# Industrialization and Pollution: The Long-term Impact of Early-Life Exposure on Human Capital Formation

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**Abstract**

Air quality in developing countries is often much worse than in developed economies, yet evidence on the long-term human capital effects of air pollution in these settings is limited. This paper uses a cohort difference-in-differences approach to examine the impact of early-life exposure to air pollution during China's 1950s industrialization on human capital formation. It assumes that economic opportunities linked to industrial plants impact upwind and downwind counties similarly within a 30-mile radius. The results indicate that moving from the 25$^{th}$ to 75$^{th}$ percentile of exposure reduces children's education by approximately 0.11 years. This effect size is notably larger than the impacts of three other factors affecting educational attainment in both China and the United States.

**Keywords**: Industrialization; Air Pollution; China; Human Capital

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# 1 Introduction

Early-life exposure to air pollution is known to impair children's cognitive abilities (e.g., Lopuszanska and Samardakiewicz, 2020; Wodtke et al., 2022; Ni et al., 2022). Yet a crucial question remains: do these cognitive impacts translate into long-term losses in human capital? This question is particularly important for developing countries, where air quality is significantly worse than in developed economies (Greenstone and Jack, 2015), and where families and schools may be more constrained in their ability to compensate for early-life impairments. However, empirical evidence on the long-term effects of air pollution on human capital in these settings remains scarce, hindering effective policy-making.

Isolating the long-term adverse effects of pollution on human capital is challenging, especially when considering migration. Population mobility can obscure the true relationship between pollution exposure and human capital outcomes, as individuals may selectively relocate to avoid pollution, making it difficult to establish causality. The context of 1950s China, marked by rapid industrialization and highly restricted migration, offers a unique setting to examine these effects.

This paper investigates the long-term effects of early-life exposure to air pollution during China's 1950s industrialization on educational attainment.[1] In the early 1950s, China's central government embarked on an ambitious mission to transition from an agrarian society to an industrial powerhouse. Mao's vision was to "Surpass Britain and Catch Up with America."[2] Central to this ambition was the establishment of steel plants, which were major consumers of coal and significant emitters of pollutants such as dust, nitrogen oxides ($NO_X$), sulfur dioxide ($SO_2$), particulate matter (PM), and carbon monoxide (CO).

In the absence of air pollution monitoring data, I use pig iron production between 1959 and 1970 as a proxy for plant emissions.[3] Wind pattern data for steel plant locations are used to

[1] Early childhood or early life is defined as the period from birth to 4 years old.

[2] "Chao Ying Gan Mei" (in Chinese). This directive aimed to match Britain in steel production within 15 years and surpass the United States within 20 years.

[3] Most steel plants built during the late 1950s could produce pig iron, though only a few had the capacity to produce steel. Note that the Great Leap Forward's campaign for iron and steel production in 1958–59 lasted only a few months and had no substantial impact on iron production (Wagner, 2013).

calculate the dispersion of air pollution. This data is combined with individual-level census data to form a dataset focusing on counties near the plants.[4]

The challenge in identification stems from the dual nature of industrialization: economic opportunity effects and pollution issues.[5] To address this challenge and isolate the negative impact of pollution from the overall effects, I use a cohort-difference-in-differences (DiD) approach incorporating spatial dimensions based on distance to the pollution source (i.e., the steel plant). This approach assumes that the economic opportunities linked to steel plants affect upwind and downwind counties similarly within a 30-mile radius. Variation in air pollution due to wind patterns allows the double difference approach to mitigate economic opportunity effects and isolate the negative impacts of pollution.[6] I compare cohorts born after a steel plant's opening (treatment cohorts, 1959–1966) with those born four or more years earlier (control cohorts, 1946–1954).[7] To isolate the impact of pollution, I take a second difference between counties with varying pollution levels within the 30-mile radius. A simplified dispersion model calculates exposure levels in nearby counties.

I find that moving from the 25$^{th}$ to 75$^{th}$ percentile of exposure intensity, an increase of approximately 10.43 units of pig iron production,[8] results in a reduction in educational attainment by 0.11 years. This effect size is about six times the impact of early-life wildfire smoke exposure in the United States from 1930 to 1969 (Neller and Arenberg, 2023), and more than twice the effect of compulsory education laws in the United States between 1915 and 1939 (Lleras-Muney, 2005).

[4]The census data only contains information about the county where an individual was living at the time of the survey.

[5]Industrialization can spur local economic growth while potentially negatively affecting education, as young labor may prioritize work over schooling, and introduce substantial pollution issues.

[6]In this paper, "pollution" specifically refers to air pollution resulting from industrialization. Water pollution from industrial plants is not considered, as my identification strategy relies on variation in wind patterns, which are less likely to be correlated with water pollution. Additionally, the counties where industrial plants are located are excluded from the sample, further mitigating any potential influence of water-related pathways on the results.

[7]The four-year gap is chosen to minimize changes in early brain development, as over 80% of an infant's brain functions develop in the first three years of life. (The United Nations Children's Fund). Source: https://www.unicef.org/parentingtips/baby-milestones. Currie and Almond (2011) highlights that early experiences shape human capital, and Colmer, Voorheis, and Williams (2023) shows that pollution affects children up to age twelve, with significant effects until age five. In the robustness check, cohorts born after the steel plants' openings are compared with those born five or more years earlier.

[8]One unit represents 10,000 tons of pig iron.

When evaluated at the average exposure intensity, this effect is roughly twice that of the Send-Down Movement in China during the late 1960s to the 1970s (Chen et al., 2020).[9] Additionally, moving from the 25$^{th}$ to 75$^{th}$ percentile of exposure intensity significantly reduces primary and junior high school graduation rates by 0.51 and 1.43 percentage points, respectively. These results are robust across various settings.

I also find that boys are three times more affected by the negative impact associated with steel plant openings compared to girls, aligning with findings that males are more adversely affected by pollutants in exams (Ebenstein, Lavy, and Roth, 2016; Roth, 2020). This gender difference may be explained by the "weak male" hypothesis (Kraemer, 2000), which suggests that human males are generally more vulnerable than females. No significant differences are observed between urban and rural residents.

This paper contributes to the literature on the detrimental impacts of air pollution on human capital. A large body of literature shows that air pollution reduces performance on academic and cognitive tests.[10] However, most of these studies focus on short-term effects. While growing literature examines the long-term human capital effects of air pollution (Sanders, 2012; Voorheis, 2017; Bharadwaj et al., 2017; Colmer and Voorheis, 2020; Persico, 2022; Neller and Arenberg, 2023), it predominantly centers on U.S. cases,[11] with little attention to developing countries where air quality is remarkably worse (Greenstone and Jack, 2015). Additionally, migration presents a major concern in these settings. My paper fills this gap by investigating the long-term impact of air pollution on human capital formation in China, a developing country characterized by stringent migration controls and top-down policy.[12] The findings reveal a substantial reduction in children's

[9]Note that the effect in Chen et al. (2020) is evaluated at the average exposure intensity. The Send-Down Movement refers to a phenomenon during the Cultural Revolution (1966–1976) in China, which sent educated youth to rural areas. Approximately 16 million educated youths were mandated to go to rural and border areas of China (Chen et al., 2020).

[10]These include lower academic test scores (Ebenstein, Lavy, and Roth, 2016; Zivin et al., 2020; Roth, 2020; Bedi et al., 2021), worse cognitive performance (Zhang, Chen, and Zhang, 2018; La Nauze and Severnini, Forthcoming; Carneiro, Cole, and Strobl, 2021; Lai et al., 2022; Krebs and Luechinger, 2024), and more school absences (Currie et al., 2009; Liu and Salvo, 2018; Persico, Figlio, and Roth, 2020). See Aguilar-Gomez et al. (2022) for a complete review.

[11]The exception is Bharadwaj et al. (2017), which studies the impact of fetal exposure to air pollution on fourth-grade test scores in Chile.

[12]Relatedly, there is a vast literature on fetal origins, which explores the impact of early-life shocks on later-life out-

educational attainment due to early-life exposure to pollution.

The remainder of this paper is organized as follows. Section 2 offers background information on the construction of steel plants, infrastructure, and the education system in 1960s China. Section 3 outlines the data employed in this study. The identification strategy is presented in Section 4. Section 5 presents the empirical findings. Section 6 conducts a series of robustness checks an analysis of heterogeneity. Finally, Section 7 offers concluding remarks.

# 2 Background

## 2.1 Industrialization in Mid-20th Century China

In the mid-20th century, China had a relatively underdeveloped economy, with an urbanization rate of only 10.64% by the end of 1949.[13] Mao Zedong highlighted this deficiency, stating: "Now, what can we produce? We can make tables and chairs, tea cups and teapots, grow grains, grind them into flour, and make paper. However, we cannot produce a car, an airplane, a tank, or a tractor" (Mao, 1961). To address this, China prioritized heavy industry, notably steel production, to bridge the industrial gap. The Korean War (1950–1953) underscored China's need for rapid industrialization to enhance national defense capabilities.[14]

During the First Five-Year Plan (1953–1957), major steel plants such as Anshangang, Wuhangang, and Baotougang were established.[15] Mao's 1956 speech, "On the Ten Major Relationships," acknowledged the challenges of industrialization and emphasized the need for balanced development,

comes (e.g., Barker, 1990; Schultz and Strauss, 2008; Deschênes, Greenstone, and Guryan, 2009; Isen, Rossin-Slater, and Walker, 2017; Hoynes, Schanzenbach, and Almond, 2016; Bharadwaj, Eberhard, and Neilson, 2018) (see Almond and Currie (2011) and Almond, Currie, and Duque (2018) for a more complete review). As Almond, Currie, and Duque (2018) emphasizes, understanding the "missing middle" years and whether long-term effects can be predicted using early and middle childhood indicators is crucial. My paper contributes to this body of literature by showing that early-life exposure to industrial pollution adversely affects educational outcomes during middle childhood in a developing-country setting with highly restricted migration.

[13]Source: https://www.chinadaily.com.cn/a/202203/09/WS6227e5cfa310cdd39bc8b4be.html.

[14]The outbreak of the Korean War highlighted the equipment gap between China and the United States on the battlefield, underscoring China's weak industrial capacity and its impact on the stability of the military situation. This stark contrast made it especially urgent for China to achieve industrialization and modernize its national defense capabilities.

[15]The term "gang" in Chinese represents "steel." Anshangang is located in Anshan city, Liaoning Province, and was expanded from an existing facility. Baotougang is in Baotou city, Inner Mongolia, while Wuhangang is situated in Wuhan city, Hubei Province.

utilizing both coastal and inland industrial bases.[16] Consequently, the Ministry of Metallurgical Industry and local governments planned and established additional medium and small-sized steel plants, leading to a broad distribution of steel facilities, as illustrated in Appendix Figure B2. Steel plants were strategically located near water bodies and resources, such as coal and iron ore, to enhance production efficiency. For example, the location of Wuhangang was approximately 3 miles from the Yangtze River and was chosen for its favorable topography, meteorology, and transportation infrastructure.

Compared to U.S. steel plants, those in China during the 1960s were relatively small. The largest U.S. steel plant, Gary Works, produced an estimated 4.6 million tons annually between 1909 and 1996,[17] while U.S. Steel's Fairfield plant had a capacity of 3 million tons of raw steel.[18] In contrast, Wuhangang, the largest plant in my sample, produced only 0.9 million tons annually between 1959 and 1970.

The 1991 China Environmental Status Report indicated that half of the top ten cities with high atmospheric dustfall had steel plants.[19] Statistics from 2005 show that producing 1 million tons of pig iron was associated with 5,700 tons of TSP (Total Suspended Particulates) emissions.[20] Based on this emission intensity, Wuhangang, the largest steel plant in my sample, increased daily TSP concentrations in Qingshan district by about 55 $\mu g/m^3$ during the study period.[21]

## 2.2 Education Changes in the 1960s

Changes in the education system during the 1960s, particularly the shift in schooling structure, are relevant as they may amplify or moderate the effects of early-life pollution on educational attainment. The 1960s were a distinctive period for China's education system due to the Cultural

[16] Source: https://www.marxists.org/history/erol/periodicals/call/call-6-3-supp.pdf.

[17] This figure is calculated from the total production of approximately 400 million tons of steel over that period. Source: https://www.chicagotribune.com/1996/02/26/gary-works-made-of-steel/#:~:text=Since%20starting%20production%20on%20Feb,400%20million%20tons%20of%20steel.

[18] Source: https://www.bhamwiki.com/w/Fairfield_Works.

[19] "Dustfall" refers to dust particles settling from the atmosphere. Source: https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/201605/P020160526547820754160.pdf.

[20] Source: https://www.mee.gov.cn/gkml/zj/bgth/200910/W020071018462849552438.pdf, page 6.

[21] Back-of-the-envelope calculation assuming a 1,000-meter atmospheric mixing layer. Qingshan, a county-level district in Wuhan city, covers an area of 108 square miles (or 280 square kilometers).

Revolution (1966–1976). Before this period, the education system adhered to a standardized 6-3-3 structure: six years of primary education, followed by three years each of junior and senior high school. During the Cultural Revolution, significant disruptions led to a shift to a 5-2-2 system,[22] which shortened the duration of both primary and secondary education as part of broader ideological shifts. The education system eventually reverted to the 6-3-3 structure after the revolution (Hannum, 1999; Chen, Jiang, and Zhou, 2020; Chen et al., 2020).

### 2.3 Road Infrastructure

Understanding China's historical transportation infrastructure is crucial for our identification strategy, as limited mobility reduced families' ability to relocate in response to air pollution. In mid-20th century China, heavy industry was prioritized, leading to the neglect of light industry, agriculture, and passenger transport (Hunter, 1965). Prior to the Reform and Opening-up (1978),[23] road infrastructure was underdeveloped, particularly in rural areas, with most roads being unpaved or poorly maintained. It wasn't until 1988 that the first expressway on China's mainland was built.[24] During this period, primary modes of transportation included bicycles, walking, and limited public transit in urban areas, with motorized vehicle availability being very low, especially in rural regions. In 1980, the motorization rate was only 1.70 vehicles per 1,000 population (Riley, 2002), and personal vehicle ownership was restricted until the mid-1980s due to its association with capitalism.

## 3 Data

My paper draws data from three main sources: census data obtained from the Integrated Public Use Microdata Series (IPUMS) (Minnesota Population Center, 2020), plant-level production statistics from the "Compilation of Fifty Years of China's Steel Industry Statistics" (Editorial Board, 2003),

[22] Exploiting this shift, Chen, Jiang, and Zhou (2020) estimates returns to education at 12.7%, while Giles, Park, and Wang (2019) uses the Cultural Revolution as an exogenous variation to estimate a return to college education of 37.1%. Note that in the empirical analysis of my paper, county fixed effects and province-by-year fixed effects are included to account for policy changes, with the Cultural Revolution considered in the robustness checks.

[23] "Reform and Opening-up" refers to the economic reforms China began in 1978, transitioning from a planned economy to a market-oriented one.

[24] Source: http://www.china.org.cn/china/70-years-of-chinas-transport-development/index.html.

and wind direction and speed data from the ERA5-Land reanalysis dataset (Muñoz Sabater, 2019).

