ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
16 February 2024

REVISED
11 April 2024

ACCEPTED FOR PUBLICATION
24 May 2024

PUBLISHED
18 June 2024

LETTER

Unappreciated healthcare inequality against $PM_{2.5}$-related mortality risk

Haofan Zhang[1,2], **Dianyu Zhu**[1], **Miaomiao Liu**[1,*], **Jianxun Yang**[1], **Zongwei Ma**[1], **Wen Fang**[1], **John S Ji**[3], **Pan He**[2,*] **and Jun Bi**[1]

[1] State Key Laboratory of Pollution Control and Resource Reuse, School of the Environment, Nanjing University, Nanjing, People's Republic of China
[2] School of Earth and Environmental Sciences, Cardiff University, Cardiff, United Kingdom
[3] Vanke School of Public Health, Tsinghua University, Beijing, People's Republic of China
[*] Authors to whom any correspondence should be addressed.

E-mail: liumm@nju.edu.cn and HeP3@cardiff.ac.uk

Keywords: environmental health inequality, daily $PM_{2.5}$ exposure, mortality, healthcare expenditures

Abstract

Understanding the inequality of $PM_{2.5}$-related health is crucial for promoting health, building a just society, and advancing multiple Sustainable Development Goals goals. However, previous research has predominantly concentrated on $PM_{2.5}$ exposure inequality, neglecting varied prompt responses and protective behaviors against it. Here, we established the relationship between short-term healthcare expenditure and $PM_{2.5}$ concentration using the number and amount of healthcare transactions across all healthcare categories based on the Union Pay data. We also assessed daily city-specific $PM_{2.5}$-related mortality and healthcare expenditures and evaluated their inequalities among cities according to the income inequality index, the Gini coefficient. The results show that short-term exposure to $PM_{2.5}$ leads to severe physiological and health-related economic burdens on Chinese residents. From 2017 to 2019, 77.8 (34.5–121.1) thousand deaths were attributed to daily $PM_{2.5}$, with healthcare expenditures reaching 93.7 (69.1–118.3) billion Chinese Yuan. Additionally, there were significant inequalities in $PM_{2.5}$-related mortality and healthcare expenditures among cities. The inequality index for $PM_{2.5}$-related healthcare expenditures was 0.53, while the inequality index for $PM_{2.5}$-related mortality was 0.13. The greater inequality in healthcare expenditures than in mortality, implying inadequate healthcare resources amplify the health inequality related to $PM_{2.5}$ exposure. 28.6% of Chinese cities lacked affordable healthcare resources to address the high physiological burden attributable to $PM_{2.5}$. Our multidimensional exploration is essential for formulating effective policies addressing environmental health inequality. Focusing on these cities with disproportionate challenges is crucial for creating a more equitable and sustainable society.

1. Main

Environmental health equality [1] refers to ensuring all individuals, regardless of socioeconomic status, race, or geographic location, have equal access to a healthy environment and are equally protected from environmental hazards. Achieving environmental health equity improves the environment quality, reduces health disparities, promotes social justice, and enhances the overall well-being of communities, aligning with the Sustainable Development Goals (SDGs) [2]. In China, environmental health inequality is a critical concern, particularly in the context of fine particulate matter ($PM_{2.5}$) [3]. Despite the implementation of strict control policies, $PM_{2.5}$ remains a severe issue, with a 37% increase in the number of deaths attributable to it between 2000 and 2017, reaching nearly one million [4]. $PM_{2.5}$ not only imposes a heavy physiological burden but also presents substantial disparities in its impacts [5]. Understanding the inequality in $PM_{2.5}$-related health is significant for formulating policies to promote Universal Health Coverage from an environmental perspective.

Two primary factors contribute to the inequality in $PM_{2.5}$-related health in China. On the one hand, atmospheric $PM_{2.5}$ concentration exhibits notable spatial disparities [6, 7], with higher pollution levels observed in the northern regions compared to the southern regions, higher pollution levels in inland areas compared to coastal regions, and significantly higher pollution levels in urban areas compared to rural areas. These pronounced regional disparities exacerbate exposure risks faced by populations residing in highly polluted regions, leading to disparities in $PM_{2.5}$ exposure and associated physiological health inequality. On the other hand, healthcare resources are insufficient, and the availability of high-quality healthcare is limited [8, 9]. The scarcity of healthcare resources creates disparities in access to healthcare, with underprivileged populations facing difficulties in receiving appropriate healthcare after suffering $PM_{2.5}$ exposure. The discrepancy in healthcare resource allocation compounds the environmental health equality challenge, as individuals exposed to higher pollution levels may also encounter obstacles in accessing healthcare services. The lack of insight into exposure disparities and unequal access to healthcare resources will lead to increased environmental health inequality.

