# Coal Power Expansion and Long-Term Human Capital in India*

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**Abstract**

India and other developing countries have witnessed an unprecedented increase in coal-fired power capacity over the last two decades. This expansion in coal-based power production has led to a rise in air pollution, resulting in negative health outcomes, particularly for children living in affected areas. In this paper, I exploit variation in the expansion of coal-fired power units across India between 2005 and 2015 to identify their impact on long-term educational outcomes of children. Using a Difference in Difference (DiD) and Hybrid Event Study framework, I find that an increase in coal-fired power units in a district negatively affects children's long-term educational outcomes. Furthermore, exposure to coal-fired power plants leads to lower contemporaneous test scores and enrollment in schools. I identify increased air pollution as the primary driver of these effects. These results are not driven by differential pre-trends or endogenous migration of people living in districts with coal-fired power plants. My findings contribute to the literature on the adverse consequences of coal-based energy reliance in developing countries, particularly its effects on human capital development.

**Keywords:**

**JEL Codes:**

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# 1 Introduction

Coal remains the backbone of electricity generation in developing countries, providing more than half of power supply in regions such as South and South East Asian. Within the energy sector, coal power production disproportionately contributes up to 70 percent of green house gas emissions worldwide (Foster and Bedrosyan, 2014). Further, coal power production poses great risks to both the human health and the environment as it is a major source of local air pollutants. In a highly polluted country like India[1], for instance coal power generation is the single largest source of sulfur dioxide and nitrogen oxide emissions (Barrows et al., 2019). This problem is particularly acute in developing countries owing to less stringent and limited enforcement of environmental regulations.

With global climate agreements and investment in cleaner energy sources, coal power is being phased out in the developed countries, but it is still on rise in many developing countries such as India, where demand for electricity has outpaced investment in cleaner energy sources (Global Energy Monitor, 2025; Montrone et al., 2023). This is especially true in the last decade, were a bout in economic growth, led to a a exponential rise in coal capacity additions. This recent expansion provides an unique setting to examine the effects of air pollution caused by electricity generation in the country.

Existing studies in the environmental health and economics literature document negative effects of air pollution on health (Anderson, 2020; Bharadwaj et al., 2017, 2016; Coneus and Spiess, 2012; Currie et al., 2009, 2014; Graff Zivin and Neidell, 2013; Greenstone and Hanna, 2014; Greenstone and Jack, 2015; Jayachandran, 2009; Luechinger, 2014). This is particularly bleak in developing countries where recent evidence indicate even worse outcomes on health. A large number of these studies highlight infants to be the most vulnerable to air pollution, raising questions on their later life performance in school and work (Currie et al., 2014). Thus in this paper I attempt to examine if early-life exposure to pollution translate to long-term loses in human capital.

In the context of developing countries there are a few recent studies documenting negative human capital effect of pollution, however they largely focus on contemporaneous pollution and not on early life exposure to pollution which is considered the most damaging (Balakrishnan and Tsaneva, 2021). Despite the importance, there are no paper in the context of developing countries that have looked at impact of pollution from electricity generation such as coal on long-term educational outcomes of kids in a exhaustive manner.

I leverage the temporal and spatial variation in coal capacity expansions during the years 2005-2015, when the coal power capacity in the country rose exponentially (see Figure A.1).

[1] According to the World Bank, India consistently has higher air pollution than the WHO guideline value.

I combine this with a data on education attainment, test scores and enrollment from a variety of sources. My main results are based on schooling and educational attainment data from the DHS as it is more granular and has information on location coordinates which I can use to identify the children born near an expanded coal power unit. For the other outcomes related to test scores, I perform the analysis at the district level using variation in coal capacity additions across districts.

I find that coal capacity additions lead to significant declines in a range of education-related outcomes, including schooling, educational attainment, test scores, and enrollment. Children born during periods of increased air pollution following a coal capacity expansion experience a 1.4 percentage point decline (significant at a 1% level) in the likelihood of completing primary education and are 1.5 percentage points less likely (significant at a 1% level) to study in the grade appropriate for their age. In addition, a one GW increase in coal capacity is associated with a 0.07 SD contemporaneous decline in test scores (significant at a 5% level) and a reduction of 0.349 children per school-year in enrollment (significant at a 1% level). These results remain robust after accounting for demographic and household-level factors. This is particularly important, as pollution can undermine children's long-term educational attainment and negatively affect the Indian economy, given that human capital investment is a well-established driver of economic growth (Mankiw et al., 1992).

Examining the effect on education is especially important in the context of India as it faces significant "learning crisis" (Pritchett, 2013). Many children struggle to acquire basic reading and math skills. According to the 2019 Annual Status of Education Report (ASER)[2], about 44 percent of children aged 5-10 were unable to read a simple paragraph, while nearly 50 percent could not perform basic arithmetic operations like subtraction.

I conduct a series of robustness and falsification checks to validate the main findings. Air pollution emerges as the primary channel through which coal plant expansions affect children's educational outcomes. This is consistently established as coal capacity additions lead to higher pollution in exposed areas, while the negative effects on education attenuate with distance. I further confirm this channel by showing that infants born after a coal capacity expansion exhibit lower height-for-age, highlighting adverse health impacts as an important mechanism. I also confirm that these results are not driven by household migration or avoidance behavior in response to rising pollution. Moreover, the expansion of coal power units does not generate disproportionate local economic benefits, as the electricity produced is largely transmitted to distant locations. Evidence from night lights and survey data shows no significant increase in local energy access or prosperity near the plants. I also rule out concerns about systematic differences in plant placement by showing no pre-trends in areas

[2] 2019 ASER report link

that did not experience coal plant additions. Finally, to address concerns regarding the timing of exposure, I estimate alternative and stricter specifications and find the results remain robust.

This paper makes several contributions to the literature on environmental health and economics. First, it adds to the evidence on air pollution and cognitive outcomes in the context of a low- and middle-income country. Various studies in developed countries have documented a negative relationship between air pollution and cognitive outcomes, largely relying on short-term changes in exposure[3] to identify impacts on exam performance (Duque and Gilraine, 2022). In the context of India, emerging literature also finds that short-term variation in pollution negatively affects immediate cognitive outcomes such as test scores and court judgments (Balakrishnan and Tsaneva, 2021; Sarmiento and Nowakowski, 2023). This paper contributes to this growing body of work in two ways. First, it provides evidence from a developing country setting where baseline levels of pollution are higher and environmental regulations weaker. Second, unlike most studies that focus on short-term cognitive impacts, I examine the long-term effects of early-life exposure to pollution. In doing so, my paper relates more closely to the literature in developed countries that has examined the lasting impacts of early-life pollution exposure (Bharadwaj et al., 2017; Currie et al., 2014).

Second, it contributes to the active literature on coal-based power production and health outcomes in India. Recent studies indicate adverse health impacts of coal-based energy generation, especially among children (Barrows et al., 2019; Datt et al., 2023; Gupta and Spears, 2017; Vyas, 2023). These studies document increased prevalence of anemia, stunting, and infant mortality in coal-exposed areas. However, the effect on education has not yet been explored. This paper extends the literature by examining later-life educational outcomes of children exposed to coal-related pollution. I consider a wide range of educational outcomes, from long-term education attainment to short-term effects on test scores and school enrollment. The findings add to the evidence on the negative consequences of coal-based power production and show that its effects persist into later life.