## 3.1 Census Data

My paper mainly uses the 1990 China census data, specifically the 1% systematic sample from the IPUMS. The 1982 and 2000 censuses are used for reference.[25] In these censuses, the smallest administrative unit is a county (or district), which is a lower level within a city's administrative hierarchy.[26] Note that the census data only provides information on the county (or district) where individuals resided at the time of the survey, with no data on previous locations.[27]

Given the data availability and research objectives, years of education are used as the primary outcome variable. To minimize variability in educational outcomes, the sample is restricted to individuals aged 20 or older, excluding cohorts born after 1970. Since the censuses provide education levels rather than years of schooling, I use the coding method from Chen et al. (2020) to address this issue.

## 3.2 Pig Iron Production

I collect historical production data from 15 steel plants that began operations around early 1959 (referred to as "1959 openings").[28] These plants are distributed across 13 provinces in China.[29] Appendix Figure B1 shows the aggregated production from 1959 to 1970, and Appendix Figure

[25]The 1982 census is unsuitable for post-treatment analysis because the treatment cohorts (born 1959–1966) were under 20, making their educational attainment unreliable for long-term effects. The 2000 census, conducted after the relaxation of migration policies, shows significant internal migration. China did not ease restrictions on rural-urban migration until at least 1993(Chan and Zhang, 1999), following Deng Xiaoping's 1992 Southern Tour Speech, which initiated substantial economic reforms and increased migration.

[26]In China, a city includes multiple counties or districts. The sample comprises 124 counties.

[27]Based on my calculations using the 1990 census data, approximately 95% of individuals reported that their usual residence in 1990 was the same as that in 1985. In the robustness check, I exclude individuals who reported migration in the last 5 years.

[28]Among these 15 plants, two started around 1952 but had significantly lower production before 1958. Ten plants began roughly in mid-1958, and three started in 1959. Since most plants began in late 1958, 1959 is designated as the starting point for the treatment period. The yearbook lists over 60 steel plants with pig iron production data, mostly concentrated around 1958 and 1970. This paper focuses on the 1959 openings, as they align with the early stages of China's industrialization and the 1990 census data, a period with stringent migration controls. Besides the 15 plants, 21 other active plants in 1959 are considered. Eight of these, established more than 10 years earlier, were renovated or expanded in 1959 and are used for falsification tests in Section 5.3 to evaluate the distribution of economic opportunities around steel plants. Most of the remaining 21 plants operated briefly from 1959 to 1966 with negligible production, so they were not included. Appendix Table A1 summarizes information on the 36 plants.

[29]These plants have virtually no overlap in space with other plants outside the sample within a 30-mile radius.

B2 displays their geographical locations. The dataset for the 1959 openings is matched with the 1990 census data. To supplement the primary findings, it is also matched with the 1982 and 2000 censuses.

Due to the lack of pollution monitoring data, total emissions from a plant are proxied by aggregate pig iron production from 1959 to 1970. Cohorts born between 1967 and 1970 are excluded from the sample because they had less than four years of overlap with the 1959–1970 production period during their early childhood.[30] The resulting dataset includes cohorts born between 1946 and 1966. Figure 1 illustrates the cohort definitions.

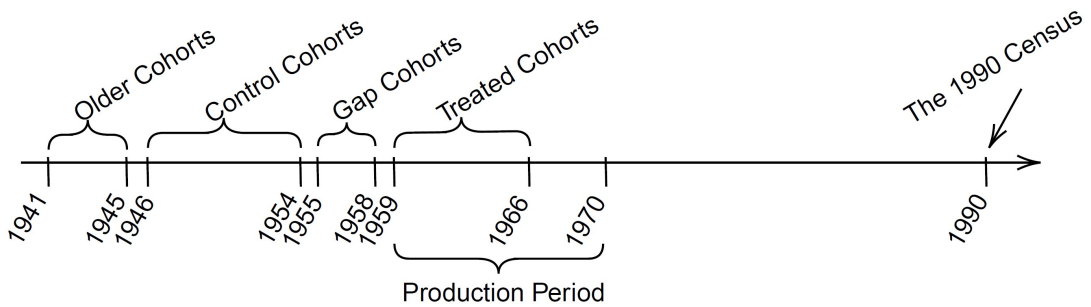


**Figure 1:** Definition of Cohorts, Production Period, and the Census Used. *Notes*: Cohorts born between 1955 and 1958 fall within the "gap period" and experienced partial exposure to pollution during their early childhood. They are dropped when running the Eq. 2. Cohorts born between 1967 and 1970 were excluded from the sample since they had less than four years of overlap with the 1959–1970 production period during their early childhood.

My paper focuses on pig iron to avoid the statistical challenges associated with raw material variability and to ensure consistency, as many plants produce only pig iron. It also avoids using plant capacity as a proxy for pollution due to frequent discrepancies between designed capacity and actual output.

[30] My paper does not aggregate production data from 1959–1974 to include cohorts born between 1967 and 1970. This is because production from 1971–1974 was approximately 1.8 times higher than from 1967–1970, and accounted for roughly 69% of the total production during the treatment period. Including these years would shift the variation in production, introducing larger measurement errors.

## 3.3 Wind Direction and Speed

I collect historical daily wind direction and speed data for the locations of steel plants from the ERA5-Land reanalysis dataset via Google Earth Engine.[31] This dataset provides wind data for each plant from 1959 to 1970.

## 3.4 Summary Statistics

My empirical strategy focuses on steel plants and their surrounding counties within a 30-mile radius. Table 1 presents summary statistics for the steel plants and the 1990 census data.

Panel A of Table 1 shows that half of the 15 steel plants produced less than 1 million tons of pig iron during the period of 1959–1970. Based on production levels, the plants are categorized as large, medium, or small. Panel B of Table 1 presents county-level statistics from the 1990 census, segmented by distance from a steel plant. Counties within a 30-mile radius exhibit higher average years of education compared to those 30 to 60 miles away. This suggests that steel plants were strategically placed in areas with higher educational levels, rather than randomly. Additionally, counties within a 30-mile radius have a higher proportion of individuals with urban Hukou status.[32]

The selection of steel plant locations and their scale considered multiple factors, including transportation, meteorological conditions (particularly wind direction), and regional demographics.[33] However, my identification strategy outlined in the following section relies on the parallel trend assumption rather than random selection.

[31] Source: https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_LAND_DAILY_AGGR#description.

[32] "Hukou" refers to China's household registration system, which restricted rural-to-urban mobility. Rural Hukou holders were expected to remain in rural areas and could not freely migrate to cities.

[33] Appendix Table A2 shows the correlations between exposure intensity (based on production, distance, and wind direction) and local characteristics.

**Table 1:** Summary Statistics of Steel Plants and the 1990 Census

| **Panel A: Summary Statistics of the Steel Plants** | | | | |
|---|---|---|---|---|
| Steel Plant Size | All Plants | Small (Prod $\leq$100) | Medium (100<Prod<500) | Large (Prod$\geq$500) |
| Number of Plants | 15 | 8 | 5 | 2 |
| Average Production | 187.19 | 40.19 | 162.84 | 836.05 |
| | (286.04) | (16.29) | (38.25) | (346.27) |
| **Panel B: Summary Statistics of the 1990 Census** | | | | |
| Distance from steel plant | Within 30 miles | | Between 30 and 60 miles | |
| Cohort | Control group (1946–1954) | Treatment group (1959–1966) | Control group (1946–1954) | Treatment group (1959–1966) |
| Years of education | 7.04 | 9.24 | 6.14 | 8.47 |
| | (3.49) | (2.96) | (3.45) | (2.96) |
| Gender (male = 1) | 0.51 | 0.51 | 0.52 | 0.51 |
| | (0.50) | (0.50) | (0.50) | (0.50) |
| Ethnic (Han = 1) | 0.98 | 0.97 | 0.96 | 0.96 |
| | (0.13) | (0.16) | (0.18) | (0.19) |
| Hukou (urban = 1) | 0.39 | 0.36 | 0.18 | 0.18 |
| | (0.49) | (0.48) | (0.38) | (0.38) |
| Observations | 92571 | 102030 | 118568 | 135209 |

*Notes*: Panel A categorizes 15 steel plants into small, medium, and large sizes based on their production from 1959 to 1970 (in 10,000 tons). Panel B displays mean values of key 1990 census variables for counties within 30 miles of a plant and those between 30 and 60 miles. The Han ethnic group is the majority, while non-Han represent minorities. "Hukou" refers to China's household registration system, which restricted migration for rural Hukou holders. Standard deviations are in parentheses.

# 4 Dispersion Model and Empirical Strategy

I use a 30-mile radius as the study region, which is a distance commonly used by professional dispersion models such as AERMOD.[34] This radius also serves as the boundary within which a simplified dispersion model calculates pollution levels for each county; counties beyond this radius are assumed to experience minimal or no pollution due to the plant. I further justify the choice of a 30-mile radius as the study area with a placebo test in Section 5.

## 4.1 Dispersion Model

This paper uses a simplified dispersion model to calculate exposure intensity measures and evaluates its effectiveness using a representative steel plant. Details on the model selection and its effectiveness are provided in Appendix Section C.

The model construction follows established methodologies from existing literature, including Schlenker and Walker (2016), Herrnstadt et al. (2016), Heyes and Zhu (2019), and Wang, Lin, and Qiu (2022). It incorporates key factors such as distance from the pollution source, wind direction, and wind speed.

**Measures of Exposure Intensity**

I derive two measures of exposure intensity from the dispersion model. *Measure 1* is used in the main analysis, while *Measure 2* serves as a robustness check. Both measures assign standardized weights to counties within a 30-mile radius of a steel plant. The weight calculation involves two components: the distance from county $i$ to steel plant $j$, and the wind speed-weighted average of the projection of the wind direction (where the wind blows to) on the line joining the administrative central point of county $i$ and steel plant $j$. The key difference between the measures is that *Measure 1* calculates a single weight for the production period (1959–1970), while *Measure 2* accounts for annual fluctuations in steel production and calculates weights annually. Further details are provided in Appendix Section C. Maps illustrating the distribution of exposure intensity for the 15 steel plant

[34] Source: https://www.epa.gov/sites/default/files/2020-09/documents/aermet_userguide.pdf.

areas are available in Appendix Figures C2 through C5.

## 4.2 Empirical Strategy

According to UNICEF (United Nations International Children's Emergency Fund), over 80% of an infant's brain development occurs within the first three years of life.[35] This early stage of brain development is particularly vulnerable to pollution, which has been shown to adversely affect cognitive development in children (World Health Organization, 2018).[36]

To assess the impact of pollution, I compare cohorts born after the establishment of steel plants (treatment cohorts, born between 1959 and 1966) with those born four years prior (control cohorts, born between 1946 and 1954). The four-year gap ensures that the brain development of control cohorts is near completion. However, economic opportunity effects associated with industrialization, represented by steel plant operations, could confound the assessment of the negative impact.

To address this, my paper focuses on counties within a 30-mile radius of the steel plants, assuming economic opportunities are evenly distributed within this range. I use a cohort-DiD approach to estimate the negative impact of steel plant operations.[37] The key assumption is the parallel trends, which suggest that, in the absence of steel plant operations, trends between more and less treated locations would have been similar. This strategy does not require random selection of plant locations. As noted, the selection of steel plant locations and their scale considered various factors, including transportation, meteorology (to minimize impact on major city areas), and regional demographics.

To mitigate the concern about the influence of heavy investments and the recruitment of experienced workers, individuals from the counties (or districts) where the steel plants are located are excluded from the sample.

The identification relies on two sources of variation: first, within a 30-mile radius, counties receive different exposure levels based on pig iron production, considering distances and wind

[35] Source: https://www.unicef.org/parentingtips/baby-milestone.

[36] Source: https://www.who.int/news/item/29-10-2018-more-than-90-of-the-worlds-children-breathe-toxic-air-every-day.

[37] This methodology follows Duflo (2001) and Chen et al. (2020).

patterns. Second, cohorts born before 1954 and after 1959 experience different levels of exposure to steel plant operations before age four.

## 4.3 Setup for Event Study

The parallel trends assumption cannot be directly tested, but we can examine its plausibility through an event study model. As previously mentioned, cohorts born between 1955 and 1958 fall within the "gap period" and experienced partial exposure to steel plant openings during their early childhood. In the event study (or the by-cohort specification), these "gap cohorts" are included to examine the trends. However, in the formal analysis, these cohorts are excluded from the sample due to concerns about their partial exposure and potential overlap with the construction process of the steel plants. In Eq. 1, the cohort born in 1954 serves as the reference point for comparison.

$$\begin{aligned} Y_{i,t,c,p} =& \alpha + \sum_{\lambda=1946}^{1953} \beta_\lambda \times expo\_intensity_{c,p} \times \mathbf{1}\{t = \lambda\} \\ &+ \sum_{\lambda=1955}^{1966} \beta_\lambda \times expo\_intensity_{c,p} \times \mathbf{1}\{t = \lambda\} + \varphi X_{i,t,c,p} \\ &+ \gamma_{c,p} + \Delta_c \times \tau_t + \mu_{prov} \times \tau_t + \epsilon_{i,p,c,t} \end{aligned} \tag{1}$$

$Y_{i,t,c,p}$ represents an outcome of interest for an individual $i$ born in year $t$, residing in county $c$ associated with steel plant $p$. $expo\_intensity_{c,p}$ indicates the exposure intensity of county $c$ from plant $p$. The function $\mathbf{1}\{t = \lambda\}$ is an indicator that equals 1 when an individual's birth year $t$ matches the specified parameter $\lambda$. $X$ includes a vector of individual-level control variables, such as ethnicity, gender, and Hukou type (indicating rural or urban residence). Note that Hukou type is available only from the 1990 census onward. The term $\gamma_{c,p}$ captures fixed effects specific to the county-plant pair, which essentially functions as county fixed effects due to the unique association of each county with a particular plant. $\tau_t$ represents birth year or cohort fixed effects.

My identification strategy mitigates concerns about confounding factors by concentrating on a 30-mile radius around each steel plant. Counties within this radius are closely related either

geographically or in terms of local characteristics. The primary challenge is addressing potential unobserved time-varying determinants of outcomes that could be correlated with exposure intensity, influenced by factors such as plant size, distance, and wind direction. Additionally, the assumption of uniform economic opportunity effects of steel plants within the 30-mile radius may be overly simplistic.

To mitigate these concerns, the model introduces interaction terms between county base education and birth year dummies ($\Delta_c \times \tau_t$). The county base education, derived from primary and junior high graduation rates of individuals born between 1941 and 1945 from the 1990 census, serves as a proxy for local human capital.[38] These interaction terms account for heterogeneous trends across counties. Note that adding these terms may reduce variation in exposure intensity due to the nonrandom selection of plant locations, which often correlates with local characteristics (see Appendix Table A2 for details on the correlation between exposure intensity and educational base).

The model also incorporates province $\times$ birth year fixed effects ($\mu_{prov} \times \tau_t$) to control for heterogeneous trends across provinces. The error term is denoted as $\varepsilon$, and standard errors are clustered at the county level.