Previous studies have helped us to understand the inequality in exposure to air pollution, including different distributions of air pollutants among nations [10], regions [11], and populations. In the United States, the population weighted $PM_{2.5}$ emission for individuals in poverty was 1.35 times higher than the overall population, while non-Whites had a 1.28 times higher burden [12]. However, previous research relevant to air pollution-related health inequality solely depends on exposure inequality, often overlooking the disparities in protective behaviors, such as seeking medical care against adverse physiological health impacts. A lack of affordable healthcare resources may exacerbate inequality in $PM_{2.5}$-related health among residents having high exposure. Research addressing the identification of vulnerable areas confronting dual challenges of high $PM_{2.5}$-related physiological burdens and financial constraints for healthcare is significant for policymakers to prioritize areas with significant reductions in air pollutants and increase investments in healthcare resources to achieve environmental health equality.

Additionally, it is worth noting that socioeconomic factors are fundamental determinants of health. Previous research has showed that individuals with higher socioeconomic status tend to have longer life expectancies compared to those with lower socioeconomic status [13], even when facing similar environmental risks. Socioeconomic factors can influence the exposure-response relationship through various intricate pathways [14, 15], including disparities in baseline exposure concentrations, differences in physiological adaptation among populations, and variations in the treatment of diseases. However, insufficient attention has been paid to the impact of other prompt responses and protective behaviors against environmental health risks beyond hospital care. For instance, actions such as purchasing masks, over-the-counter medications, and health supplements from pharmacies, as well as seeking consultations at health service stations, have not been adequately examined in relation to environmental health outcomes and associated inequalities.

In this study, we investigate the essential question of which cities in China experience a high $PM_{2.5}$-related physiological burden while their residents lack access to affordable healthcare resources for timely and protective responses against it. We constructed regression models to establish the relationship between healthcare expenditures and short-term exposure to $PM_{2.5}$. We calculated city-specific $PM_{2.5}$-related mortality and healthcare expenditures and assessed their inequalities among cities using the Lorenz curves and Gini coefficient. Furthermore, we employed K-means cluster analysis to identify cities characterized by high $PM_{2.5}$-related physiological burdens with comparatively less $PM_{2.5}$-related healthcare expenditure. We found that between 2017 and 2019, an average of 77.8 (34.5–121.1) thousand deaths per year were attributed to exposure to daily $PM_{2.5}$, with 93.7 (69.1–118.3) billion Chinese Yuan in expenditures for $PM_{2.5}$-related healthcare. In addition to the substantial health burden, China bears high inequalities in $PM_{2.5}$-related physiological health effects and healthcare expenditures. The inequality index for $PM_{2.5}$-related healthcare expenditures was 0.53, while the inequality index for $PM_{2.5}$-related mortality was 0.13. The greater inequality in healthcare expenditures than in mortality, implying inadequate healthcare resources amplify the health inequality related to $PM_{2.5}$ exposure. Ninety-one cities were disadvantaged regarding health equality related to $PM_{2.5}$ exposure, as they bear a significant physiological burden, yet their healthcare expenditures remain comparatively low. To achieve the SDGs, the government should not only encompass targeted regional emissions reduction strategies but also necessitate a substantial increase in healthcare resource allocations, particularly in disadvantaged regions.

