures that minimize or account for the potential adverse health outcomes identified in this study, as highlighted by Yang et al. (2017). By informing decision-making processes, our research contributes to a more comprehensive understanding of the implications of power plants on public health, particularly in the context of developing nations. Our quantitative estimates can be used as input in comparing the costs and benefits of constructing new power plants as policymakers formulate strategies that promote sustainable energy development while safeguarding the health and well-being of the population.

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APPENDIX

Table A1. Descriptive statistics for children within varying proximities to power plants

Variable	Definition	Mean (Standard Deviation)		
		Distance Thresholds Defining Treatment		
		5 km	10km	15km
Treatment	1 if an infant is born around operational powerplant and 0 otherwise	0.261 (0.439)	0.191 (0.393)	0.167 (0.373)
Neonatal Mortality Rate	1 if an infant around a power plant died within the first month of life, and 0 otherwise	0.039 (0.195)	0.043 (0.202)	0.044 (0.204)
Post-neonatal Mortality Rate	1 if an infant around a power plant died within the first 12 months but not in the first month of life, and 0 otherwise	0.022 (0.146)	0.026 (0.159)	0.027 (0.162)
Infant Mortality Rate	1 if an infant around a power plant died within the first 12 months of life, and 0 otherwise	0.060 (0.238)	0.068 (0.251)	0.070 (0.254)
One-to-Four	1 if an infant around a power plant died after the first year of life but before they are five years old, and 0 otherwise	0.017 (0.128)	0.022 (0.148)	0.023 (0.150)
Under-Five	1 if an infant around a power plant died before the first five years of life, and 0 otherwise	0.076 (0.265)	0.088 (0.284)	0.091 (0.288)
Mother Age	Mother's age in years	28.452 (5.913)	28.107 (6.351)	27.991 (6.456)
Birth Spacing	The interval between the infant's birth and the birth of its preceding sibling (if any) in months	38.008 (23.139)	37.435 (22.479)	37.091 (22.355)
Single Birth	1 if the birth is single and 0 otherwise	0.96 (0.201)	0.957 (0.206)	0.958 (0.204)
Sex	1 if the infant is male and 0 female	0.533 (0.499)	0.517 (0.500)	0.515 (0.500)
Installed Capacity	Installation Capacity (MW)	32.095 (135.73)	33.096 (156.15)	31.371 (149.98)
Rich	1 if the infant's household is categorized as rich and 0 poor	0.774 (0.418)	0.618 (0.486)	0.552 (0.497)
Low Education	1 if the mother is below secondary education and 0 otherwise	0.330 (0.47)	0.468 (0.499)	0.489 (0.500)
Urban	1 if the survey cluster is urban and 0 otherwise	0.696 (0.46)	0.575 (0.494)	0.504 (0.500)
Hospital	1 if the infant is born at the hospital and 0 otherwise	0.681 (0.466)	0.567 (0.495)	0.540 (0.498)
Birth Year	Year of birth	2010.543 (4.966)	2010.127 (4.897)	2010.397 (4.926)
Birth Order	1 for the first infant born to a mother, 2 for the second, etc.	3.198 (2.145)	3.487 (2.317)	3.570 (2.376)
Total number of observations		3605	7612	10480