## 4.4 Baseline Specification

This paper uses a cohort-DiD approach to estimate the effects. The baseline estimation equation is specified as follows:

$$\begin{aligned} Y_{i,t,c,p} =& \alpha + \beta \times expo\_intensity_{c,p} \times \mathbf{1}\left\{1959 \leq t \leq 1966\right\} + \varphi X_{i,t,c,p} \\ &+ \gamma_{c,p} + \Delta_c \times \tau_t + \mu_{prov} \times \tau_t + \epsilon_{i,p,c,t} \end{aligned} \tag{2}$$

In this setup, cohorts born between 1946 and 1954 are defined as comparison cohorts. Note that cohorts born between 1955 and 1958 are excluded when running Eq. 2 due to their partial exposure during the "gap period." All notations here are consistent with those in Eq. 1.

[38]The calculation of county base education follows the methodology outlined in Chen et al. (2020).

While this paper makes efforts to control for various trends, it is essential to acknowledge the potential influence of other unobservable factors on the results. Following Section 5, a series of robustness checks is presented to mitigate these concerns.

# 5 Empirical results

## 5.1 Results of Event Study

The primary dataset used for analysis is the 1990 census, with supplementary results from the other two included in the appendix to enrich the core analysis. Note that the sample comprises individuals aged 20 or above, as their educational attainments are less prone to substantial fluctuations over time.

During the construction and operation of steel plants, a substantial number of workers, including recent graduates and experienced technicians, were recruited from other provinces and settled in the counties where the plants are located.[39] These individuals typically have higher levels of education compared to the general population. To account for the human capital shock introduced by these workers, all regressions in this paper exclude counties where the plants are located.

Figure 2 presents cohort-specific estimates of $\beta_\lambda$ using data from the 1990 census. With the cohort born in 1954 serving as the reference, the results strongly support the parallel-trend assumption. Cohorts born prior to 1954 generally exhibit similar trends before the opening of the plants.[40] Furthermore, Figure 2 reveals a clear decreasing trend in the estimates for cohorts born between 1955 and 1958, known as the "gap cohorts" between the vertical dashed lines.

[39]News can be found here https://zqb.cyol.com/html/2020-09/29/nw.D110000zgqnb_20200929_5-01.htm. (In Chinese)

[40]Panel (a) and (b) of Appendix Figure B3 present results using data from the 1982 and 2000 censuses, respectively, and consistently support the parallel-trend assumption. The results from the 2000 census data are limited to cohorts born up to 1966, aligning with the 1990 census data. This restriction is due to the continuous production activity after 1970, which means cohorts born after this year experienced different levels of treatment. Additionally, considering the onset of mass migration in China in the mid-1990s, later cohorts, particularly those with higher education levels, might have relocated to urban areas near steel plants for better opportunities. This migration-related positive sorting effect underscores the necessity to restrict the event study analysis to cohorts born before 1966.

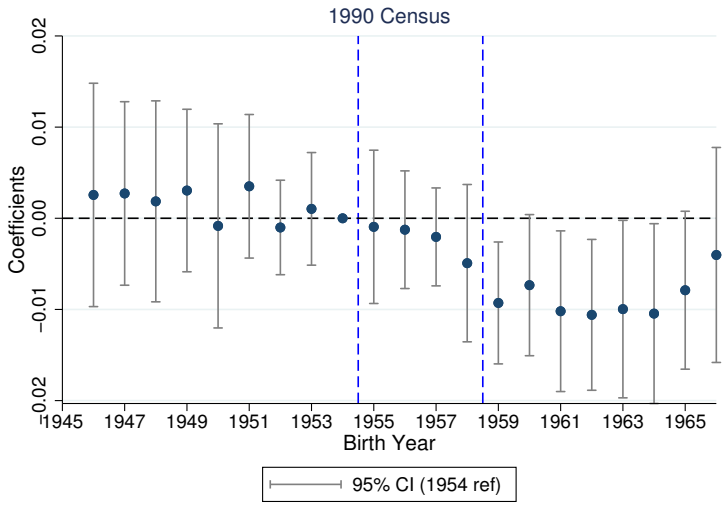


**Figure 2:** Results of Event Study. *Notes*: The y-axis displays the coefficients derived from Eq. 1. Cohorts falling between the two dashed lines are classified as "gap cohorts" and are excluded from the baseline regression.

## 5.2 Results of Baseline Specification

In the baseline specification, I use data from the 1990 census to estimate the effects. The first column of Table 2 reveals that individuals born after the establishment of a steel plant, completed significantly fewer years of education compared to their counterparts born four or more years before the plant's opening. Moving from the 25$^{th}$ to the 75$^{th}$ percentile of exposure intensity (an increase of approximately 10.43 units, where one unit represents 10,000 tons of pig iron) results in a reduction in educational attainment by 0.11 years ($10.43 \times 0.01022$).

Column (2) of Table 2 reports the results without controlling for county-level heterogeneous trends (base education $\times$ birth year fixed effects). The estimate in this column is larger in magnitude and statistically significant. Notably, the standard error and R-squared in column (2) are nearly identical to those in column (1), the baseline specification result. This suggests that the additional interaction terms do not enhance the explanatory power but absorb some variation from the key independent variable. Additionally, this presents a trade-off between sacrificing some variation to control for heterogeneous time trends or retaining the larger effect. My paper opts for the former, adopting a conservative approach. However, if there are additional time-varying un-

observables correlated with the key independent variable but not captured by the base education interaction terms, or if these time trends are not truly linear, the estimates may still be somewhat biased.

Columns (3) and (4) of Table 2 use alternative outcome variables: primary and junior high school completion, respectively. The results indicate that moving from the 25$^{th}$ to the 75$^{th}$ percentile of exposure intensity decreases primary graduation rates by 0.51 percentage points (10.43 $\times$ 0.00049), and this effect demonstrates statistical significance. The same level of exposure reduces junior high school graduation rates by 1.43 percentage points (10.43 $\times$ 0.00137), also statistically significant. Note that the average primary graduation rate in the sample is around 84%, while the average junior high school graduation rate is approximately 56%.

The final two columns of Table 2 report the results of two placebo tests. First, I split the comparison cohorts (1946–1954) into two distinct groups: the control group (1946–1950) and the placebo-treatment group (1951–1954). I then conduct regression analysis under the baseline specification. Column (5) reveals that the effect is statistically insignificant. In the second placebo test, I designate a ring with a 30–60-mile radius around a steel plant as the placebo-treated region. Using the simplified dispersion model, I calculate the exposure intensity for each county within this ring. This test checks whether the 30-mile treated radius is appropriate. If the impact primarily occurs within the 30-mile circle, the 30–60-mile ring should show an insignificant or smaller effect. Column (6) supports this, with a coefficient of -0.00331, smaller (in terms of effect size) than in column (1).

## 5.3 Discussion

How large is the effect? To provide context, I compare my estimates with findings from literature on the impact of three other factors on educational attainment.[41]

My findings show that moving from the 25$^{th}$ to the 75$^{th}$ percentile of exposure intensity de-

[41]Outcome variables in other studies examining the long-term human capital effects of air pollution, such as Sanders (2012); Voorheis (2017); Bharadwaj et al. (2017), focus on test scores or college attendance, which are not directly comparable to my paper.

creases educational attainment by 0.11 years. This effect size is about six times the impact of early-life wildfire smoke exposure in the United States from 1930 to 1969 (Neller and Arenberg, 2023), and more than twice the effect of compulsory education laws in the United States from 1915 to 1939 (Lleras-Muney, 2005).[42] When evaluated at the average exposure intensity of 14.07 units in my study,[43] the operation of steel plants reduces educational attainment by approximately 0.14 years ($14.07 \times 0.01022$) under the baseline specification. This effect is also substantial, being roughly twice the impact of the Send-Down Movement in China during the late 1960s to the 1970s (Chen et al., 2020). A summary of these comparisons can be found in Appendix Table A5.

It's important to note that the control cohorts were exposed to pig iron production at later ages. If this later exposure had no effect on the control cohorts, the observed treatment effect would accurately reflect the impact of early-life air pollution. However, given the well-documented detrimental effects of air pollution, it is likely that the control cohorts were also adversely affected, which could lead to an underestimation of the true size of the treatment effect.

[42] In Lleras-Muney (2005), the exposure intensity is a binary variable.

[43] In all regressions within my paper, exposure intensity is measured in units of 10,000 tons. Note that the effect in Chen et al. (2020) is evaluated at the average exposure intensity.

**Table 2:** Results of Baseline Specification and Placebo Tests (1990 Census)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent var: | Years of education | Years of education | Complete primary school | Complete junior high | Placebo I (1946–1950) versus (1951–1954) | Placebo II 30–60 miles placebo-treated |
| Exposure intensity × affected cohorts (1959–1966)[a] | -0.01022*** | -0.01830*** | -0.00049** | -0.00137*** | | |
| | (0.00231) | (0.00210) | (0.00023) | (0.00026) | | |
| Exposure intensity × affected cohorts (1951–1954) | | | | | -0.00074 | |
| | | | | | (0.00432) | |
| Exposure intensity × affected cohorts (1959–1966) | | | | | | -0.00331 |
| | | | | | | (0.00228) |
| Mean of dep var | 8.109 | 8.109 | 0.840 | 0.562 | 6.951 | 7.384 |
| Observations | 178,169 | 178,169 | 178,169 | 178,169 | 84,835 | 253,219 |
| R-squared | 0.407 | 0.405 | 0.237 | 0.345 | 0.365 | 0.359 |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province × birth year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Base education[b] × birth year FE | Yes | | Yes | Yes | Yes | Yes |

*Notes*: Column (1) presents the baseline results. Column (2) excludes base education × birth year fixed effects. Column (3) and column (4) use the completion of primary and junior high school as alternative outcome variables, respectively. Column (5) and column (6) report the results of two placebo tests. In the former I divide the control cohorts (1946–1954) into two distinct groups: the control group (1946–1950) and the placebo-treatment group (1951–1954). In the latter I designate a ring with a 30–60-mile radius around a steel plant as the placebo-treated region. Note that the placebo-treated region may also be polluted (however, the exposure level is lower compared to counties within the 30-mile radius). Standard errors are clustered at the county level.

[a] Exposure intensity × affected cohorts (1959–1966) indicates the interaction between exposure intensity and the treated cohorts (born between 1969–1966).

[b] Base education is calculated as the primary and junior graduation rates of individuals born between 1941–1945 in the 1990 census.

# 6 Robustness Check and Heterogeneity

In this section, I start with a series of robustness checks, followed by examining the heterogeneity in the effects.

## 6.1 Robustness Check

This subsection demonstrates the robustness of the baseline result presented in column 1 of Table 2 through a series of robustness checks. These include: (i) an alternative measure of exposure intensity, (ii) exclusion of individuals with a migration history in the last five years when surveyed in 1990, (iii) inclusion of the 1967–1970 cohorts in the treatment group, (iv) adopting a 5-year cohort gap, (v) exclusion of two steel plants with pre-treatment production, and (vi) inclusion of the 1958 cohort in the treatment group. Major political events in 1960s China and concerns over unevenly distributed economic opportunities are also considered.

**Alternative Measure of Exposure Intensity**. *Measure 1*, used in previous regressions, does not account for annual variation in production. *Measure 2* addresses this by calculating annual exposure intensity and then aggregating these values over the study period, providing a more nuanced measure of exposure. Column (1) of Table 3 applies this alternative measure, and the results remain robust. This paper favors *Measure 1* for its simplicity and efficiency in capturing pollution variation.

**Migration**. Migration is a major concern in pollution impact research. While migration was highly restricted before 1990, avenues like graduating from college provided opportunities for relocation to urban areas. To mitigate this, two robustness checks are conducted. The first excludes individuals eligible for migration, such as graduates of technical secondary schools, two-year colleges, and colleges. The second removes individuals with migration records in the last five years, reflecting conditions in 1985 when migration policies were presumed stricter. Columns (2) and (3) of Table 3 show that the coefficient of interest remains robust despite these adjustments. Concerns may still arise regarding intra-city migration. Note that approximately 95% of residents reported in 1990 that their usual residence was the same as in 1985, indicating a low migration rate overall.

**Including 1967–1970 Cohorts**. The baseline specification includes cohorts born between 1959 and 1966 to prevent any partial overlap with the production period (1959–1970). Column (4) of Table 3 shows that including cohorts from 1967 to 1970 slightly decreases the coefficient magnitude but does not affect its statistical significance. The core finding remains robust with the inclusion of these additional cohorts.

**Wider Cohort Gap**. I use a 4-year cohort gap to ensure that the last control cohort had developed adequately by the time steel plants began operations. While it is well established that over 80% of an infant's brain is developed by age 3, some may argue that the remaining undeveloped parts at age 4 could still be crucial to cognitive ability. Colmer, Voorheis, and Williams (2023) suggests that pollution can affect children up to age twelve, with significant effects up to age five. To alleviate this concern, I use a 5-year cohort gap.[44] Column (5) of Table 3 shows that the coefficient of interest remains robust.

**Dropping Pre-treatment Production**. Two steel plants in the dataset began operations in 1950 and 1952, respectively. These plants are included due to minimal pre-1959 aggregate production (25% or less of post-treatment levels). To assess their influence, these plants are excluded, resulting in a sample of 13 steel plants. The coefficient of interest in column (6) of Table 3 shows only slight changes from the baseline.

**1958 Cohort Being Treated**. The baseline specification designates the 1959 cohort as the first treatment cohort. To assess the impact of this choice, the 1958 cohort is considered as the first treatment cohort while maintaining the 4-year cohort gap, with the last comparison cohort being those born in 1953. Aggregate production is summarized from 1958 to 1970. Column (7) of Table 3 shows that including the 1958 cohort in the treatment group does not significantly alter the results.

**Events in the 1960s**. It's essential to consider the significant upheavals in China from the late 1950s to early 1970s, including the Great Famine, the Cultural Revolution, and the Send-Down Movement. These events might confound the impact of steel plant openings on nearby

[44] Events happened before age 5 can have large long-term impacts on later life outcomes Currie and Almond (2011).

**Table 3:** Robustness Check (Adjustments to Exposure Intensity Measure, Migration, and Sample)

| Dependent var: | Years of education | | | | | | |
|---|---|---|---|---|---|---|---|
| Robustness Checks: | (1) Alternative intensity measure | (2) Exclude eligible migration | (3) Remove migration records | (4) Include cohorts (1967–1970) | (5) 5-year cohort gap | (6) Drop pre-treatment production | (7) Include cohort (1958) |
| Exposure intensity × affected cohorts (1959–1966) | | -0.00820*** | -0.01108*** | -0.00817** | -0.01054*** | -0.01007*** | -0.00963*** |
| | | (0.00225) | (0.00197) | (0.00334) | (0.00231) | (0.00234) | (0.00219) |
| Exposure intensity measure 2[a] × affected cohorts (1959–1966) | -0.01014*** | | | | | | |
| | (0.00231) | | | | | | |
| Mean of dep var | 8.109 | 7.720 | 8.020 | 8.395 | 8.155 | 8.019 | 8.182 |
| Observations | 178,169 | 166,846 | 167,755 | 237,132 | 165,904 | 148,256 | 176,314 |
| R-squared | 0.407 | 0.370 | 0.400 | 0.438 | 0.408 | 0.415 | 0.405 |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Province × birth year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Base education × birth year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: In Column (1), an alternative measure of exposure intensity is employed. Column (2) excludes individuals eligible for migration to urban areas. Column (3) removes individuals with migration records in the last five years from the sample. Column (4) presents the results of including cohorts born between 1967 and 1970. Column (5) utilizes a 5-year cohort gap between control and treatment cohorts. In Column (6), two steel plants with pre-treatment production are dropped from the sample. In the last column, cohort born in 1958 is treated. Standard errors are clustered at the county level.