Finally, this paper contributes to the broader literature on environment and development economics. It econometrically identifies the impact of coal-based electricity generation and air pollution on human capital formation. In doing so, it deepens the questions posed by Greenstone and Hanna (2014) on the paradox of why people in developing countries do not demand better environmental quality Gupta and Spears (2017).

The reminder of this paper is as follows. Section 2 provides contextual information on the role of coal in India's energy sector. The data and empirical strategy are elaborated in Section 3 and Section 4 respectively. Section 5 outlines the main results of this paper

[3]For example, pollution on the day of an exam.

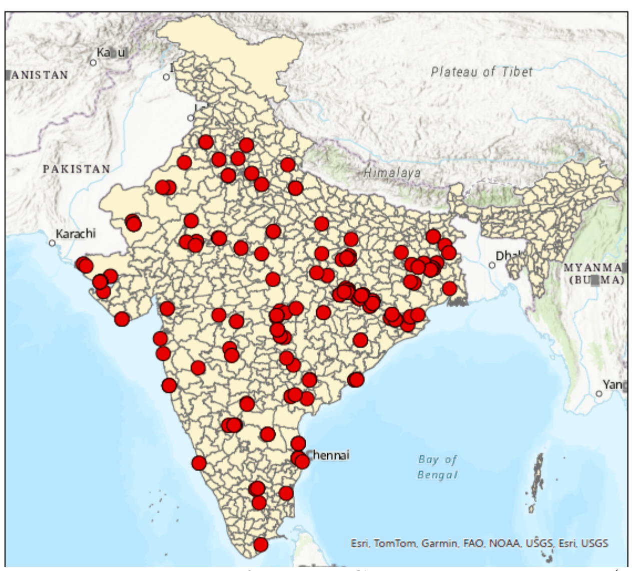
and its followed by Section 6 with robustness checks. Section 7 explores the impact of coal power expansion on other educational outcomes such as test scores and enrollment. Section 8 concludes the paper with discussion of findings and main results.

# 2 Background

Globally, India is the second largest generator of coal-fired power ranking second just behind China. It meets up to 70% of its energy demand by relying on coal based power (Steckel and Jakob, 2021). In recent years there has been a massive increase in construction of new coal-fired power units across the country to reduce power shortages and increase electricity access. This led to a 225% increase in coal capacity from 55 GW to 176 GW just within a decade from 2008 to 2018. During this period the number of coal-fired power plants also tripled from just 81 in 2004 to 245 in 2015.

Most of these coal-fired power plants are owned either by the Central (Federal) or State government led power companies (Ordonez et al., 2023). In recent years, the role of private power companies in coal-fired power generations is also increasing. Most of these power companies produce electricity for supply to the national power grid which distributes power across the country to meet the demands of both households and firms Barrows et al. (2019). There exists also captive power plants which are largely run by heavy industries such as steel or cement manufacturing to have small coal units to meet their own electricity demand.

**Figure 1:** Spatial Distribution of Coal Fired Units in India from 2005–2012




*Note:* Authors own calculation from the Global Energ Monitor (2024). This figure shows the location of coal-fired units operational during 2005–2012.

Figure 1 shows the spatial distribution of all coal power plants in India. Location of the coal plants are largely determined by the access to coal and other raw materials. This has led to higher concentration of coal plants in east and central India which have large coal reserves (Ordonez et al., 2023). Coal plants that rely on imported coal are located in the costal areas of the country. Notably, despite access to large coal reserves India is also the second largest importer of coal in the world, with 31% of coal being imported (Standard, 2025). Since coal-fired power plants require water to produce steam and run turbines, some coal fired power plants are also located near water reservoirs Barrows et al. (2019). Setting up of coal-fired power plants are subject too environmental regulation too. These regulations which came force in recent years prohibit setting up of these plants close to cities, eco-sensitive zones and require all coal plant proposals to get a environmental clearance. All these above described factors on location of coal-fired power plants establishment are not tied to pre-existing trends in health or economic outcomes.

Coal-fired power plants are a major source of air pollution in India. They are the single largest contributor of $NO_2$ and $SO_2$ emissions in the country (Barrows et al., 2019), and also account for a substantial share of PM2.5 emissions, which are tiny particles capable of entering the bloodstream. Despite their highly polluting nature, environmental regulations remain weak. Most coal-fired power plants in India lack abatement technologies to reduce emissions, and there are major gaps in the real-time monitoring of emissions (Ghosh, 2025).

Coal-fired power plants in India continue to expand despite the country's commitments to renewable energy. Various analyses project that coal capacity will continue to increase (Global Energy Monitor, 2025).

# 3 Data

This paper utilizes a number of datasets from different sources to explore the effects of coal plant expansion on human capital:

**Coal power plants:** The data on coal power plants was obtained from the Global Coal Plant Tracker (GCPT) database which is part of the Global Energy Monitor (GEM). The coal plant tracker tracks all the coal-fired power units that are above 30 Megawatts across the world and provides various useful information such as information on the ownership, date of opening, location coordinates and capacity (MWs). It is important to note that one or several coal-fired power units can form a full-fledged coal power plant, and the GCPT database tracks each of these units. I used the location coordinates of the coal-fired power units to match the districts in which these plants are in India. The GCPT database obtains information on coal-fired units from both government sources like the India Central Electricity Authority and private sources. Thus, in comparison with the Indian Central Authority database which previous studies have used, the GCPT database also includes captive coal-fired units that are used for industrial purposes.

**Education attainment data**: The data on educational attainment are obtained from the Indian Demographic and Health Survey (DHS) 2019-2021[4]. DHS is a nationally representative survey conducted in collaboration with US Aid and is widely used by researchers for studying questions related to demography and health in developing countries, including India. The DHS gathers information on educational attainment of all members in a household along with other demographic information such as age, sex, religion and caste. Education attainment data includes total years of schooling, highest level of education achieved such primary, secondary or tertiary and whether a member is attending school in the surveyed year.

Importantly the survey provides coordinate information of survey locations called primary sampling units (PSUs). These PSUs (henceforth village) are a village in rural areas and a city block in urban areas. The coordinates of these locations help me identify children residing near coal-fired power unit[5]. There are 465,000 kids surveyed by the DHS and for my main results I restrict my sample to children who are in the age between 5-16.

**Test scores data:** For test scores, the data is based on the two rounds of the Indian Human Development Survey (IHDS) conducted jointly by the University of Maryland and the National Council of Applied Economic Research (NCAER) in Delhi. IHDS is a nationally representative panel of 40,000 households surveyed first in 2004-05 and followed again in 2011-12. The main variable of interests for us are the test scores from basic competency tests in reading and arithmetic administered on children aged 8-11 at their household. The reading test tested if the children have ability to identify letters, words, read paragraphs and stories. The test score ranged from 0-4, where children with no reading ability were given a score of 0 and the children with the highest ability of reading a story were given the maximum score of 4. These tests were administered in the kid's native language. Similarly for arithmetic, the test checked if students could identify numbers, perform subtraction and division. Children with no ability to recognize numbers were given 0 and children who can perform arithmetic operations up to division were given the maximum score of 3.