2. Methods

2.1. Data

2.1.1. Healthcare expenditures

All categories of health expenditure data originate from bank card (credit and debit card) transactions processed through the UnionPay network. The data accessible to us do not contain any personal information and are aggregated by city on a daily and categorical basis. We analyze data collected between 1 April 2017, and 31 December 2019, before the outbreak of the COVID-19 pandemic, to mitigate its impact on healthcare consumption behaviors. UnionPay is the only interbank payment network in China, with a total transaction volume of 82.23 trillion yuan and a cumulative issuance of 8.53 billion bank cards in 2019 (www.cebnet.com.cn). UnionPay transactions cover the entire nation, including both urban and rural areas. At the end of 2019, the average number of credit and debit cards per person in China was 6.01, with 89.90% of the adult population having active transaction records within six months. In rural areas, this proportion was 83.37% (www.cafi.org.cn). UnionPay transaction records cover various products and services, spanning over 300 merchant categories. The UnionPay network represents the most comprehensive dataset available on consumption activities in China, capturing the majority of healthcare expenditures. In particular, for government medical insurance, medical expenses are directly billed on Medicare cards, with settlements facilitated via UnionPay. Meanwhile, for commercial insurance, patients are typically billed upfront and later reimbursed by insurance companies. These reimbursement fees are commonly transferred to the patients' bank accounts via UnionPay. Similarly, for out-of-pocket payments, incurred expenses are recorded within the UnionPay when settled through bank card transactions. Notably, in 2015, UnionPay accounted for approximately 51% of total out-of-pocket healthcare spending [16]. Regardless of the payment method and source of funds, as long as non-card payments are not systematically biased towards more or less polluted days, the usage of UnionPay cards can serve as a reliable proxy for consumer health expenditure. UnionPay transaction data has been widely utilized in empirical research. Existing research has used UnionPay transaction data to investigate the impact of heat adaptation on household consumption expenditures [17], as well as the influence of China's nationwide, real-time air quality monitoring and disclosure program on households' shopping trips [18]. In this study, we focused on all transactions across the entire healthcare industry, including pharmacies, public hospitals, nursing and care services, unclassified healthcare services, unclassified medical practitioners, and ambulance services. Compared to previous studies that primarily focus on emergency visits and hospital admissions expenditures for specific populations, our dataset covers the entire population and extends beyond hospital-based healthcare services. Our research highlights the importance of residents' prompt response and protective actions to air pollution.

2.1.2. Air quality and meteorological data

We collected hourly $PM_{2.5}$ measurements from 1 582 stations nationwide from the China National Environmental Monitoring Centre (www.cnemc.cn/). Daily $PM_{2.5}$ concentration is calculated for each city by averaging data across monitoring stations. We collected daily monitoring data from 2 456 meteorological stations across China from the China Meteorological Administration (www.cma.gov.cn/). City-level daily meteorological variables were aggregated from all the national stations within the cities. We include variables for maximum temperature, relative humidity, precipitation, wind speed, and wind direction in statistical models for analyzing the impacts of $PM_{2.5}$ on healthcare expenditure.

2.1.3. Mortality and concentration-response functions

We collected annual city-level non-accidental mortality rates from city statistical yearbooks and computed monthly mortality rates for each city based on the proportion of monthly deaths to the total number of deaths nationwide from the Sixth National Population Census. The city-specific concentration-response function of daily $PM_{2.5}$ and mortality were derived from Chen *et al* [19]. We further estimated the provincial concentration-response functions by Bayesian hierarchical models, which were widely used in multisite epidemiologic studies to combine risk estimates across sites. We employed provincial-level exposure-response relationships because the exposure-response relationship is influenced not only by physiological vulnerability but also by socioeconomic factors [20]. Provincial-level exposure-response relationships enable consideration of physiological differences among regional populations and mitigate some of the exposure-response disparities attributed to socioeconomic variations. We conduct sensitivity analyses using exposure-response relationships at both the national and city levels to ensure the robustness of our results.

2.2. Empirical strategies

2.2.1. Causal effects of $PM_{2.5}$ and daily healthcare expenditures

We first estimated the effect of short-term exposure to $PM_{2.5}$ on healthcare expenditures, as in other existing studies [16, 21, 22]. We specified our two-way fixed effects model as the following regression equation:

$$\ln \text{Healthcare}_{ct} = \beta \text{PM2.5}_{ct} + \gamma \text{Weather}_{ct} + \alpha_c + \alpha_y + \alpha_{my} + \text{DOW}_t + \text{Holiday}_t + \omega_{ct}, \tag{1}$$

where PM2.5_{ct} is the daily average $PM_{2.5}$ concentration in the city on date t. The dependent variable, Healthcare_{ct} is a three-day total number of healthcare transactions or total healthcare expenditures based on the date t and the following two days. Similar to previous research, a three-day measure allows us to mitigate the influence of time-invariant unobservables [23, 24]. We also used various window times in our sensitivity analysis to provide additional insights into the lagged effects. The matrix of weather controls, $\mathrm{Weather}_{ct}$ consists of flexible functions of the daily maximum temperature bins (in 5 °C, starting from −20 °C), deciles of relative humidity, and deciles of precipitation. The variable α_c is the city-fixed effect, controlling for the time-invariant attributes of the city, such as household vulnerability in cities. The time-fixed effects α_y and α_{my} include the year-fixed effect and the month-of-year fixed effect. The time-fixed effects capture the time-varying factors across years and seasons, such as economic development and changes in local air pollution control policies. DOW is day-of-week fixed effects. $\mathrm{Holiday}_t$ is a dummy variable for holidays. The ε_{ct} is the error term. The parameter of interest is β, interpreted as a percentage change in healthcare outcome per $\mu\mathrm{g\,m^{-3}}$ increase of $PM_{2.5}$.