[a] See Section 4 for more information on *Measure 2*.

populations. Therefore, any studies covering this period must carefully consider these factors. The results presented in Appendix Table D1 show robustness even when accounting for these major events. Detailed information on these robustness checks can be found in Appendix Section D.

**Distances within the 30-mile Radius**. A potential concern is that counties within the 30-mile radius of steel plants have varying distances to the plants, which might cause uneven economic opportunity effects. In other words, the 30-mile radius might be too large. Although this radius is more conservative than that used by Clay, Lewis, and Severnini (2024), the concern remains due to substantial developmental disparities between urban and rural areas in China. To address this concern, I introduce interaction terms between the squared distance and birth year dummies into the baseline regression model.[45] Column (1) of Appendix Table D2 shows that the coefficient of interest remains significant and close to the baseline result (column 1 of Table 2). However, including these interaction terms reduces variation in exposure intensity. Therefore, the baseline setup without distance-related interaction terms is preferred. Appendix Figure D1 presents the event study results that include these interaction terms, further reinforcing the validity of the main findings.

**Economic Opportunities**. There is a concern that the job opportunities provided by steel plants might have led individuals in the treatment cohorts to drop out of school early. To mitigate this, I exclude counties where steel plants are located and assume economic impacts are uniformly distributed within the 30-mile radius.

The remaining question is whether economic opportunities are uniform around steel plants. To address this, I conduct two additional falsification tests, shown in columns (2) and (3) of Appendix Table D2. These tests assess whether the treatment significantly affects the likelihood of individuals working in agriculture or manufacturing, the two largest occupations according to the 1990 census. As shown in the table, neither test yields statistically significant results.

To further address this concern, I use data from eight steel plants built more than ten years

[45] Here, "distance" refers to the distance between a county's administrative center and the steel plant. Adding just "distance" is insufficient as it is absorbed by county fixed effects.

before 1959, with production records dating back to 1949, as a falsification test.[46] Note that these plants also underwent various renovations and expansions around 1959, as indicated by the fact that aggregate production from a five-year window before 1959 was 1.53 times less than that after 1959. Ideally, if production had remained constant and economic opportunities were evenly distributed around these plants, we would expect no effect under the baseline specification. However, given the increase in post-1959 production compared to pre-1959, assuming uniform economic opportunities, the baseline specification should yield a slightly negative effect. The results in column (4) of Appendix Table D2 show that the coefficient of interest is significantly smaller compared to that in column (1) of Table 2, representing only about 5.6% of the latter (in terms of effect size).

Apart from the above checks, this paper also considers: (1) the influence of infant mortality, childcare availability, and the influx of workers associated with the construction and operation of steel plants, (2) an expanded geographic radius of 60 miles to include more counties in the sample, (3) an identification strategy that accounts for varying cohort-specific exposure intensities to ensure the robustness of the binary treatment assignments, and (4) potential spatial correlation. My results remain robust across these specifications. Further details are provided in Appendix Section D.

## 6.2 Heterogeneity

Considering that plants of different scales might yield varying effects, I categorize the plants into three distinct groups: large, medium, and small. Large plants are defined by an aggregate production exceeding 500 units, medium plants have aggregate production between 100 and 500 units, and small plants have aggregate production of less than 100 units. Column (1) of Table 4 presents the results. Generally, all categories of plants exhibit a negative impact on the treatment cohorts, with only the coefficient for large plants showing statistical significance. Interestingly, although imprecisely estimated, small plants show an impact more than twice as large as that of large plants.[47]

Column (2) of Table 4 incorporates interaction terms between exposure intensity and an indi-

[46] Appendix Figure D2 provides the production of the 8 plants.

[47] Evidence suggests that small furnaces during this period had higher production costs than larger ones, largely due to excessive fuel consumption. Source: https://donwagner.dk/Fate/Fate.html and http://www.csteelnews.com/special/602/604/201206/t20120618_67577.html(in Chinese).

cator function for household registration (Hukou) status.[48] The indicator function is set to 1 for urban residents and 0 otherwise. The findings reveal no significant difference in the impact on urban versus rural residents.

Column (3) of Table 4 includes interaction terms between gender (binary, 1 for male and 0 for female) and exposure intensity. The results indicate that plant operations significantly affect both genders, but the impact on males is nearly three times greater than on females. This aligns with findings that males are more affected by pollutants in exams (Ebenstein, Lavy, and Roth, 2016). A possible explanation for this difference could be the "weak male" hypothesis (Kraemer, 2000), which suggests that human males are generally more vulnerable than females.[49]

[48]Hukou type data are only available in the 1990 and later censuses, so the urban and rural subsamples reflect conditions in 1990 rather than the 1960s.

[49]This hypothesis is supported by various health outcomes; for instance, boys exhibit higher susceptibility to respiratory conditions such as wheeze and asthma compared to girls (Fuseini and Newcomb, 2017; Chowdhury et al., 2021).

**Table 4:** Results of Heterogeneity Analysis

| Dependent var: | Years of education | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Heterogeneity: | Impact by scale | Urban versus rural | Male versus female |
| Exposure intensity × large plants | -0.01076*** | | |
| × affected cohorts (1959–1966) | (0.00240) | | |
| Exposure intensity × medium plants | -0.00421 | | |
| × affected cohorts (1959–1966) | (0.01318) | | |
| Exposure intensity × small plants | -0.02693 | | |
| × affected cohorts (1959–1966) | (0.04260) | | |
| Exposure intensity | | -0.00902*** | -0.00493** |
| × affected cohorts (1959–1966) | | (0.00271) | (0.00225) |
| Exposure intensity × urban | | -0.00129 | |
| × affected cohorts (1959–1966) | | (0.00299) | |
| Exposure intensity × male | | | -0.01043*** |
| ×affected cohorts (1959–1966) | | | (0.00207) |
| Mean of dep var | 8.109 | 8.109 | 8.109 |
| Observations | 178,169 | 178,169 | 178,169 |
| R-squared | 0.407 | 0.407 | 0.408 |
| County FE | Yes | Yes | Yes |
| Province × birth year FE | Yes | Yes | Yes |
| Base education × birth year FE | Yes | Yes | Yes |

*Notes*: Column (1) reports the results by grouping the sample into three categories based on plant size in order to examine the nonlinear impacts of industrial pollution. Large plants: production of 5 million tons or more. Medium plants: production between 1 and 5 million tons. Small plants: production of 1 million tons or less. Column (2) compares urban and rural residents. Column (3) analyzes differences between males and females. Standard errors are clustered at the county level.

# 7 Conclusions

Air pollution presents a critical global challenge that extends far beyond immediate health concerns. Yet, empirical evidence on the long-term effects of air pollution on human capital in developing settings remains surprisingly scarce. This paper leverages data on pig iron production from Chinese steel plants between 1959 and 1970 to investigate the causal effects of early childhood exposure to air pollution on human capital formation.

My identification strategy assumes that economic opportunities associated with the steel plants impact upwind and downwind locations similarly, allowing the cohort-DiD approach to isolate the negative effects of steel plant operations. Given that I use wind speed and direction as sources of variation, the observed negative impact is most likely attributable to air pollution from these plants.

The main findings reveal that the openings of steel plants decreased educational attainment in children residing in nearby counties, with the impact exhibiting a nonlinear pattern. Notably, the negative effects are more pronounced among boys. This paper contributes to the literature on the long-term impact of early-life exposure on human capital accumulation by providing empirical evidence in a developing-country setting. Unlike much of the existing literature, this paper is less influenced by migration due to China's limited mobility before the mid-1990s.

My findings suggest that the environmental drawbacks of heavy industry development could counterbalance the benefits of investments in human capital. Both historical and contemporary experiences show that early industrialization often involves high-pollution and high-energy industries. It is crucial to focus on the well-being of young children, as pollution during this critical developmental period can cause irreversible harm.

# Declaration of competing interest

The author has no competing interests to declare in this paper.

## Data Availability

All data is publicly available from the sources listed in the Data section.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT in order to improve the language. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

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# Appendix A: Tables

**Table A1:** Steel Plants and Their Inclusion in the Sample Based on Operating Years

| Steel plant name | Opening year | Included in the sample or not[a] |
|---|---|---|
| Shoudugang | 1949 | Old steel plant, not included |
| Tangshangang | 1958 | Only operating during 1958–1962 and negligible production, not included |
| Handangang | 1958 | Included |
| Chengdegang | 1958 | Included |
| Xuanhuagang | 1951 | Old steel plant, not included |
| Taiyuangang | 1949 | Old steel plant, not included |
| Changzhigang | 1949 | Old steel plant, not included |
| Xinlingang | 1958 | Included |
| Baotougang | 1959 | Included |
| Anshangang | 1949 | Old steel plant, not included |
| Benxigang | 1949 | Old steel plant, not included |
| Xinfugang | 1958 | Only operating during 1958–1961 and negligible production, not included |
| Tonghuagang | 1958 | Only operating during 1958–1961, not included |
| Nanjinggang | 1959 | Only operating in 1959, 1960, 1966, and negligible production, not included |
| Suzhougang | 1958 | Included |
| Xuzhougang | 1958 | Included |
| Hangzhougang | 1958 | Included |
| Maanshangang | 1953 | 1953–1959 considerable production, not included |
| Hefeigang | 1958 | Only operating during 1958–1962, not included |
| Xinyugang | 1959 | Only operating during 1959–1962, not included |
| Nanchanggang | 1959 | Only operating during 1959–1963, not included |
| Pingxinggang | 1957 | Negligible production, not included |
| Sanminggang | 1959 | Only operating during 1959–1962, not included |
| Jinangang | 1958 | Included |
| Qingdaogang | 1958 | Only operating during 1958–1961, not included |
| Anyanggang | 1958 | Included |
| Wuhangang | 1958 | Included |
| Echenggang | 1958 | Only operating during 1958–1961 and negligible production, not included |
| Lianyuangang | 1958 | Included |
| LengshuijiangGang | 1959 | Negligible production, not included |
| Guangzhougang | 1958 | Included |
| Liuzhougang | 1958 | Included |
| Chongqinggang | 1950 | Included (pre-1959 small), excluded in robustness check |
| Chuanweigang | 1951 | Old steel plant, not included |
| Kunminggang | 1952 | Included (pre-1959 small), excluded in robustness check |
| Xinjiangbayigang | 1952 | Old steel plant, not included |

*Notes*: The table only includes plants producing pig iron. Few steel plants operated before 1949.

[a] I only look if a steel plant was operating between 1959 and 1966.

**Table A2:** Correlations between Exposure Intensity and Pre-Treatment Observables (County Level)

| Dependent var: | Exposure Intensity | | | | | |
|---|---|---|---|---|---|---|
| | (1) Educational attainment | (2) Female percentage | (3) Non-Han ethnic percentage | (4) Urban resident percentage | (5) Base education | (6) Base education |
| Years of education (control cohorts)[a] | 4.477*** | | | | | |
| | (0.750) | | | | | |
| Share of female (control cohorts) | | -22.631 | | | | |
| | | (28.882) | | | | |
| Share of minority (control cohorts) | | | 19.682 | | | |
| | | | (20.149) | | | |
| Share of urban Hukou (control cohorts) | | | | 15.134*** | | |
| | | | | (3.483) | | |
| Primary school graduation rate (older cohorts)[b] | | | | | 42.167*** | |
| | | | | | (11.462) | |
| Junior high graduation rate (older cohorts) | | | | | | 31.263*** |
| | | | | | | (7.576) |
| Observations | 124 | 124 | 124 | 124 | 124 | 124 |
| R-squared | 0.729 | 0.641 | 0.643 | 0.693 | 0.703 | 0.703 |
| Plant (or Circle)[c] FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

[a] Cohorts born between 1946 and 1954.

[b] Cohorts born between 1941 and 1945.

[c] "Circle" refers to a 30-mile radius around the steel plant, covering the counties within that zone.

**Table A3:** Pearson Correlations between Interaction Terms

| | Exposure intensity × affected cohorts (1959–1966) | Primary graduation rate (older cohorts) | Junior high graduation rate (older cohorts) | Send-down youths density × affected cohorts (1959–1966) | Great Famine severity × affected cohorts (1959–1961) | Cultural Revolution severity × affected cohorts I (1959–1961) |
|---|---|---|---|---|---|---|
| Primary graduation rate | 0.1624*** | | | | | |
| Junior high graduation rate | 0.2625*** | 0.7920*** | | | | |
| Send-down youths density × affected cohorts (1959–1966) | 0.3701***[a] | -0.1287*** | -0.1775*** | | | |
| Great Famine severity ×affected cohorts (1959–1961) | 0.1293*** | -0.0003 | -0.0042** | 0.1731*** | | |
| Cultural Revolution severity ×affected cohorts I (1959–1961) | 0.0547*** | 0.1026*** | 0.1426*** | 0.0434*** | 0.3457*** | |
| Cultural Revolution severity ×affected cohorts II (1962–1966) | 0.0918*** | 0.1376*** | 0.1848*** | 0.1060*** | -0.1332*** | -0.0954*** |

*Notes*: This table presents the Pearson correlations between various regressors used in the regressions. *** p<0.01, ** p<0.05, * p<0.1.

[a] For example, this number suggests a high correlation between the term Exposure intensity × affected cohorts (1959–1966) and the term send-down youths × affected cohorts when running the regression corresponding to the result in column 3 of Table D1.

**Table A4:** Pearson Correlations between Simplified Model-Generated Data and AERMOD

| | Simplified dispersion model generated | AERMOD generated | | | |
|---|---|---|---|---|---|
| | Exposure intensity | TSP | $PM_{10}$ | $PM_{2.5}$ | $SO_2$ |
| TSP | 0.9249*** | | | | |
| $PM_{10}$ | 0.9240*** | 0.9892*** | | | |
| $PM_{2.5}$ | 0.9162*** | 0.9811*** | 0.9936*** | | |
| $SO_2$ | 0.9007*** | 0.9200*** | 0.9623*** | 0.9578*** | |
| $NO_2$ | 0.8842*** | 0.9082*** | 0.9543*** | 0.9517*** | 0.9990*** |

*Notes*: This table displays the Pearson correlations between exposure intensity calculated using the simplified dispersion model and concentrations of various pollutants obtained from AERMOD. This analysis pertains specifically to the steel plant located in Wuhan city and does not represent the full sample case. There are 15 observations (15 counties) on a single pollutant. *** p<0.01, ** p<0.05, * p<0.1.