The advantage of using the IHDS data comes from the availability of rich information

[4]DHS in India is alternately referred to as the National Family Health Survey (NFHS)

[5]To protect the identity of the respondents DHS randomly displaces the coordinates of PSU from the actual survey location. The coordinates are displaced by zero to two km in urban areas and zero to five km in rural areas, with one percent of household displaced by zero to ten km. This is bound to create measurement error in our analysis but we overcome this by checking for different distance bins from the coal-fired power unit

**Table 1:** Main Outcome Variables

| Variable Name | Description |
|---|---|
| Total Years of Education | Total number of years of schooling completed by the individual. |
| Primary School Completion (0/1) | Whether the individual had completed primary school at the time of interview. |
| Middle School Completion (0/1) | Whether the individual had completed middle school at the time of interview. |
| On-Track (0/1) | Whether the individual is at the right grade for his/her age |

on the kids and their home, social and parental background (Desai et al., 2010). The data unlike ASER also includes kids from both rural and urban areas. The first round of IHDS tested around 12,290 for children and the second round tested 11,631. The average reaing score in 2005 was 2.62 and in 2011 was 2.54. Its also important to note that it was not possible to follow the same set of kids across both the rounds as kids who were in the age group of 8-11 during 2005, were outside the testing age range in 2011.

**Enrollment and school amenities data:** To evaluate if coal-fired power led to dropouts and eventual reduction in enrollment in schools, I rely on the District Information System for Education (DISE). DISE is administrative data of all schools in India and is collected by the Ministry of Human Resource Development of the Government of India from 2005 onward. This dataset has school-level information on enrollment and facilities like availability of electricity and classrooms which I will be using in this study. It also has precise coordinate locations of schools which helps me to map schools that are close to a coal plant for my analysis.

**Pollution and night lights data:** To examine the channels through which coal power expansion affects children, I rely on PM 2.5 and night lights data from SHRUG Development Database (Asher et al., 2021). SHRUG is a open access repository containing village-level datasets on India. They host estimates of surface PM 2.5 particulate pollution calculated from Aerosol Optical Depth (AOD) data obtained from satellite based instruments (cite). AOD indicates how much of sunlight is absorbed or scattered by tiny particles like dust, pollution and smoke in a column of air. Data from satellites is preferred in my context due to lack of monitoring stations across all parts of the country. These PM 2.5 estimates are available at the village level and thus enable me to focus on pollution levels in areas close to the coal-fired power units.

In order to check if coal-fired power units contributed to electrification and local economic development, I rely on the DMSP-OLS annual measures of night time luminosity available at village level in the SHRUG database. Average luminosity can range between 0-63, with dark villages with no or very limited lighting having 0 values. These luminosity measures were calculated based on nigh-time imagery from satellite based instruments. Night light data is widely used as a proxy for electrification or economic activity in contexts such as this where high-frequency granular level data is not available.

# 4 Descriptive Statistics

Table 1 describes the variables used in the main analysis, which examines the effect of coal power generation on long-term educational outcomes. Summary statistics for these variables are presented in Table A.1. Column (1) reports means for households living beyond 50 km of a coal plant (unexposed), while column (2) reports means for households living within 50 km of a coal plant (exposed). Children in exposed villages have, on average, more years of education, higher rates of primary and middle school completion, and are more likely to use LPG for cooking. At the same time, households in exposed villages are less urban, have larger family sizes, and are more likely to belong to scheduled castes.

# 5 Empirical Strategy

To establish the effect of coal power expansion on education, I rely on multiple empirical strategies and identification assumptions, which I outline below:

## 5.1 Cohort Based Approach

I use a Two-way Fixed Effects (TWFE) estimation strategy to evaluate the impact of coal power expansion on education attainment. While DHS data is cross-sectional and does not follow children over time, it has information on children born across multiple birth cohorts. This allows me to use a cohort based approach where by using village and cohort fixed effects, I estimate the within village and within cohort impact of coal power expansion. This empirical specification is similar to Vyas (2023) and is as follows is:

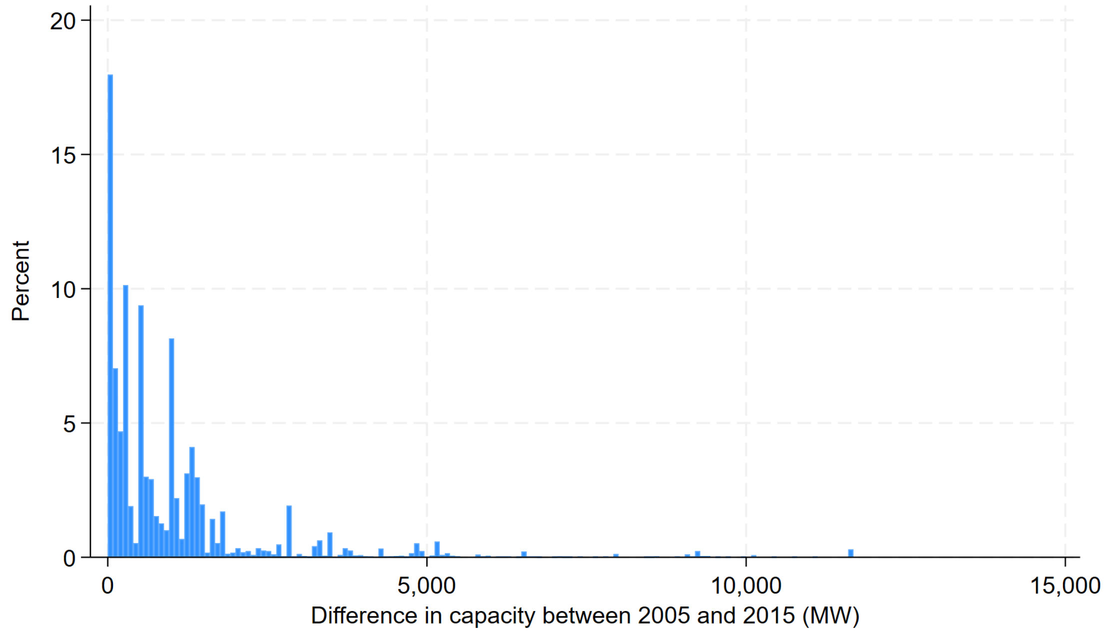
$$y_{ihvt} = \beta CoalCapacity_{vt} + \theta_1 H_{hvt} + \alpha_v + \gamma_t + \epsilon_{ihvt} \tag{1}$$

here $y_{ivt}$ relates to various education attainment measures discussed above for child $i$, belonging to household $h$, born in year $t$ in village $v$. $CoalCapacity$ is the total capacity measured in Gigawatts (GW) at the coal-exposed villages village $v$ in year of birth $y$. A village is considered exposed if it lies with 50 km from a coal power unit Vyas (2023). In an alternate specification I replace capacity with total coal power units as coal power expansion can occur both through increase in capacity and through building of additional units. $H$ controls for various demographic and household related factors such as gender, religion, caste and household size. I include $\alpha$ village fixed effects to control for time-invariant characteristics of a village and $\gamma$ cohort fixed effects defined using year of birth, to account for shocks and national trends affecting individuals born in the same year. Standard errors are clustered at the village level.