Endogeneity can arise through unobservable affecting daily $PM_{2.5}$ levels and healthcare behaviors simultaneously. For example, traffic congestion worsens air quality and increases travel expenditures, which might prevent people from visiting hospitals. To solve the endogeneity problem and infer the causal relationship between $PM_{2.5}$ and healthcare outcomes (transactions and expenditures), we used spatial spillovers of $PM_{2.5}$ for an IV estimation, the validity of which has been verified by multiple existing air pollution studies [23, 25, 26]. The idea is that $PM_{2.5}$ from upwind affects regional air quality. Other than this pathway, $PM_{2.5}$ concentrations in other regions can hardly affect local healthcare consumption behavior and thus can meet the exclusive restriction for a valid IV.

We made each city a pollution source and a receptor to predict the air pollution level of a given city based on the $PM_{2.5}$ in other cities, wind direction, wind speed, and distances and directions between cities. To eliminate spatial correlation in local unobservable, we use 120 km as a buffer zone, and our results are robust to this choice of distance [16]. We assigned different weights to nearby cities for the local city.

$$\begin{aligned}\mathrm{PM2.5}_{ct} = {} & \lambda \mathrm{Upwind}_{ct} + \gamma \mathrm{Weather}_{ct} + \alpha_c + \alpha_y \\ & + \alpha_{my} + \mathrm{DOW}_t + \mathrm{Holiday}_t + \omega_{ct} \end{aligned} \tag{2}$$

$$\mathrm{Upwind}_{ct} = \sum_j \mathrm{Weight}_{cjt} \times \mathrm{PM2.5}_{jt} \tag{3}$$

$$\mathrm{Weight}_{cjt} = \left\{ \begin{array}{l} \frac{1}{d_{cj}} \text{ if } g_{cj} = wd_{ct},\ \mathrm{d}_{cj} \leqslant wv_{ct} \\ 0 \end{array} \right\},$$

$$\mathrm{d}_{cj} \geqslant 120\mathrm{km} \tag{4}$$

where $\mathrm{PM2.5}_{jt}$ is city j ‘s $PM_{2.5}$ concentration in date t, Weight_{cjt} is the weight of every city j relative to the local city c in date t, d_{cj} is the linear distance between the centroid of city j and the city c, g_{cj} is the azimuthal angle of city j relative to city c, and wd_{ct} is the predominant wind direction in city c in date t. wv_{ct} is the average wind speed (meters per day) for city c in date t. The other control variables and the fixed effects are defined as equation (1).

2.2.2. Mortality burden and healthcare expenditures attributable to $PM_{2.5}$

To ensure comparability between the mortality burden and healthcare expenditures, short-term $PM_{2.5}$ exposure-related health outcomes for both variables. Daily deaths attributable to $PM_{2.5}$ for city c were calculated as follows:

$$\begin{aligned}\triangle\,\mathrm{Death}_{ct} &= \mathrm{POP}_{ct} \times \mathrm{Mortality}_{ct} \times \left\{1 - \frac{1}{\mathrm{RR}_{ct}}\right\} \\ &= \mathrm{POP}_{ct} \times \mathrm{Mortality}_{ct} \\ &\quad \times \left\{1 - \frac{1}{\exp\left[\delta_p \times (C_{ct} - C_0)\right]}\right\} \end{aligned} \tag{5}$$

where $\triangle\,\mathrm{Death}_{ct}$ is the attributed death due to $PM_{2.5}$ exposure, $\mathrm{Mortality}_{ct}$ is the baseline mortality rate for city c in date t and equal to the baseline mortality rate for city c in the month of t from China Health Statistical Yearbook and Seventh National Population Census, POP_{ct} is the total population in the year of t from China City Statistical Yearbook, RR_{ct} refers to the relative risk (RR) of death attributable to the change in $PM_{2.5}$ concentration in date t, which can be calculated according is the effect of national concentration-response functions δ_p from previous study and $PM_{2.5}$ concentration for city c in date t (C_{ct}).