**Table A5:** Comparison with Estimates from Other Studies

| | Setting | Coefficient | Mean of independent var | $25^{th}$-$75^{th}$ percentile difference | Effect (unit: year) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| My paper | China | -0.01021 | | 10.43 | -0.1065 |
| Neller and Arenberg (2023) | US | -0.0035 | | 5 | -0.0175 |
| Lleras-Muney (2005) | US | 0.046 | Dummy variable | | 0.046 |
| My paper | China | -0.01021 | 14.07 | | -0.1437 |
| Chen et al. (2020a) | China | 3.237 | 2.2% | | 0.0719 |

*Notes*: This table compares my estimates of the effect on educational attainment with those from other studies. While the independent variables vary across the studies, the outcome variable–years of education–remains consistent. The effect size in column (5) is derived from the product of the values in columns (2) and (3)/(4).

# Appendix B: Figures

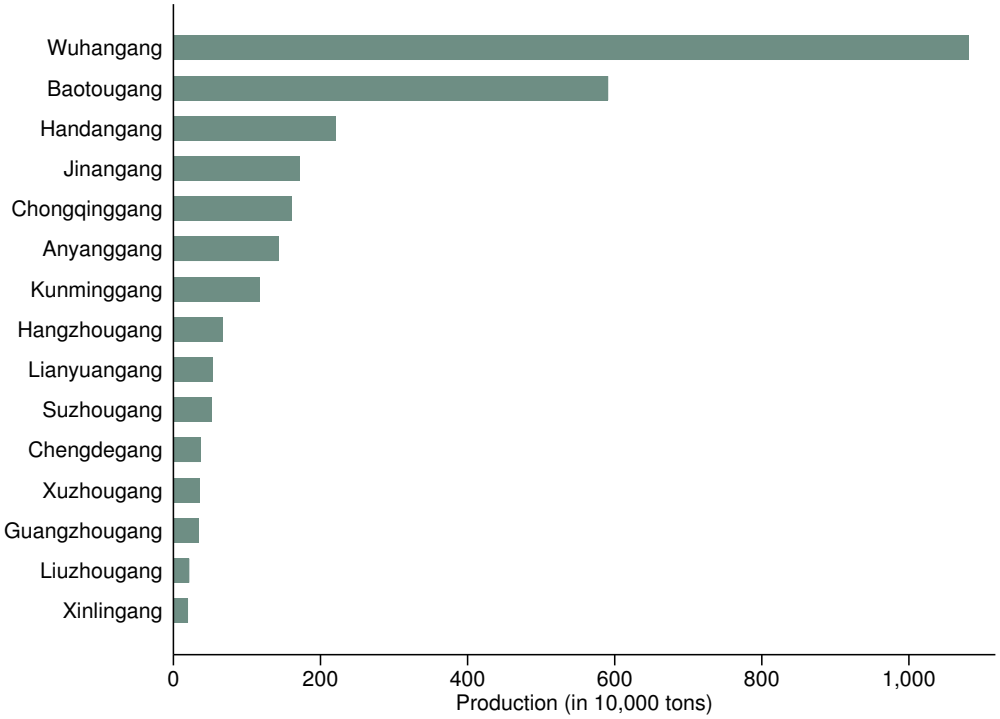



**Figure B1:** Aggregate Production (1959–1970) of the Steel Plants. *Notes*: In the figure, "Production" denotes the aggregate production over the period spanning 1959 to 1970.

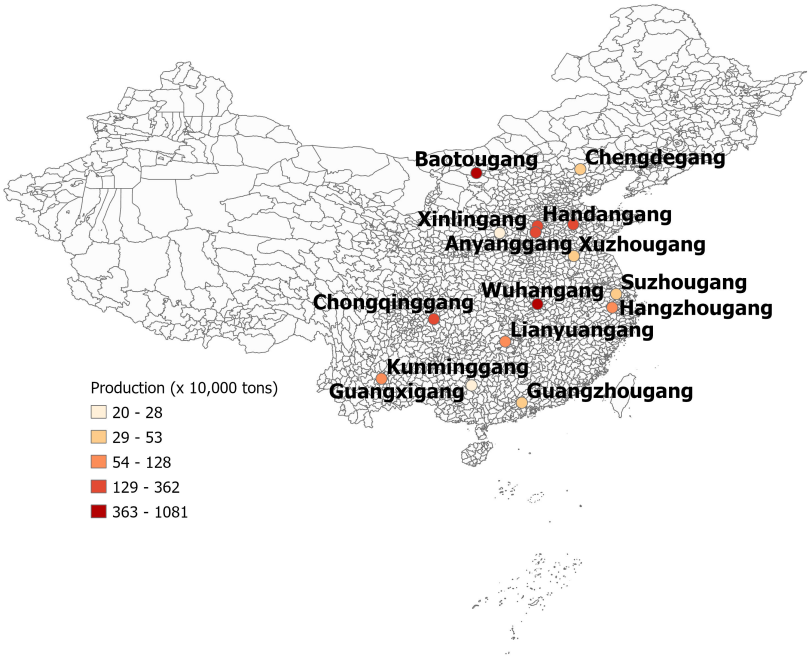
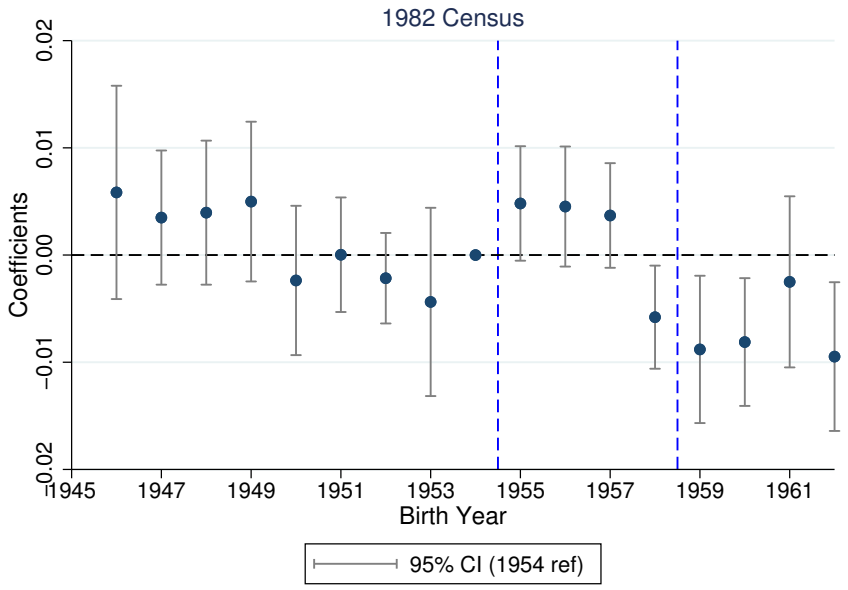
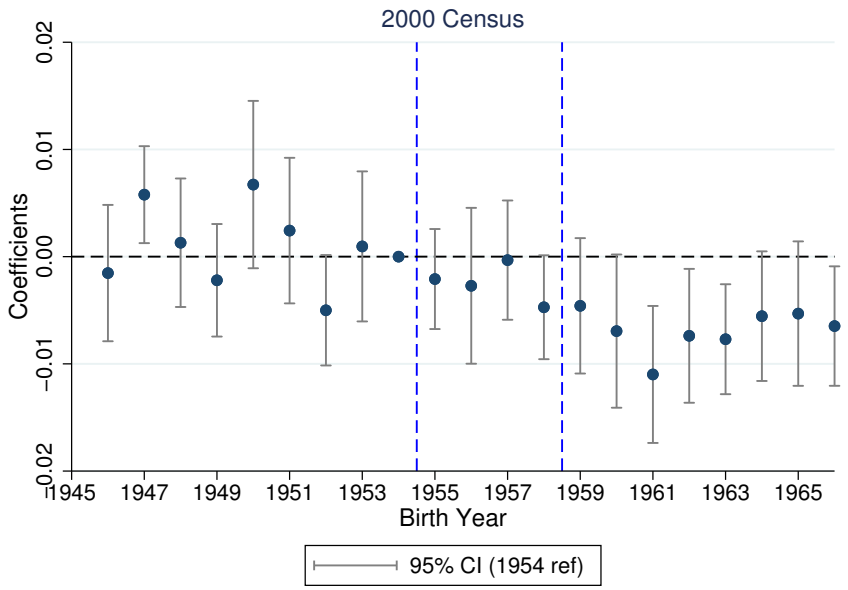



**Figure B2:** Geographic Locations and Aggregate Production (1959–1970) of the Steel Plants. *Notes*: In the figure, "Production" denotes the aggregate production over the period spanning 1959 to 1970.




**(a)** 1982 Census




**(b)** 2000 Census

**Figure B3:** Results of By-cohort Specification: 1982 and 2000 Censuses. *Notes*: Panel (a) and (b) depict the outcomes of event study using data from the 1982 and 2000 censuses, respectively. The 1982 census data is less suitable for post-treatment analysis since most treatment cohorts (born between 1959 and 1966) were under 20 years old at that time, making their educational attainment likely unstable and less reliable for assessing long-term effects. On the other hand, the 2000 census was conducted after significant relaxation of migration policies and captured a marked increase in internal migration.

# Appendix C: Dispersion Model

Standard air pollution dispersion models like the AERMOD Modeling System, CTDMPLUS, or OCD require meticulously formatted meteorological data and comprehensive information about the steel production equipment to yield precise predictions.[1] However, upper air meteorological data, detailed equipment parameters, and raw materials information for all steel plants during the study period are unavailable. Using these dispersion models to obtain precise pollutant concentration predictions in this scenario is therefore impractical.

As an alternative approach, I could approximate the meteorological data, particularly upper air sounding data from the 1960s, using more contemporary data (e.g., data from the 2000s) under the assumption that meteorological conditions remained relatively stable over this short time span in history. However, detailed equipment parameters and raw material information for all steel plants are still not available.[2] Given these limitations, I choose to use a simplified dispersion model and select a representative steel plant to assess its effectiveness.[3]

**Measure 1**

For county $i$ located within a 30-mile radius of steel plant $j$, the weight, denoted as $weight_i$, is calculated using the formula specified in Eq. C1.

$$weight_i = \frac{\frac{\sum_{d \in D} windspeed_{jd} \times cos\left(\left|\theta_{ij} - \theta_{jd}\right|\right) \times \mathbf{1}\{cos\left(\left|\theta_{ij} - \theta_{jd}\right|\right) > 0\}}{\sum_{d \in D} windspeed_{jd}}}{r_{ij}} \tag{C1}$$

The calculation of $weight_i$ involves two components: first, the distance, denoted as $r_{ij}$,[4] from county $i$ to steel plant $j$, and second, the wind speed weighted average of the projection of the

[1] Source: https://www.epa.gov/scram/air-quality-dispersion-modeling-preferred-and-recommended-models. The equipment-related information is used to estimate the pollution source strength.

[2] Only some general information from the 1960s is available for a few plants.

[3] Wuhangang, the largest steel plant built by the central government since 1949, has some general equipment information that aids in inferring additional parameters.

[4] Specifically, $r_{ij}$ denotes the distance between the administrative central point of county $i$ and the exact latitude/longitude location of steel plant $j$.

wind direction on the line joining the administrative central point of county $i$ and steel plant $j$.[5] $windspeed_{jd}$ represents wind speed on day $d$ at the location of steel plant $j$, and $D$ denotes the set of observations during the study period.

The angle between the wind direction ($\theta_{jd}$) and the line connecting the administrative central point of county $i$ and steel plant $j$ ($\theta_{ij}$) is represented by $|\theta_{ij} - \theta_{jd}|$. Here, $\theta$ falls within the range of $[0°, 360°]$, with $0°$ signifying true north. Only positive values of $\cos(|\theta_{ij} - \theta_{jd}|)$ are considered when calculating the weight. In other words, only cases where steel plant $j$ is upwind of county $i$ is taken into account in this context. Figure C1 visually depicts the decomposition of wind direction.

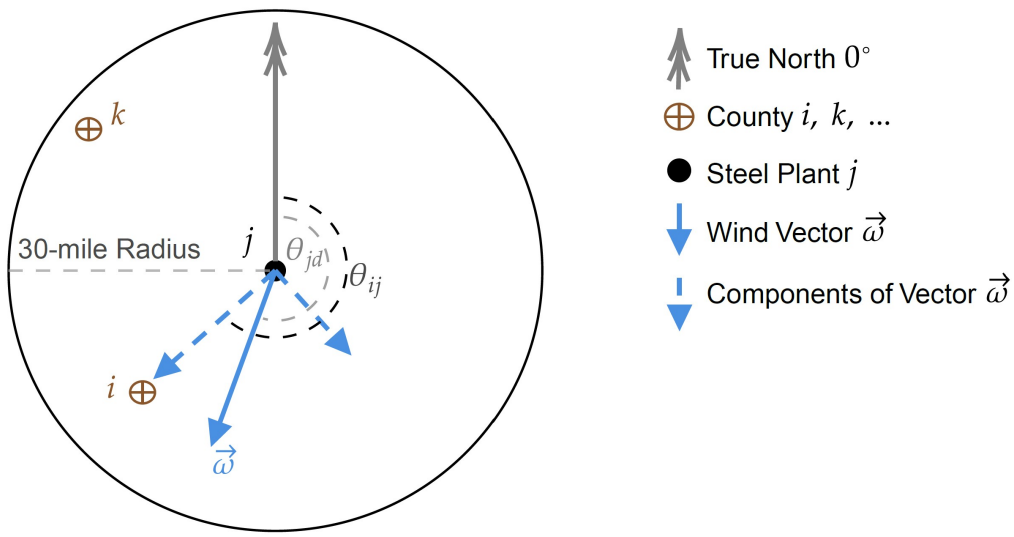



**Figure C1:** Decomposition of Wind Vector. *Notes*: $\theta_{jd}$ denotes the angle between the true north and the direction in which the wind blows. $\theta_{ij}$ represents the angle between the true north and the line connecting the administrative central point of county $i$ and steel plant $j$. The wind vector $\vec{\omega}$ can be decomposed into two components (indicated by dashed arrows). To make ensure pollutant dispersion towards county $i$, only positive values of $\cos(|\theta_{ij} - \theta_{jd}|) > 0$ are considered when calculating the weight. This means that only situations where steel plant $j$ is upwind of county $i$ are taken into account.