**Identifying Variation:** The identifying variation in this setup is the spike in coal capacity within a village during the coal power expansion phase between 2005-2014. Following (Vyas, 2023) in Figure 2, I depict the spike in capacity within a village during the coal expansion years of 2005-2015: Figure 2 includes both villages that historically had a coal power unit and villages were new coal power units were established. Among the villages that historically had a coal power units, about 18% of them did not witness any expansion in power capacity during 2005 to 2015. However, the reminder of the villages saw an increase in power capacity up to 12,000 MW during 2005-2015.

Since early-life exposure to pollution is widely documented to have detrimental effects on long-term health and human capital, I consider kids born during the expansion year as

**Figure 2:** Variation in Coal Power Capacity across DHS villages




treated (Currie et al., 2014). In later sections for robustness, I test by varying the timing of exposure.

**Identifying Assumption** The key identifying assumption in this setup is parallel trends, that is in absence of treatment, villages that got exposed to a coal power expansion would have trended parallel to those village which did not witness any expansion. This plausible only if setting up of coal power units did not follow any health or economic trends. As seen in Section 2, coal plant locations are predetermined by location of mines and are regulated by various rules, thus they do not follow any systematic trends. However, I formally test the parallel trends assumption by checking for pre-trends in Section 6.

Another concern is that households may endogenously migrate after the capacity expansion of a coal power unit. For instance, coal plants can degrade surrounding areas and lower real-estate values, which may in turn attract low-income households to move closer to coal-exposed areas. Such selective migration could bias the estimates and push the results in a more negative direction. To address this concern, in Section 6 I show that the main results remain robust when restricting the sample to households that have not migrated post the coal expansion.

Finally, recent literature on TWFE highlights limitations in settings with time-varying treatment, such as this one. In such cases, the TWFE estimator can produce ‘forbidden comparisons,’ where not-yet-treated units are compared with already-treated units. Since treatment effects may evolve over time, already-treated units can be on a different trajectory than not-yet-treated units, and such comparisons can generate negative weights (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020). To address these concerns, I use the *did_multiplegt* estimator proposed by de Chaisemartin and D'Haultfœuille (2020), which uses appropriate comparison groups and computes group-time average treatment effects, thereby avoiding the negative weighting problem

# 6 Results

## 6.1 Coal Power Expansion and Air Pollution

I first examine whether the expansion of coal power plants led to a rise in air pollution in coal-exposed areas. To test this, I employ a TWFE specification similar to Equation 1 and assess whether contemporaneous increases in coal capacity translated into higher PM 2.5 levels. The empirical specification is as follows:

$$y_{vt} = \beta\, CoalCapacity_{vt} + \alpha_v + \gamma_t + \epsilon_{vt} \tag{2}$$

where $y_{vt}$ denotes PM 2.5 levels in village $v$[6] at year $t$. The explanatory variable and fixed effects are defined as in Equation 1, but measured contemporaneously.

**Table 2:** Coal power expansion and air pollution

| | (1)<br>Mean PM2.5 detected in polygon | (2)<br>Minimum PM2.5 detected in polygon | (3)<br>Maximum PM2.5 detected in polygon |
|---|---|---|---|
| cum_capacity | 1.049*** | 1.033*** | 1.064*** |
| | (0.008) | (0.007) | (0.008) |
| Observations | 6557782 | 6557782 | 6557782 |
| Year FE | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes |

Standard errors in parentheses
* p¡0.10, ** p¡0.05, *** p¡0.01

The results in Table 2 indicate that a 1 GW increase in coal capacity is associated with a rise of 1.04 $\mu g/m^3$ in mean PM 2.5 concentrations. This suggests that air pollution is a key mechanism through which coal power expansion may affect educational outcomes. Coal power production in India is considered to be a significant cause of air pollution in the country, with it nationally being a major emitter of gases like $NO_2$ and $SO_2$ along with $PM2.5$ (Barrows et al., 2019). The pollution is estimated to travel up to 600km and

[6] Here, village corresponds to SHRIDS given in the SHRUG database. SHRIDS are equivalent to census villages and towns in India. More information can be found here: https://docs.devdatalab.org/SHRUG-Construction-Details/location-identifiers/town-and-village-identifiers/

thus this estimates are likely to be attenuated as its limited to 50km range (E. Somanathan et al., 2023). It is important to note that these results indicate air pollution to be a possible mechanism without ruling out other forms of pollution such as ground water.

## 6.2 Coal power expansion and education attainment

Table 3 presents the estimated effect of coal power expansion on education attainment. I find that a 1 GW increase in coal capacity results in reduction in likelihood of completion of primary and middle school by 1.4 and 1.2 percentage points. I also find that these children are less likely to be at the right grade corresponding to their age and are less likely to be attending school in the current year. These results are not sensitive to inclusion of various demographic and household controls such as gender of the child, religion, caste and household size.

**Table 3:** Main Results: Coal power expansion and educational outcomes

| | (1)<br>total_education_years | (2)<br>primary | (3)<br>middle | (4)<br>on_track | (5)<br>at_school_current_year |
|---|---|---|---|---|---|
| Capacity (GW) | -0.088*** | -0.014*** | -0.012*** | -0.014*** | -0.014*** |
| | (0.007) | (0.002) | (0.002) | (0.002) | (0.003) |
| Observations | 506846 | 506846 | 506846 | 506846 | 506846 |
| Cohort FE | Yes | Yes | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes | Yes | Yes |
| Demographic/Household Controls | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses
* p¡0.10, ** p¡0.05, *** p¡0.01

In Table A.2, I replace the main regressor with the number of coal power units as an alternative specification. Although the magnitude of the effects differs, the results remain largely consistent with the main findings: additional coal power units are associated with decreases in schooling and in the likelihood of completing different levels of schooling. Coal capacity is preferred as the main regressor because it more directly reflects emissions, whereas the number of units is less precise since units can vary in size and assuming equal capacity across them is unrealistic, as shown in Table A.2.

**Table 4:** Within Household Results: Coal power expansion and educational outcomes

| | (1) total_education_years | (2) primary | (3) middle | (4) on_track | (5) at_school_current_year |
|---|---|---|---|---|---|
| cum_capacity | -0.077*** | -0.015*** | -0.004 | -0.015*** | -0.016*** |
| | (0.010) | (0.003) | (0.003) | (0.003) | (0.005) |
| Observations | 369583 | 369583 | 369583 | 369583 | 369583 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes | Yes | Yes |

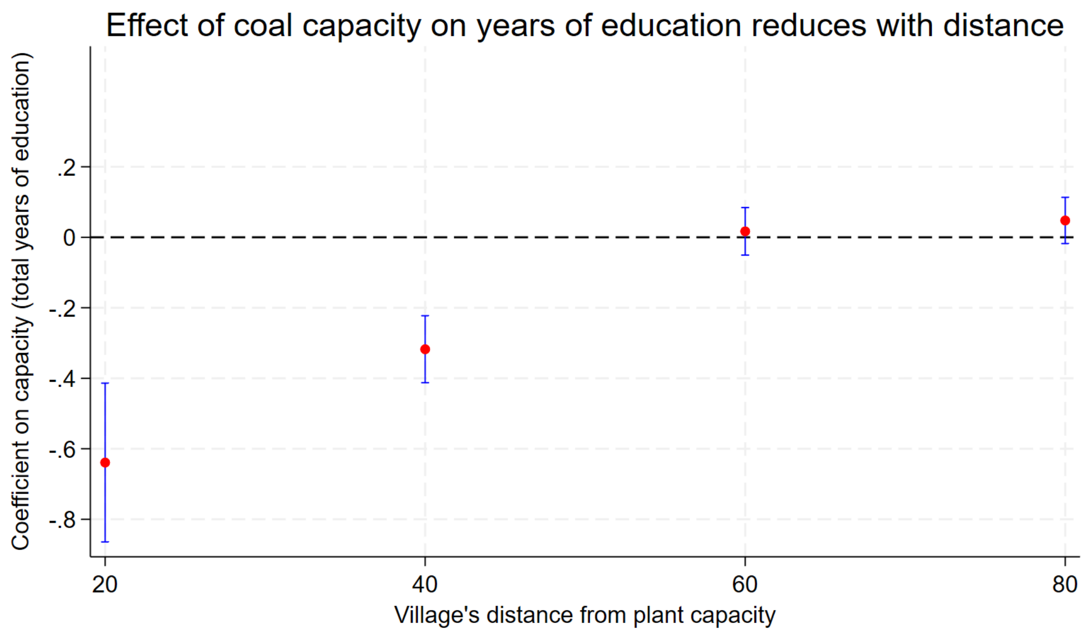
Standard errors in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

In Table 4 I replace village fixed effects with household fixed effects. This leads to estimating the effect of coal capacity expansion within a household, essentially comparing siblings within the same household. I find the results to be consistent with the main results, indicating that within a household, siblings born after a coal-power expansion acquire less schooling compared to the elder sibling. These estimates are robust to inclusion of controls such as gender and cohort fixed effects, thus controlling for age and gender differences between the siblings. Further, the sample is limited only to those households that have more than one kid and as a result there is a drop in the sample size as well.

These result highlight the negative impact of coal capacity on education. These results are not surprising and are similar to various studies in the Indian context that have documented prevalence of stunting and anemia among kids born after a coal capacity expansion (Datt et al., 2023; Vyas, 2023). These negative health effects can be a major health burden for the kids affecting their human capital accumulation as well.

**Figure 3:** Coal Capacity on Years of Education in Different Distance Bandwidths




Since I consider air pollution to be the main mechanism behind this negative effect, I examine whether children born farther from a coal plant experience a smaller decline in educational attainment. I modify Equation 1 by regressing the outcome on coal capacity within different distance intervals: 0–20 km, 20–40 km, 40–60 km, and 60–80 km [7]. In Figure 3, I plot the coefficients from these regressions and find that the effect of coal capacity on education weakens with distance. This suggests that air pollution is a key mechanism driving the results. It also supports the choice of 50 km as the main exposure threshold in the baseline specification, as the effect attenuates beyond 60 km.

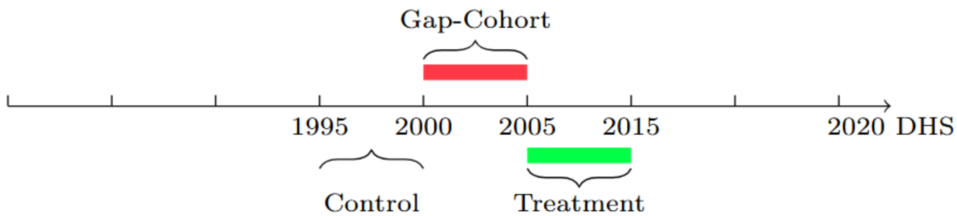
# 7 Robustness Checks

## 7.1 Contamination of the Control Group

A potential concern with the main empirical strategy is that children born in the year immediately preceding a coal plant expansion may also be affected by the spike in pollution, as they are still in the early infant stage. Although Vyas (2023) find that the effect of coal power expansion on child height attenuates after 16 months, I nevertheless conduct robustness checks by altering the composition of the reference group.

[7] The households can be exposed to multiple coal plants located in different distances. Thus these intervals are not mutually exclusive

**Figure 4:** Example timeline showing cohorts




Specifically, I modify Equation 1 to compare children born before the year 2000, that is well before any coal plant was established. This approach effectively compares older and younger cohorts within a village, while controlling for age-related shocks that are common across all villages. As illustrated in Figure 4, children born after a coal expansion (which could occur anytime between 2005 and 2015) are compared with children born during 1995–2000 in the same village, after accounting for cohort fixed effects. In doing so, I exclude the cohorts born immediately prior to a coal expansion (i.e., those born between 2000 and the year of expansion, such as 2005 in the example shown), since they may still be affected by early-life exposure.

**Table 5:** Comparing the effect of coal expansion on young vs old cohorts

| | (1)<br>total_education_years | (2)<br>primary | (3)<br>middle | (4)<br>on_track |
|---|---|---|---|---|
| Capacity (GW) | -0.089*** | -0.009*** | -0.010*** | -0.005** |
| | (0.018) | (0.001) | (0.002) | (0.002) |
| Observations | 604872 | 604872 | 604872 | 604872 |
| Cohort FE | Yes | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes | Yes |
| Demographic/Household Controls | Yes | Yes | Yes | Yes |

Standard errors in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

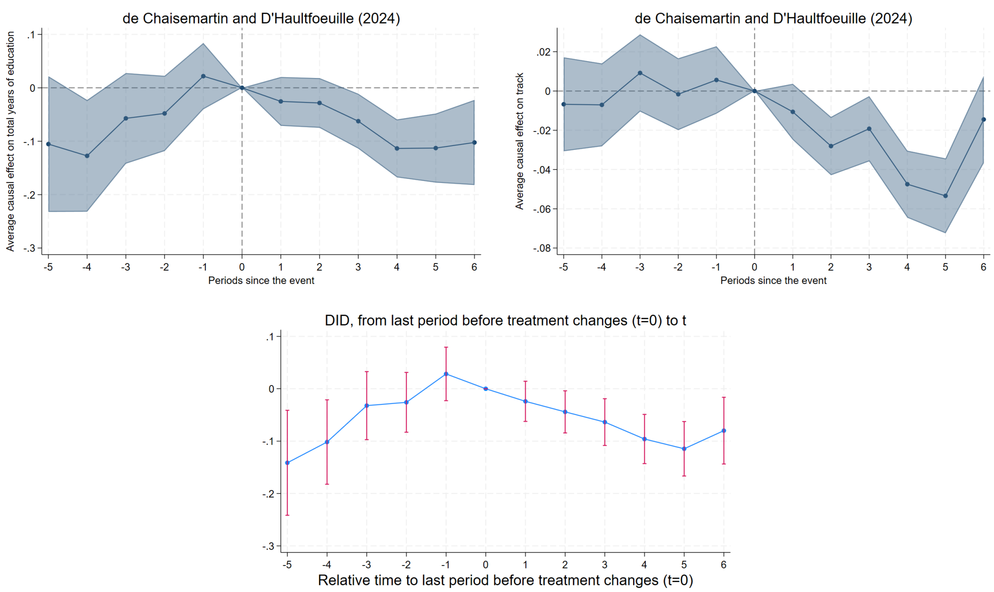
Table 5 presents the results from this alternative specification. By excluding cohorts born immediately prior to plant expansion, I mitigate the risk of control group contamination, as these children may still have been exposed during their early years. The findings remain consistent with the main results, showing a significant decline in schooling outcomes. The likelihood of completing primary and middle school falls by 0.9 and 1.0 percentage points, respectively, while the probability of being on track decreases by 0.5 percentage points. These results are robust to the inclusion of additional controls.