Next, the term $intensity\_index_i$ is derived, as shown in Eq. C2, which represents a standardized weight assigned to county $i$. $I$ denotes the set of all surrounding counties of plant $j$. As Eq. C3 illustrates, $intensity\_index_i$ essentially encapsulates the disparities in the allocation of production

[5]For ease of calculation, in this paper, "wind direction" refers to the direction it blows to, as opposed to the conventional definition.

among the counties located within a 30-mile radius circle.

$$intensity\_index_i = \frac{weight_i}{\sum_{i \in I} weight_i} \tag{C2}$$

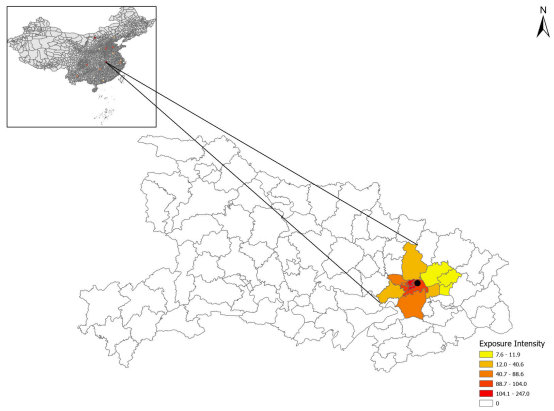
Finally, I obtain $expo\_intensity_i$ in Eq. C3, representing the quantity of iron production that county $i$ receives from steel plant $j$. $total\_production_j$ is the aggregate production of plant $j$ during 1959–1970. Maps of the 15 steel plant areas, illustrating the distribution of exposure intensity, are provided in Appendix Figure C2 through C5.

$$expo\_intensity_i = intensity\_index_i \times total\_production_j \tag{C3}$$

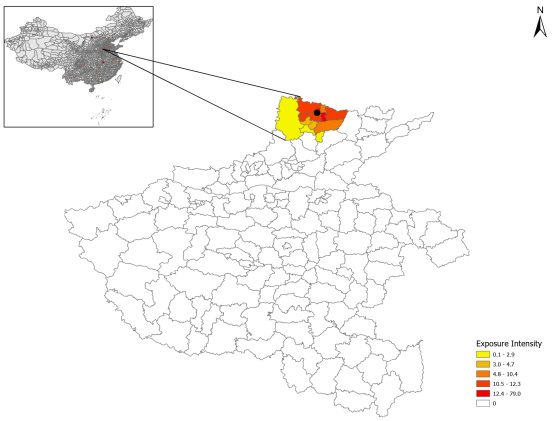
**Effectiveness of the Simplified Dispersion Model**

A limitation of this paper is the absence of observed actual pollution exposure. To assess the effectiveness of the simplified dispersion model in capturing pollution variation, I obtained simulated pollutant data for a representative steel plant using 2020 meteorological data and AERMOD, a widely used atmospheric dispersion modeling system. Appendix Table A4 shows the correlations between pollutant concentrations derived from AERMOD and exposure intensity calculated using the simplified dispersion model (with a 30-mile radius). These correlations range from 0.88 to 0.92 and are all statistically significant at the 0.01 level. This strong correlation is expected, given that in any dispersion model, pollution intensity (which is proportionate to production), wind direction, and wind speed are the primary inputs. These results validate the simplified dispersion model's ability to capture pollution variation. Further discussion on AERMOD is provided in Appendix Section D.

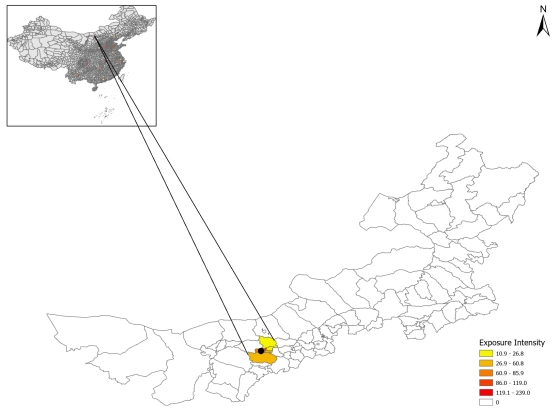
Another method to validate the simplified dispersion model is by comparing its results with satellite observations, which are available only for later years. Given that wind patterns are relatively stable over time (see Appendix Figure C6), if the steel plant remains the primary pollution source in the area, a strong correlation between the simplified model-generated measure and satel-



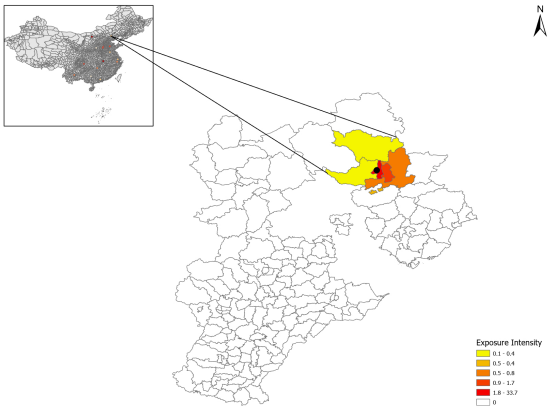

**(a)** Distribution of Exposure Intensity around Wuhangang




**(b)** Distribution of Exposure Intensity around Anyanggang

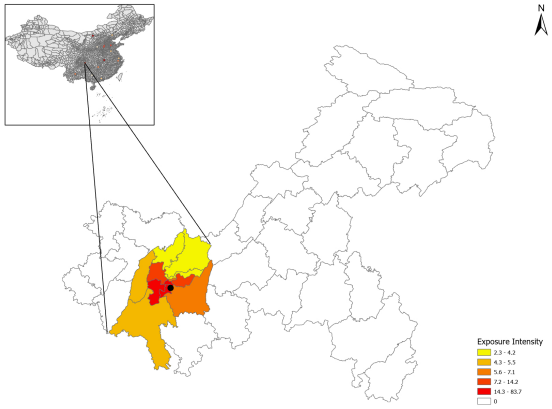



**(c)** Distribution of Exposure Intensity around Baotougang

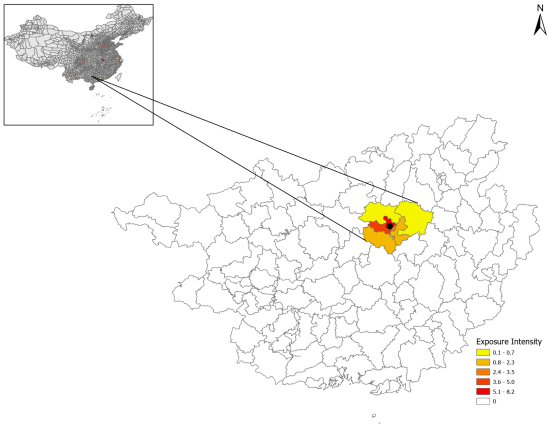



**(d)** Distribution of Exposure Intensity around Chengdegang

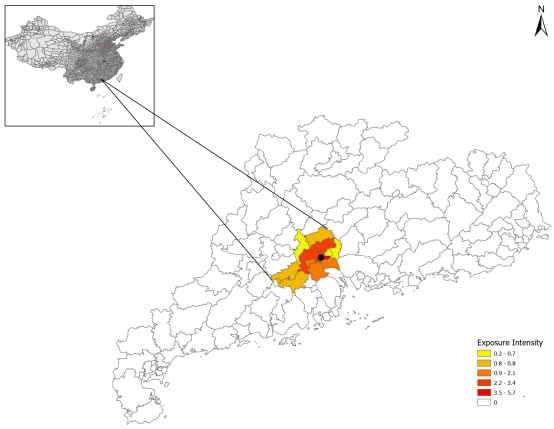
**Figure C2:** The Distribution of Exposure Intensity of the 15 Steel Plant Areas within a 30-Mile Radius (part 1). *Notes*: The figures display the distribution of exposure intensity around the steel plants at the county level, including the provinces to which these counties belong. The black dot marks the location of each steel plant. The legend's color style remains consistent across all maps, although the corresponding values differ.



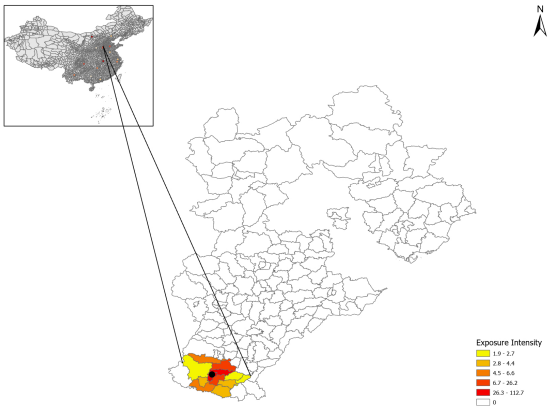

**(a)** Distribution of Exposure Intensity around Chongqinggang




**(b)** Distribution of Exposure Intensity around Guangxigang

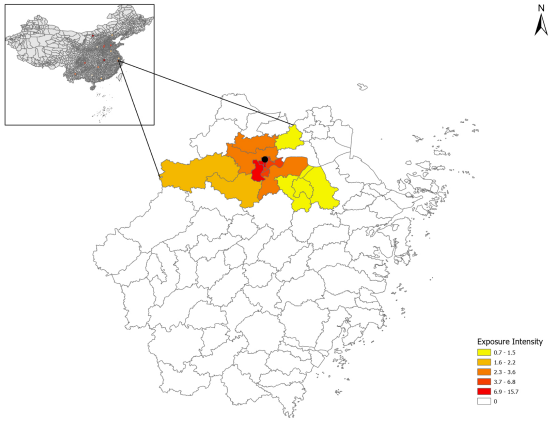



**(c)** Distribution of Exposure Intensity around Guangzhougang

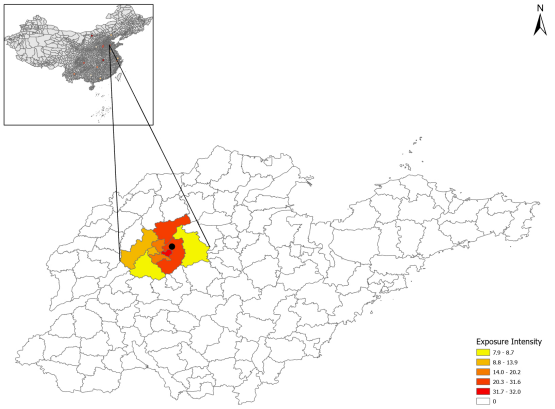



**(d)** Distribution of Exposure Intensity around Handangang

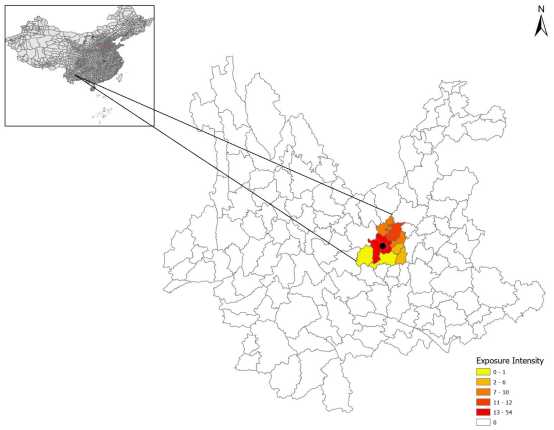
**Figure C3:** The Distribution of Exposure Intensity of the 15 Steel Plant Areas within a 30-Mile Radius (part 2). *Notes*: The figures display the distribution of exposure intensity around the steel plants at the county level, including the provinces to which these counties belong. The black dot marks the location of each steel plant. The legend's color style remains consistent across all maps, although the corresponding values differ.



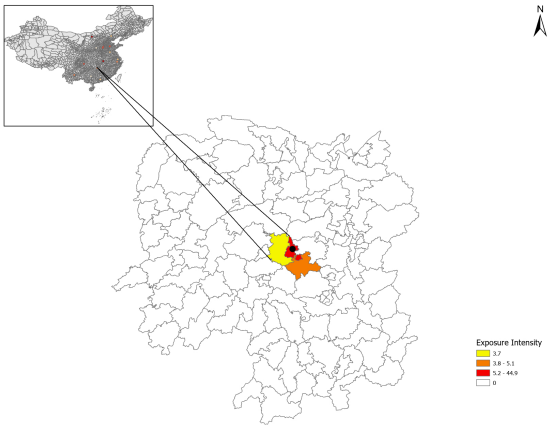

**(a)** Distribution of Exposure Intensity around Hangzhougang




**(b)** Distribution of Exposure Intensity around Jinangang

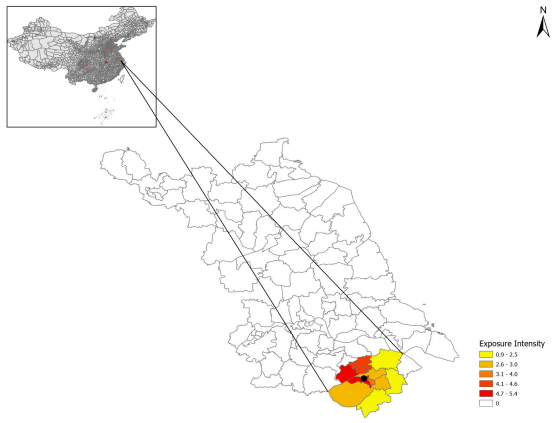



**(c)** Distribution of Exposure Intensity around Kunminggang

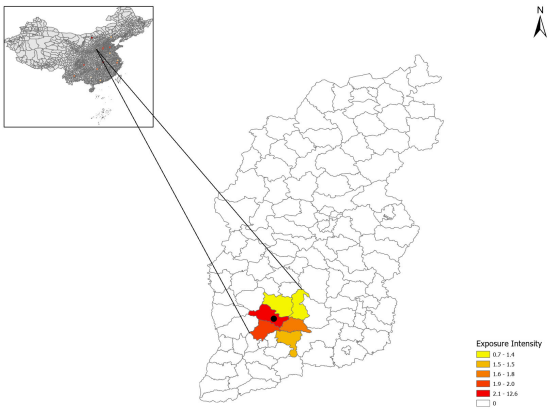



**(d)** Distribution of Exposure Intensity around Lianyuangang

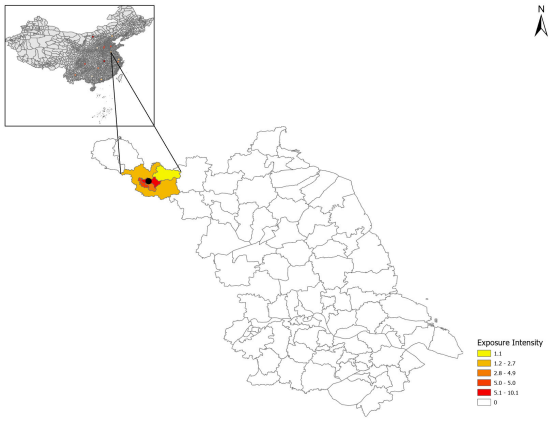
**Figure C4:** The Distribution of Exposure Intensity of the 15 Steel Plant Areas within a 30-Mile Radius (part 3). *Notes*: The figures display the distribution of exposure intensity around the steel plants at the county level, including the provinces to which these counties belong. The black dot marks the location of each steel plant. The legend's color style remains consistent across all maps, although the corresponding values differ.