## 7.2 Event Study

Coal plant expansions can occur either through construction of a new plant or by increasing the capacity of an already existing plant. In the main results, I use variation from both these type of expansions to identify the effect on education. However, there could be concerns in the placement of these new plants if they followed any health or economics trends. To assuage concerns on this in Table A.3, I present results only from expansions of existing coal plants. The results are similar to the main results across all the variables.

I further check for pre-trends with variation from both kinds of expansions, i.e. both new plant construction and capacity additions of an existing plant. For this, I rely on the *did_multiplegt* estimator proposed by de Chaisemartin and D'Haultfœuille (2020). As described earlier this estimator avoids the negative weights problem by selecting appropriate comparison groups to compute group-time average treatment effects.

**Figure 5:** Event Studies with total years of education, "on-track" and highest grade attained




Note: Here event is exposure at birth, meaning the child was born in a year when the first coal plant was commissioned.

Figure 5 presents the results from the event study. The findings suggest that children born in periods following coal expansion complete fewer years of education and are less likely to be on track. There are no concerning pre-trends in the years of education and "on-track" figures; however, in the figure with highest grade attained, some concerns remain. Overall, the event studies indicate that children born after coal power expansion obtain less education. Unlike Equation 1, the regressor here is a dummy variable that switches on after a coal capacity expansion occurs in an exposed village, since the hybrid DiD approach with continuous treatment is subject to many restrictions.

### 7.3 Migration

In settings involving pollution, endogenous migration can threaten identification. Households may respond to coal expansion by relocating: richer households may move away from polluted areas, making the treated group negatively selected relative to controls, while new economic opportunities from coal may attract skilled migrants, leading to positive selection (Moretti and Neidell, 2011).

In the Indian context, however, migration tends to be relatively constrained in the due to caste-based social capital and residential segregation, which also keep housing prices relatively inelastic in the short run (Munshi and Rosenzweig, 2009). The DHS only surveys households that remain in place after a coal expansion, meaning that out-migrants are not observed. Nevertheless, the DHS asks eligible women how long they have resided in the same locality, allowing me to identify households that recently moved into a locality [8]

**Table 6:** Results after controlling for migration

| | (1) total_education_years | (2) primary | (3) middle | (4) on_track | (5) at_school_current_year |
|---|---|---|---|---|---|
| Capacity (GW) | -0.147*** | -0.018*** | -0.023*** | -0.028*** | -0.014 |
| | (0.020) | (0.003) | (0.004) | (0.006) | (0.010) |
| Observations | 116871 | 116871 | 116871 | 116871 | 116871 |
| Cohort FE | Yes | Yes | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes | Yes | Yes |
| Demographic/Household Controls | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

I use this information to restrict my sample to only those households who have lived in the same village from 2004. This essentially results all in-movers who would have moved after a coal-plant expansion. Table 6 reports the results after controlling for migration. The results are similar to the main results as increase in coal capacity leads to reduction in years of schooling and education attainment. The sample size decreases when using women's migration histories to proxy for household migration, since most women in India relocate at the time of marriage.

[8] The DHS does not record whether households have migrated. Instead, it asks eligible women how long they have lived in the same locality. I use this information to proxy household migration. In households with more than one surveyed woman, I take the longest reported duration of residence.

## 7.4 Falsification: Night lights

Coal plants can affect educational outcomes via local economic development. In this case, it becomes difficult to isolate the health costs of coal power, as economic development could bias estimates upward. To examine this possibility, I test whether coal power plant expansions are associated with local economic prosperity using night-lights data. Night-lights are widely regarded as a good proxy for electrification and local economic activity in low- and middle-income countries, where high-frequency local economic data are typically unavailable (Asher et al., 2021; Henderson et al., 2011).

Similar to Equation 2, I estimate whether coal capacity additions increased night-lights in coal-exposed areas.[9] Conditional on fixed effects, Table 7 shows that coal power expansions do not significantly increase either maximum or total night-lights in coal-exposed areas. As Burlig and Preonas (2024) notes, the maximum night-light value is a useful proxy for electrification: unlike the mean, which can be biased downward in villages with large tracts of unlit cropland, the maximum reflects the brightness of populated areas and thus better captures household access to electricity. I also test for total night-light within a village polygon, which is commonly interpreted as a broader measure of local economic activity (Asher et al., 2021).

Taken together, the results do not indicate that coal power plants generate local economic development. Rather, they suggest that coal power expansions do not lead to differential economic gains for populations living nearby. This is unsurprising, since coal plants primarily generate electricity for transmission through the national grid rather than for local consumption.

**Table 7:** Coal expansion on night lights

| | (1)<br>Max night light pixel value in polygon | (2)<br>Total night light (calibrated) in polygon, by year |
|---|---|---|
| Capacity (GW) | -0.044 | 751.478 |
| | (0.454) | (485.100) |
| Observations | 5365557 | 5365557 |
| Year FE | Yes | Yes |
| Village FE | Yes | Yes |

Standard errors in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

[9] $NightLight_{vt} = \beta, CoalCapacity_{vt} + \alpha_v + \gamma_t + \epsilon_{vt}$. The regression is weighted by village population.

### 7.5 Mechanisms: Impact of coal power expansion on infant height

One of the channels pollution from coal expansion can affect kids education is through infant health. Previous studies in the literature have documented increased prevalence of stunting and anemia amongst infants exposed to coal (Datt et al., 2023; Vyas, 2023). It is not possible to verify if the coal exposed kids in my sample are anemic or stunted as the DHS does not collect health related information from kids who are older (6-16 years in our case). Given this for robustness, I verify the effect of coal capacity expansion on infants in the DHS data I am using. For this I largely replicate Vyas (2023), who has already established stunting amonsgt kids in coal exposed areas using the DHS 2015 sample. The replicated results can be found in Table 8.

The results indicate decrease in heights of kids born in coal exposed areas. One GW increase in coal capacity results in 0.08 SD reduction in heights. Exposure to coal worsens the already existing height deficit amongst kids in India. These results are insensitive to inclusion of controls (2) such as religion, gender, birth order, mother age and indicator for institutional delivery. They are also robust to inclusion of Sex-by-Year fixed effects.

**Table 8:** Effect of coal capacity on infant heights

| | (1) | (2) | (3) |
|---|---|---|---|
| | height-z-score | height-z-score | height-z-score |
| Capacity (GW) | -0.0866** | -0.0890** | -0.0868** |
| | (0.0435) | (0.0434) | (0.0433) |
| $N$ | 204704 | 204704 | 204704 |
| Year of Birth FE | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes |
| Sex-by-Year of Birth FE | No | No | Yes |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

# 8 Other Educational Outcomes

I examine the impact of coal power expansion on other education related outcomes such as test scores and enrollment.