**(a)** Distribution of Exposure Intensity around Suzhougang




**(b)** Distribution of Exposure Intensity around Xinlingang




**(c)** Distribution of Exposure Intensity around Xuzhougang

**Figure C5:** The Distribution of Exposure Intensity of the 15 Steel Plant Areas within a 30-Mile Radius (part 4). *Notes*: The figures display the distribution of exposure intensity around the steel plants at the county level, including the provinces to which these counties belong. The black dot marks the location of each steel plant. The legend's color style remains consistent across all maps, although the corresponding values differ.

lite observations is expected. However, the earliest satellite observations are from 1998,[6] a period following significant economic growth due to China's Reform and Opening-up policy.[7] Consequently, other pollution sources emerging during this period might weaken the correlation, especially in areas with smaller steel plants where other sources could be more dominant. Nonetheless, focusing on the representative steel plant–the largest in the sample and less likely influenced by other pollution sources–provides a clearer picture. Appendix Figure C7 shows a strong positive correlation between the model-generated exposure measure and satellite-observed $PM_{2.5}$ concentrations, with a correlation coefficient around 0.8, statistically significant at the 0.01 level. This evidence further supports the model's reliability in capturing pollution variation.

Overall, these findings affirm the effectiveness of the simplified dispersion model, demonstrating that the exposure measure it generates is a strong predictor of air pollution from steel plants.

**Measure 2**

*Measure 1* does not incorporate the annual fluctuations in steel production. To account for this, I introduce *Measure 2*, which calculates yearly exposure intensity and aggregates these values over the study period to provide a more comprehensive measure. Specifically, for steel plant $j$ and the surrounding county $i$ located within a 30-mile radius, the exposure intensity is determined as follows:

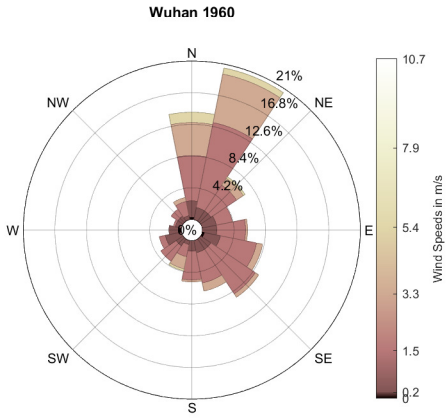
$$weight_{it} = \frac{\frac{\sum_{d\in D} windspeed_{jdt} \times cos\left(\left|\theta_{ij}-\theta_{jdt}\right|\right) \times \mathbf{1}\{cos\left(\left|\theta_{ij}-\theta_{jdt}\right|\right)>0\}}{\sum_{d\in D} windspeed_{jdt}}}{r_{ij}} \tag{C4}$$

$$intensity\_index_{it} = \frac{weight_{it}}{\sum_{i\in I} weight_{it}} \tag{C5}$$

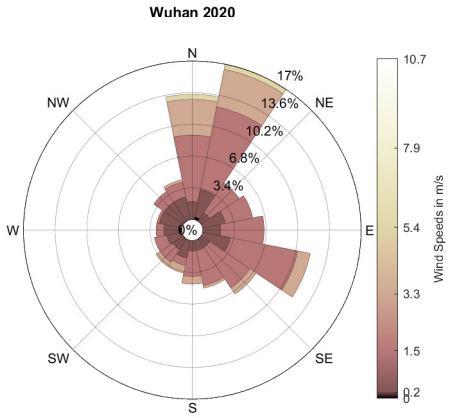
$$expo\_intensity_i = \sum_{t\in T} intensity\_index_{it} \times total\_production_{jt} \tag{C6}$$

[6]The data is provided by the Atmospheric Composition Analysis Group and is publicly available at https://sites.wustl.edu/acag/datasets/surface-pm2-5/.

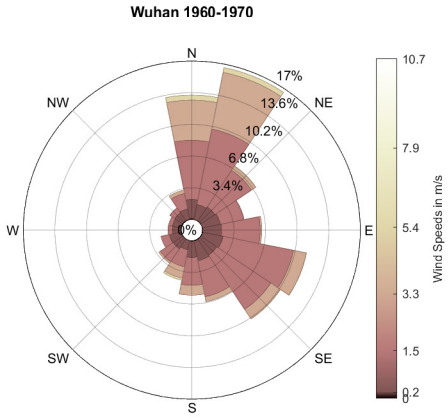
[7]"Reform and Opening-up" refers to the economic reforms China began in 1978, transitioning from a planned economy to a market-oriented one.



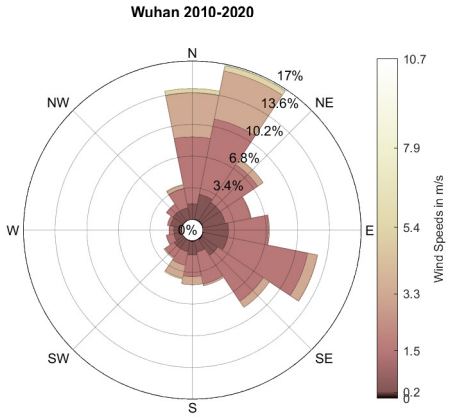

**(a)** Wind Rose of Wuhan 1960




**(b)** Wind Rose of Wuhan 2020




**(c)** Wind Rose of Wuhan 1960–1970




**(d)** Wind Rose of Wuhan 2010–2020

**Figure C6:** Wind Roses of Wuhan City. *Notes*: Panels (a) to (d) show wind patterns over different time periods. Colors indicate wind speed, while percentages represent the frequency of wind from specific directions.

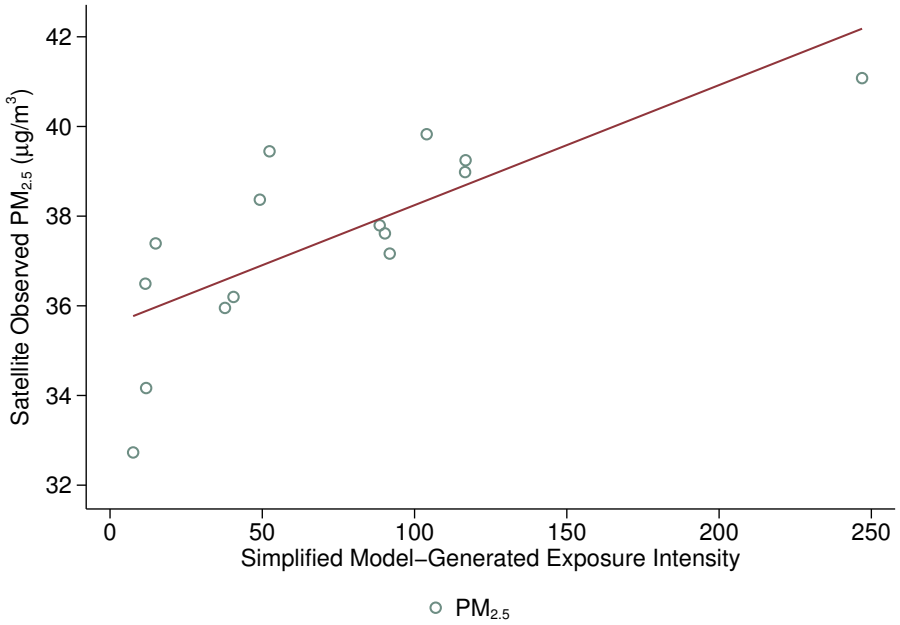



**Figure C7:** Relationship Between Satellite Observations and Simplified Dispersion Model-Generated Exposure Measure. *Notes*: This figure illustrates a strong positive correlation between the model-generated exposure measure and satellite-observed $PM_{2.5}$ concentrations, with a correlation coefficient around 0.8, statistically significant at the 0.01 level.

The subscript $t$ represents an individual year within the study period. Set $T$ in Eq. C6 spans from 1959 to 1970, covering a range of 12 years. $D$ denotes the set of observations in year $t$. All other variables and parameters remain consistent with those used in *Measure 1*. In the subsequent analysis, *Measure 2* is used as an alternative to *Measure 1* to assess the robustness of the results.

# Appendix D: Additional Robustness Check

## Events during 1960s

**Great Famine**. The Great Famine in China (1959–1961) led to significant loss of life, ranging from 16.5 to 45 million in rural areas (Meng, Qian, and Yared, 2015). Counties near steel plants were generally more developed and closer to urban areas, where higher urban population shares were correlated with lower mortality during the famine (Lin and Yang, 2000). Meng and Qian (2009) highlights that in-utero and early-childhood exposure to the famine had substantial negative effects on educational attainment. This raises concerns about potential confounding effects in my paper.

To address this, I interact famine severity with dummies for the affected cohorts (1959–1961) and include these interactions in the baseline model. Famine severity is calculated following the methodology of Meng, Qian, and Yared (2015) and Chen et al. (2020a). It is computed as 1 minus the ratio of the population of famine cohorts (1959–1961) to non-famine cohorts (1955–1957) using 1990 census data.

Column (1) of Table D1 shows that while the famine cohorts experienced severe consequences, the coefficient of interest remains robust. This indicates that the core findings are not significantly affected by including famine severity as a control variable.

**Cultural Revolution**. The Cultural Revolution (1966–1976) caused widespread disruptions, including the interruption of education in urban areas. Most schools ceased regular operations for up to six years, impacting subsequent educational attainment (Meng and Gregory, 2002). Cohorts in the study had their primary and/or lower secondary education overlap with this period, with the intensity of disruption being particularly high in the early years.

To account for the Cultural Revolution's impact, cohorts are categorized into heavy exposure (born 1959–1961) and light exposure (born 1962–1966). Cohort dummies are interacted with county-level measures of Cultural Revolution severity, calculated as the ratio of victims to the county's population in 1964.[1]

[1]The data of victims is drawn from "China Political Events Dataset, 1966–1971" at https://drive.google.com/dri

Column (2) of Table D1 presents the results. The coefficient of interest, while showing a larger magnitude compared to the baseline result (column 1 of Table 2), remains consistent with the fundamental conclusion.

**Send-Down Movement**. The Send-Down Movement, a direct result of the Cultural Revolution, involved sending educated youths to rural areas, ending in 1980 with most returning to urban areas (Chen et al., 2020a). Chen et al. (2020a) found that the movement significantly increased educational attainment in rural areas, which could potentially lead to an underestimation of the treatment effect in my paper if not accounted for.

To alleviate this concern, I match my dateset with that from Chen et al. (2020b) to obtain send-down youth density for each county. Note that the interaction terms between send-down youth density and affected cohorts (1959–1966) is highly correlated (see Appendix Table A3) with the interaction terms between exposure intensity and the treatment cohorts. This correlation likely arises because educated youths were primarily sent to rural suburbs of their cities and towns (Bonnin, 2006), where exposure to steel plant openings might be relatively high due to the initial location of the plants in suburban areas. Appendix Tables A2 and A3 support this.

Column (3) of Table D1 presents the results after adding the interaction terms of send-down youths to the baseline specification, focusing solely on the rural sample, as the Send-Down Movement primarily impacted rural areas. As anticipated, the magnitude of the coefficient of interest increases compared to that in column (3) of Table 4. However, the core conclusion of the paper remains unchanged.

The last column of Table D1 reports the results after controlling for the impacts of China's Great Famine and Cultural Revolution, while excluding send-down density to address the issue of strong correlation. The coefficient of interest remains statistically significant, supporting the robustness of the core findings.

ve/folders/1SsuHl4wEikEdCbLaJr6hHB0JK1KXpg4G. The population data for China in 1964 is sourced from Cao (2005).

**Table D1:** Results of Robustness Check (Events of the 1960s)

| Dependent var: | Years of education | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Events: | Great Famine | Cultural Revolution | Send-Down Movement | Cultural Revolution and Great Famine |
| Exposure intensity × affected cohorts (1959–1966) | -0.01009*** | -0.01929*** | -0.01703** | -0.01149*** |
| | (0.00230) | (0.00265) | (0.00680) | (0.00282) |
| Cultural Revolution × affected cohorts I (1954–1961)[a] | | -0.43643 | | 0.75016 |
| | | (1.07326) | | (1.41802) |
| Cultural Revolution × affected cohorts II (1962–1966)[a] | | -2.52103 | | 0.29887 |
| | | (1.67647) | | (1.81775) |
| Great Famine × affected cohorts (1959–1961)[b] | -0.58113*** | | | -0.47670** |
| | (0.21883) | | | (0.23298) |
| Send-Down youths × affected cohorts (1959–1966)[c] | | | 4.07642 | |
| | | | (2.60668) | |
| Mean of dep var | 8.109 | 8.181 | 6.864 | 8.181 |
| Observations | 178,169 | 157,653 | 83,011 | 157,653 |
| R-squared | 0.407 | 0.401 | 0.270 | 0.403 |
| County FE | Yes | Yes | Yes | Yes |
| Province × birth year FE | Yes | Yes | Yes | Yes |
| Base education × birth year FE | Yes | Yes | Yes | Yes |

*Notes*: In column (3), only the rural sample is included as the Send-Down Movement primarily impacts rural areas. The last column controls for the impact of China's Great Famine and Cultural Revolution while excluding send-down density to mitigate issues arising from the strong correlation. Standard errors are clustered at the county level.

[a] Cohorts are split into two groups (1954–1961 and 1962–1966) based on the Cultural Revolution's impact on education. "Cultural Revolution" measures the severity at the county level, calculated as the number of victims divided by the 1964 county population.

[b] "Great Famine" denotes county-level famine severity, calculated as 1 minus the ratio of the population in famine cohorts (1959–1961) to non-famine cohorts (1955–1957) using 1990 census data. The affected cohorts are those born between 1959–1961.

[c] "Send-Down youths" represents send-down youth density, which is calculated as the ratio of received send-down youths to the county population in 1964 (Chen et al., 2020a).

## Infant Mortality, Childcare, and Influx of Workers

Pollution exposure has been linked to increased infant mortality (e.g., Chay and Greenstone, 2003; Greenstone and Hanna, 2014). It is worth considering whether changes in infant mortality, which could alter the population composition, might influence the observed effects in my paper. While this paper cannot completely dismiss this possibility, its important to note that historical events like the Great Famine and the Cultural Revolution would have had a more pronounced effect on mortality rates and population composition than air pollution. Additionally, the inclusion of these major historical events in the analysis does not substantially alter the results.

Another concern is whether the parents of the cohorts in my study, who were employed at the steel plants, might have experienced reduced childcare at home due to their jobs or health issues from pollution exposure. This is a valid concern, as parents are typically of working age, and their well-being could impact their children's human capital formation. However, the steel plant areas were often developed as self-contained communities with specialized infrastructure and amenities. For example, in Qingshan district, where the Wuhangang steel plant is located, facilities and services were specifically designed for the needs of steel plant workers and their families. These included schools and hospitals named after the plant, such as Wugang (short for Wuhangang) schools and Wugang hospitals (see Appendix Figure D3 for a map of Qingshan District and its amenities).

All workers and their families resided in these purpose-built communities.[2] To address this concern, I exclude all districts (or counties) where the steel plants were located from the sample. Note that all regression results presented in this paper are based on this treatment.

## Expanded Geographic Radius

Building on the approach by Clay, Lewis, and Severnini (2024), I expand the geographic radius to 60 miles to include more counties in the sample. Using the same identification strategy as the

[2] As mentioned in Section 2, the selection of steel plant locations was not arbitrary; large-scale facility construction was also a consideration.

baseline specification, I estimate the treatment's impact. Column (4) of Table D2 shows that the coefficients are statistically significant and closely align with the baseline results. Although a larger sample size generally provides more robust findings, this paper focuses on the 30-mile radius due to concerns that the assumption of uniform economic opportunity effects over a 60-mile radius may not hold. While interaction terms help control for heterogeneous trends, they may not capture all variation. Thus, a more conservative approach with the 30-mile radius is preferred.

## Cohort-Specific Exposure Intensity

The baseline specification assigns a binary treatment status to both treatment and control cohorts, implying that cohorts born in 1959 experience the same exposure levels as those born in 1962 by age four. Some may raise concerns that this treatment approach overlooks valuable variation in annual production and the resulting exposure intensity. Concerns may arise that this approach overlooks valuable variation in annual production and exposure intensity. To address this, I use an identification strategy that accounts for varying cohort-specific exposure intensities, detailed in Eq. D1.

$$\begin{aligned} Y_{i,t,c,p} =& \alpha + \beta \times expo_{i,t,c,p} + \varphi X_{i,t,c,p} + \gamma_{c,p} + \Delta_c \times \tau_t \\ &+ \mu_{prov} \times \tau_t + \epsilon_{i,p,c,t} \end{aligned} \tag{D1}$$

$expo_{i,t,c,p}$ represents the cumulative exposure for individual $i$, born in year $t$ in county $c$, and associated with steel plant $p$, by the age of four. All other variables are held constant, in line with the baseline specification. Each cohort faces varying levels of early childhood exposure, reflecting the annual variability in steel production. Eq. D1 effectively constitutes a staggered-DiD framework, though detailed econometric aspects are not extensively explored in this paper. Within this framework, concerns about partial exposure are addressed, and no cohorts are omitted from the analysis. For ease of computation, production prior to 1958 is assigned the same "weight" as that of 1959, based on the simplified dispersion model, due to minimal production before 1958. Results in Column (6) of Table D2 show that the coefficient of interest remains statistically significant. Moving from the 25$^{th}$ to 75$^{th}$ percentile of exposure (about 1.68 units), results in a reduction in educational

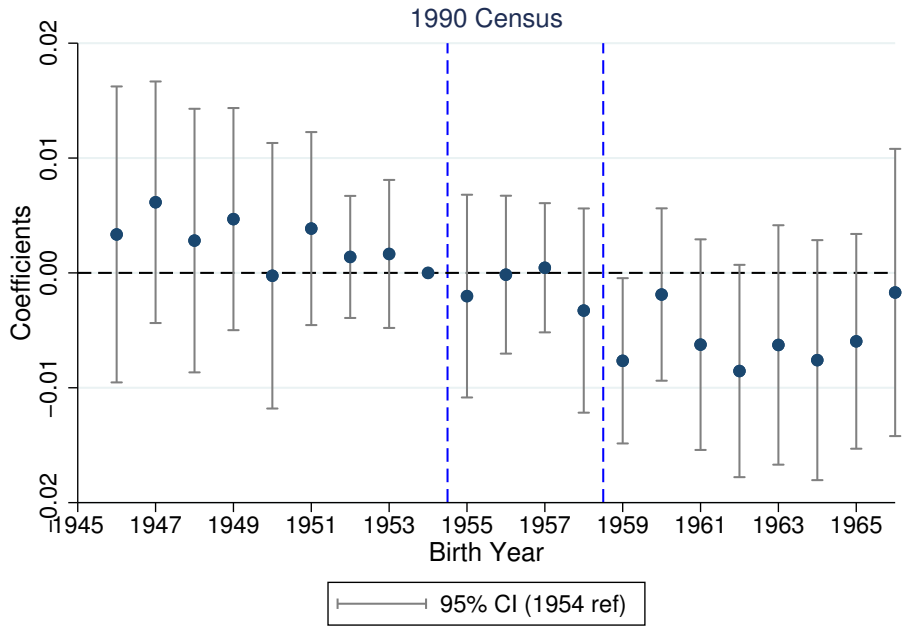



**Figure D1:** Results of By-cohort Specification: Controlling for Squared Distance. *Notes*: This figure presents results that take into account the distance of a county to a steel plant within a 30-mile radius circle. Note that including this factor can substantially reduce variation in exposure intensity. Therefore, this paper prefers the baseline setup without the distance-related interaction terms.

attainment of approximately 0.046 years ($1.68 \times 0.02757$), which is smaller than the baseline estimate. Nonetheless, this paper prefers the baseline specification for its greater flexibility and reduced reliance on econometric assumptions.

## Spatial Correlation

The baseline specification clusters standard errors at the county level. However, potential spatial correlation across counties could bias the inference. To alleviate this concern, I also cluster the standard errors at the city and province level, respectively.[3] Columns (7) and (8) of Table D2 show that the coefficient of interest remains statistically significant.

[3] In China, a city is the administrative level between provinces and counties.

**Table D2:** Distance, Economic Opportunities, Larger Radius, and Cohort-Specific Treatment

| Dependent var: | (1) Years of education | (2) Work in agriculture | (3) Work in manufacturing | (4) Years of education | (5) Years of education | (6) Years of education | (7) Years of education | (8) Years of education |
|---|---|---|---|---|---|---|---|---|
| Robustness check: | Distances within 30 miles | Employment change in agriculture | Employment change in manufacturing | Impact of older plants | Expand radius to 60 miles | Cohort-specific exposure | Cluster SD city level | Cluster SD province level |
| Exposure intensity × affected cohorts (1959–1966) | -0.00850*** | 0.00054 | -0.00000 | -0.00057*** | -0.01163*** | | -0.01022*** | -0.01022*** |
| | (0.00258) | (0.00035) | (0.00001) | (0.00019) | (0.00236) | | (0.00173) | (0.00124) |
| Cohort-specific exposure intensity | | | | | | -0.02757*** | | |
| | | | | | | (0.00627) | | |
| Mean of dep var | 8.109 | 0.468 | 0.00235 | 9.219 | 7.683 | 8.128 | 8.109 | 8.109 |
| Observations | 178,169 | 178,169 | 178,169 | 78,409 | 431,388 | 224,429 | 178,169 | 178,169 |
| R-squared | 0.407 | 0.576 | 0.172 | 0.446 | 0.383 | 0.402 | 0.407 | 0.407 |
| Squared distance × birth year FE | Yes | | | | | | | |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Province × brith year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Base education × birth year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Column (1) shows results considering the distance of a county to a steel plant within a 30-mile radius. Columns (2) and (3) present falsification tests assessing the impact of steel plants on job opportunities in the agricultural and manufacturing sectors. Column (4) reports results from a falsification test using the eight steel plants established more than 10 years before 1959. Column (5) expands the study radius from 30 to 60 miles. Column (6) adopts cohort-specific exposure intensity (Eq. D1), representing the cumulative exposure for an individual by age four. Columns (7) and (8) cluster standard errors at the city and province levels, respectively. For Columns (1)–(6), standard errors are clustered at the county level.

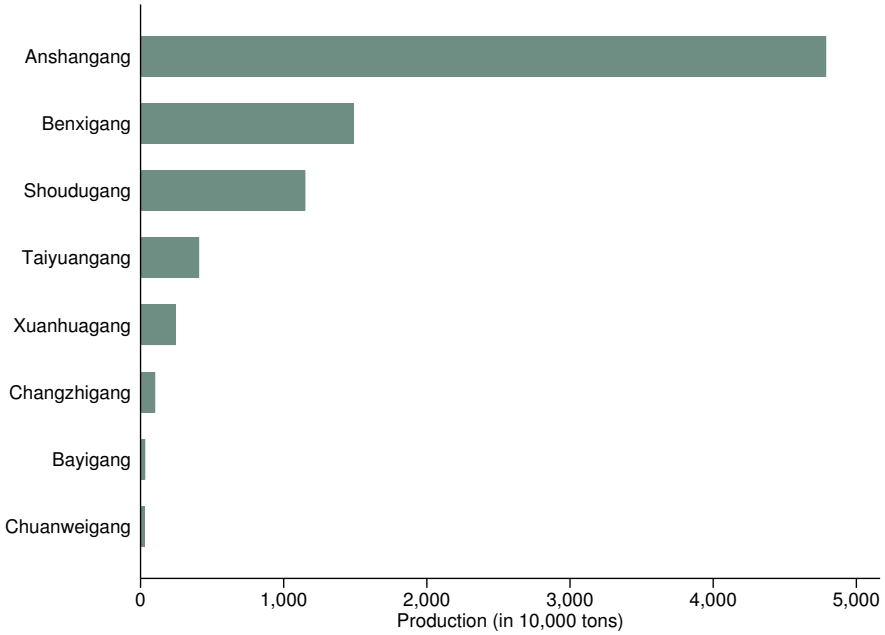



**Figure D2:** Production of 8 Older Steel Plants. *Notes*: I use data from the 8 steel plants built more than 10 years before 1959 and with production records dating back to 1949 as a falsification test.

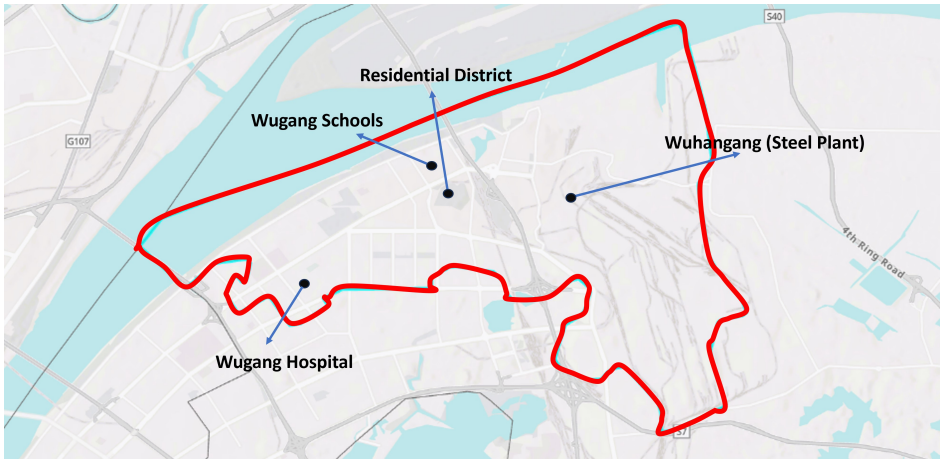



**Figure D3:** Map of Qingshan District. *Notes*: The part outlined in the map is Qingshan District, which is administratively equivalent to a county. This district is strategically designed around the Wuhangang steel plant, with all its infrastructure and amenities tailored to meet the needs of steel plant workers.

## Atmospheric Dispersion Model: A Case Study

This subsection presents a case study using AERMOD and a representative steel plant. This case study supplements the primary findings of my paper and further supports the idea that rapid industrialization in China during the 1950s had significant adverse effects on newborns living near industrial plants.

In the introduction to the dispersion model (Section 4), I previously elucidated the rationale for employing a simplified version rather than a more sophisticated professional model. Nevertheless, achieving precise estimates of the impact remains a desirable goal. In this context, developed by the U.S. Environmental Protection Agency (EPA) and the American Meteorological Society (AMS), is the most suitable model. AERMOD is the preferred regulatory model for forecasting pollutant concentrations within a 50-kilometer radius of emission sources.[4] Its input requirements include detailed meteorological data and estimates of pollution source intensities. While accessing historical meteorological data from the 1960s is challenging, more recent data can be used, assuming key climate parameters, such as wind direction and speed, have remained stable over time. Figure C6 displays wind roses for a steel plant in Wuhan city, China.[5] The upper panels show wind roses for 1960 and 2020, respectively, with minor differences and no substantial changes. The lower panels, showing data over a 10-year interval, indicate even less variation. Precise determination of pollution sources within a steel plant is another challenge, as detailed equipment parameters are not disclosed. This limitation further justifies the use of a simplified model, given that approximate equipment parameters are derived through experiential assessment.

AERMOD divides the terrain into discrete 0.5 km $\times$ 0.5 km grids and calculates pollutant concentrations within a 50 km radius circle. For this paper, I use the concentration of pollutants in the grid nearest to the administrative center of a county as the concentration value for that county. I obtain simulated results from AERMOD for a steel plant in Wuhan city using meteorological data

[4] Source: Page 1-1 at https://www.epa.gov/sites/default/files/2020-09/documents/aermet_userguide.pdf.

[5] A windrose is a chart showing the speed and direction of winds at a location. The size of each segment indicates the frequency of wind blowing from that direction. Source: https://www.climate.gov/maps-data/dataset/wind-roses-charts-and-tabular-data.

from 2020.[6]

One advantage of the Wuhan city steel plant is its status as the largest and most representative facility among those considered in this paper. The simulated dataset includes various pollutants, including total suspended particulates (TSP), particulate matter of 10 micrometers or less ($PM_{10}$), particulate matter of 2.5 micrometers or less ($PM_{2.5}$), sulfur dioxide ($SO_2$), and nitrogen dioxide ($NO_2$).[7]

Table D3 presents the results regarding the concentration of pollutants and their impact on years of education. The results show that all pollutants have statistically significant effects on educational attainment, with $PM_{2.5}$ having the most pronounced impact. This finding is consistent with existing evidence that ambient fine particulate matter ($PM_{2.5}$) is the most detrimental pollutant.[8]

**Table D3:** Impacts of AERMOD Generated Pollutant Concentrations on Years of Education

| Dependent var: | Years of Education | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| TSP[a] concentration × affected cohorts | -394.6 | | | | |
| (1959–1966) | (93.51) | | | | |
| $PM_{10}$ concentration ×affected cohorts | | -648.3 | | | |
| (1959–1966) | | (175.2) | | | |
| $PM_{2.5}$ concentration ×affected cohorts | | | -1,667 | | |
| (1959–1966) | | | (571.1) | | |
| $SO_2$ concentration ×affected cohorts | | | | -1,116 | |
| (1959–1966) | | | | (304.6) | |
| $NO_2$ concentration ×affected cohorts | | | | | -530.9 |
| (1959–1966) | | | | | (151.9) |
| Mean of dep var | 8.839 | 8.839 | 9.110 | 8.839 | 8.839 |
| Observations | 20,373 | 20,373 | 18,125 | 20,373 | 20,373 |
| R-squared | 0.440 | 0.440 | 0.427 | 0.440 | 0.440 |
| County FE | Yes | Yes | Yes | Yes | Yes |
| Province × Birth Year FE | Yes | Yes | Yes | Yes | Yes |

*Notes*: Interaction terms controlling for county-level heterogeneous trends are not included in here, primarily because they take away to much variation in key independent variable in a single-plant setting. Standard errors are clustered at the county level.

[a] TSP represents total suspended particulates.

[6]Wuhangang is one of the few steel plants with available general equipment information, allowing for the inference of additional equipment parameters.

[7]TSP includes all forms of small solid matter.

[8]The report from the United Nations ranks $PM_{2.5}$ as the number 1 dangerous pollutants in our air. Source: https://www.unep.org/news-and-stories/story/5-dangerous-pollutants-youre-breathing-every-day. The EPA also notes that particle pollution and ground-level ozone are among the most widespread health threats. Source: https://www.epa.gov/air-quality-management-process/managing-air-quality-air-pollutant-types.

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