## 8.1 Test Scores

**Specification:** I use two waves of IHDS data from 2005 and 2012, to examine the impact of coal power expansion on test scores. For this I follow this specification:

$$y_{idt} = \beta x_{dt} + \theta_1 D_{idt} + \theta_2 H_{idt} + \alpha_d + \gamma_t + \epsilon_{ipdt} \tag{3}$$

here $i$ indexes individual children, $d$ indexes the district and $t$ indexes the time of the survey round for the IHDS which are 2005 and 2012. The dependent variable $y$ measures the educational outcomes and takes the following forms: a) the age-adjusted z score of the child or b) reading or math scores, ranging from 0 to 4 measured during the survey. The main independent variable $x$ represents the number of coal-fired units or capacity (MW) additions in the districts between the 2005 and 2012 rounds of the IHDS. The IHDS allows me to include a rich set of demographic $D$ and household level $H$ controls such as family size, highest female adult education, electricity access, annual income and access to toilet, all measured during the IHDS baseline round in 2005. Since treatment occurs at the district level, I include district fixed effects $\alpha$ to control for time-invariant characteristics across districts. I also include survey fixed effects $\gamma$ and for regressions with math and reading scores, I use birth-cohort fixed effects to control for time-invariant differences between birth cohorts. Standard errors are clustered at the district level.

**Results:** Table 9 reports results on test scores for children aged 8–11. I consider age-adjusted z-scores, reading scores, and math scores as outcomes. In Panel A, I find that the addition of one coal power unit is associated with a 0.02 SD decline in overall test scores, with a larger decline in raw reading scores than in math scores. Similar effects appear in Panel B, where the main regressor is coal capacity additions. Importantly, these results are robust to the inclusion of various demographic and household-level controls, suggesting that the estimated effects are not driven by differential socioeconomic characteristics across households. This effect is large and is line with other papers in the literature looking at the impact of coal-fried power plants on test scores (**?**).

**Table 9:** Coal plant expansion on test scores

| | **Standardized Score** | **Reading Level** | **Math Level** |
|---|---|---|---|
| **Panel A: Effect of Plant Count** | | | |
| Plant Count | -0.0291*** | -0.0394*** | -0.0215** |
| | (0.0081) | (0.0120) | (0.0091) |
| **Panel B: Effect of Capacity (MW)** | | | |
| Capacity (GW) | -0.0711** | -0.0928** | -0.0517** |
| | (0.0275) | (0.0412) | (0.0233) |
| $N$ | 23531 | 23657 | 23562 |
| District Fixed Effects | Yes | Yes | Yes |
| Age Fixed Effects | Yes | Yes | Yes |
| Survey Fixed Effects | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In

**Robustness Checks:** Alike Section 6, migration can be a threat in this specification as well. Districts that witness an additional coal unit might drive-in poorer households due to fall in real estate prices due to degradation of the local environment. This might result in negative selection in the treatment group and can bias the estimates. In order to check for this I restrict my sample to households who have not moved in the last 8 years. This results only in a small drop in the sample size as 2% of the households have moved in the last 8 years. Table A.4 shows the results with this sample and unsurprisingly I find no changes in the results.

I further check if coal capacity expansion leads to increased electrification in districts that host the coal plant. Increased electricity access could be correlated with educational outcomes, thus making it difficult to identify the health impact of coal capacity additions on educational outcomes. However, Table A.5 shows no increase in both electricity access and electricity hours in districts with coal capacity additions. This is similar to the results results using night-lights in Section 6 and indicates no differential increase in electricity access in districts that get a coal plant addition.

**Pre-trends:** The placement of coal power plant expansions across districts might not be random if they follow underlying socioeconomic trends that also affect education. To test for this, I check for pre-trends to verify whether districts that received coal capacity expansions were on similar trajectories as those that did not. Since the first round of IHDS was conducted in 2005, no earlier survey data are available for such checks. I therefore rely on population census data from 1991 and 2001 to examine pre-trends. Table A.6 reports the results, showing no significant differences in trends prior to the coal capacity additions in 2005. This alleviates some concerns about non-random plant placement.

**With ASER data:** I conduct the same analysis with annual ASER data from 2007–2018[10]. The ASER data is annually available (barring a few interruptions) and covers a larger sample of kids in the age from 5–15. However, the data is only available at the district level and ASER samples kids only from rural areas. Despite this, in Table A.7 I present the results of coal capacity expansion on test scores of kids residing in districts within 50 km of a coal plant. I find that there is a significant decrease in arithmetic scores and no significant results for reading scores. Since arithmetic is generally considered more challenging, and ASER surveys consistently show that students struggle more with arithmetic compared to reading, this pattern is suggestive that coal capacity expansion adversely affects education outcomes, though the effects are not very large or consistently significant.

## 8.2 Enrollment

**Specification:** For enrollment, I use the panel data on schools from the DISE for the years 2005-2017. This data has information on number of kids enrolled in each school and can be used to estimate the impact of coal expansion on school-level enrollment. Importantly, DISE has details on school coordinates that help me isolate schools in the exposed areas 50km close to a coal power plant. The specification is as follows:

$$Enrollment_{ivt} = \beta CoalCapacity_{vt} + \alpha_v + \gamma_t + \epsilon_{vt} \tag{4}$$

Enrollment is measured at the school $i$ in village $v$ and year $t$. Similar to Equation 1, the main regressor is $\text{CoalCapacity}_{vt}$, defined as the coal capacity (GW) at the village level. I include village fixed effects $\alpha_v$ to account for time-invariant differences across villages, and state-year fixed effects $\gamma_t$ to control for common shocks in a state over time. Standard errors are clustered at the village level.

**Results:** Table 10 reports the results on school enrollment. I find that a 1 GW expansion in coal capacity reduces enrollment by 0.349 children per school-year. Similar effects are observed in column (2), where the regressor is the number of coal power unit additions. These results are robust to the inclusion of state-year and village fixed effects. The regressions use a very large sample, covering about 1.4 million schools across India tracked annually,

[10] $y_{dt} = \beta Capacity_{dt} + \alpha_d + \gamma_t + \epsilon_{dt}$. Here $t$ is all the survey years from 2007 to 2018

amounting to nearly 16 million school-year observations. Since data on the population of school-aged children is not available at the village level, it is difficult to comment on village-level enrollment rates. Nevertheless, DISE is widely used in the literature to study school enrollment in India (Adukia, 2017, 2022; Adukia et al., 2020; Sekhri and Li, 2020). Taken together with the other results, this provides further evidence of the negative effect of coal power production on education. One likely channel is health: negative health effects from coal exposure may reduce cognitive ability, increase absenteeism, and raise illness-related school dropouts, resulting in fewer children attending school in coal-affected areas.

**Table 10:** Effect of coal expansion on enrollment at the village level

| | (1)<br>Enrollment | (2)<br>Enrollment |
|---|---|---|
| Capacity (GW) | -0.349*** | |
| | (0.024) | |
| Plant Count | | -0.102** |
| | | (0.029) |
| Village FE | Yes | Yes |
| Year and State FE | Yes | Yes |
| Observations | 16,447,730 | 16,447,730 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Pre-trends:** The results from the event study are presented in Figure A.2. I find no evidence of concerning pre-trends, suggesting that treated and control villages followed similar trajectories before the coal capacity expansion. Following the expansion, however, enrollment declines noticeably, with the effect becoming statistically significant in period 3. This pattern indicates that the negative impact of coal capacity expansion on school enrollment emerges gradually rather than immediately, which is consistent with the idea that health or environmental channels take time to manifest in children's schooling outcomes. Overall, the event study highlights a persistent adverse effect of coal power expansion on educational participation in exposed areas.

# 9 Conclusion

This is one of the first studies to examine the impact of coal-based power generation on educational outcomes in the Indian context. I find that children exposed to coal emissions at birth acquire less schooling later in life. I also document a contemporaneous increase in air pollution from coal power leading to declines in test scores and village-level enrollment. These results are robust across specifications and after accounting for various demographic and household-level factors. Taken together, they add to the evidence on the negative health impacts of coal-based power production in India.

These findings highlight the need to account for the health externalities of coal power when evaluating energy policy. Greater adoption of abatement technologies is necessary, alongside a serious consideration of whether cleaner energy alternatives can replace coal as a less polluting source of power.

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# 10 Appendix

## 10.1 Tables

**Table A.1:** Summary Statistics

| | No exposure (> 50 km) | Exposure ($\leq$ 50 km) | Difference | s.e. |
|---|---|---|---|---|
| Total years of education | 3.905 | 4.121 | -0.216 | (0.0089) |
| Primary completion | 0.416 | 0.446 | -0.0296 | (0.0015) |
| Middle school completion | 0.137 | 0.167 | -0.0295 | (0.0011) |
| On track (age-grade) | 0.620 | 0.633 | -0.0133 | (0.0015) |
| At school (current year) | 1.844 | 1.840 | 0.0041 | (0.0017) |
| Hindu | 0.706 | 0.822 | -0.116 | (0.0013) |
| Scheduled caste | 0.192 | 0.243 | -0.0509 | (0.0012) |
| Scheduled tribe | 0.236 | 0.111 | 0.125 | (0.0012) |
| Urban (=1) | 1.809 | 1.721 | 0.0876 | (0.0013) |
| Household size | 5.924 | 6.010 | -0.0865 | (0.0073) |
| Child age (years) | 10.36 | 10.54 | -0.180 | (0.0088) |
| Year of birth | 2009.42 | 2009.57 | -0.148 | (0.0088) |
| Female (=1) | 1.484 | 1.480 | 0.0045 | (0.0015) |
| LPG cooking | 0.423 | 0.471 | -0.0480 | (0.0015) |
| N (children) | 371,288 | 149,386 | | |

**Table A.2:** Effect of coal power units on education attainment

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | total_education_years | primary | middle | on_track | at_school_current_year |
| Number of plants | -0.027*** | -0.005*** | -0.005*** | -0.005*** | -0.002 |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 506846 | 506846 | 506846 | 506846 | 506846 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes | Yes | Yes |
| Demographic/Household Controls | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses
* p¡0.10, ** p¡0.05, *** p¡0.01

**Table A.3:** Variation only from existing plant expansion

| | (1) total_education_years | (2) primary | (3) middle | (4) on_track | (5) at_school_current_year |
|---|---|---|---|---|---|
| cum_capacity | -0.073*** | -0.012*** | -0.008*** | -0.012*** | -0.012*** |
| | (0.009) | (0.001) | (0.002) | (0.003) | (0.004) |
| Observations | 433348 | 433348 | 433348 | 433348 | 433348 |
| Cohort FE | Yes | Yes | Yes | Yes | Yes |
| Village FE | Yes | Yes | Yes | Yes | Yes |
| Demographic/Household Controls | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

**Table A.4:** Effect of Capacity (GW) on Outcomes of Household living 8 years or more

| | (1) Standardized Score | (2) Reading Level | (3) Math Level |
|---|---|---|---|
| Capacity (GW) | -0.0735*** | -0.0972** | -0.0523** |
| | [0.0275] | [0.0406] | [0.0234] |
| $N$ | 22755 | 22879 | 22785 |
| District Fixed Effects | Yes | Yes | Yes |
| Survey Fixed Effects | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes |
| Household level Controls | Yes | Yes | Yes |
| Age Fixed Effects | Yes | Yes | Yes |

Standard errors clustered at the district level

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table A.5:** Effect of Capacity (MW) on Electrification

| | (1) Electricity Access | (2) Electricity Hours |
|---|---|---|
| Capacity (GW) | 0.000429 | 0.426 |
| | [0.00962] | [0.502] |
| $N$ | 31575 | 24732 |
| District Fixed Effects | Yes | Yes |
| Survey Fixed Effects | Yes | Yes |

Standard errors clustered at the district level

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table A.6:** Pre-program Parallel Trends

| | (1)<br>Δ total literacy rate | (2)<br>Δ female lit rate | (3)<br>Δ total schools | (4)<br>Δ total colleges |
|---|---|---|---|---|
| (sum) plant_count | 0.002 | 0.002 | 13.655 | -5.511 |
| | (0.001) | (0.002) | (27.809) | (8.101) |
| Constant | 0.120*** | 0.133*** | 499.252*** | -13.540 |
| | (0.002) | (0.003) | (29.029) | (9.788) |
| Observations | 421 | 421 | 421 | 421 |

Robust Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table A.7:** Impact on test scores using ASER

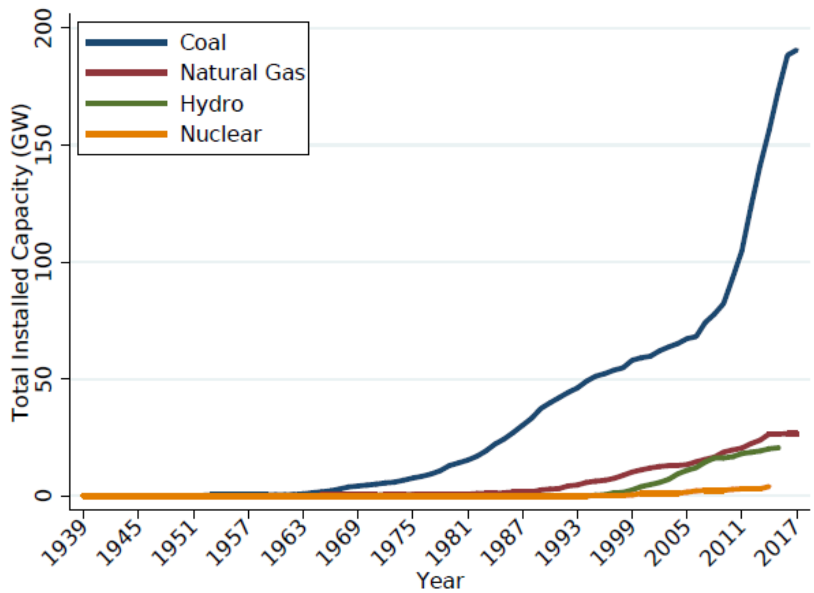
| | (1)<br>read_code | (2)<br>math_code |
|---|---|---|
| total_cap | 0.000112 | -0.000329** |
| | (0.000122) | (0.000144) |
| Observations | 674696 | 672201 District FE |
| Yes | Yes Year FE | Yes |
| Yes | | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## 10.2 Figures

**Figure A.1:** Evolution on energy mix in India




Source: Barrows et al. (2019)

**Figure A.2:** Event Study with the school enrollment data