Daily additional healthcare expenditures attributable to $PM_{2.5}$ for city c were calculated as follows:

$$\begin{aligned}\triangle\,\mathrm{Healthcare}_{ct} &= \mathrm{Healthcare}_{ct} \\ &\quad \times \left\{1 - \frac{1}{\exp\left[\beta \times (C_{ct} - C_0)\right]}\right\} \end{aligned} \tag{6}$$

where $\triangle\,\mathrm{Healthcare}_{ct}$ is the attributed healthcare transaction or healthcare cost due to $PM_{2.5}$ exposure, $\mathrm{Healthcare}_{ct}$ and β are defined as equation (1).

2.2.3. Inequality measurement of health burden

We employed the Lorenz curves and Gini coefficient to assess and measure the inequalities in the mortality and personal healthcare expenditure burdens associated with $PM_{2.5}$. The Lorenz curves was originally designed to depict wealth distribution inequality within a population. Over time, this concept has been extensively applied to assess inequality in health-related contexts. Our study employs the Lorenz curves to illustrate the inequality in $PM_{2.5}$-related mortality burden and $PM_{2.5}$-related healthcare expenditures. We categorized cities according to their per capita GDP levels, arranging them from the lowest to the highest $PM_{2.5}$ related health impact. Subsequently, we present the cumulative share of people (%) on the horizontal axis with their cumulative share of $PM_{2.5}$ related health impact (%) on the vertical axis. The Gini coefficient serves as a numerical representation of inequality, defined mathematically in reference to the Lorenz curve. The Gini coefficient G in our study was calculated as:

$$G = 1 - \left| \sum_{h=1}^{N-1} (H_{h+1} - H_h)(I_h + I_{h+1}) \right| \qquad (7)$$

Where H is the cumulative share of the population, and I is the cumulative share of $PM_{2.5}$-related health outcomes (mortality burden or healthcare expenditures). H_h indicates the cumulative number of population in cities from 1 to h based on the ranking list from lowest to highest $PM_{2.5}$-related health outcomes and divided by the total population; I_h indicates the corresponding cumulative $PM_{2.5}$-related mortality burden or healthcare expenditures by cities from 1 to h and divided by the total $PM_{2.5}$-related health outcomes.

2.2.4. Categorization of health burdens in cities

To create an economically and physiologically meaningful categorization of $PM_{2.5}$-related burden in cities, considering economic development, air quality, healthcare expenditure, and mortality, we applied the K-means clustering method, a widely used unsupervised machine learning technique. We categorize cities based on their daily $PM_{2.5}$-related death per capita, $PM_{2.5}$-related healthcare expenditures per capita, $PM_{2.5}$ concentration, and GDP per capita to gain insights into the health and medical resource allocation disparities among these. The first step is the selection of k-medoids. The second step calculates the dissimilarity matrix, and the third step assigns each observation to the closest medoids (therefore cluster) based on the calculated distance.

3. Results

3.1. Healthcare expenditures increase with $PM_{2.5}$ exposure

Our OLS and IV fixed-effects panel regressions show that a higher concentration of $PM_{2.5}$ results in a statistically significant increase in healthcare transactions and expenditures. The OLS estimations show that a 10 μg m^{-3} increase in daily average $PM_{2.5}$ exposure is associated with a 0.45% increase in the number of healthcare transactions and a 0.32% increase in healthcare expenditures (table 1). Exploiting the variation in air pollution induced by the random occurrence of upwind $PM_{2.5}$ concentration, a 10 μg m^{-3} increase in daily average $PM_{2.5}$ concentration is associated with a 0.72% increase in healthcare transactions and a 0.67% increase in healthcare expenditures (table 1). The validity of the IV estimation is supported by the first-stage regression, which shows a significant positive correlation between the daily spatial spillovers of $PM_{2.5}$ and the concentration of $PM_{2.5}$, meaning that wind in the upwind direction of pollution sources would bring higher particulate concentration. The considerable F statistics of far indicate a strong IV in the regressions for $PM_{2.5}$. Similar to previous studies on the relationship between $PM_{2.5}$ and hospital visits, our IV estimate is more than two times the magnitude of the OLS estimate. We believe that the IV estimate is more realistic because the OLS estimate is biased downward due to the endogeneity caused by omitted variables. A quasi-experimental study using medical costs from Medicare, a federal health insurance program in the United States for people aged 65 or older, finds that a 10 μg m^{-3} increase in daily $PM_{2.5}$ leads to a rise of 0.51% in three-day emergency room inpatient spending [23]. Another study based on the Urban Employee Basic Medical Insurance data from Beijing, China, indicates that a 10 μg m^{-3} increase in $PM_{2.5}$ results in a 0.387% increase in three-day healthcare visits and a 0.376% increase in three-day medical expenses [24]. In contrast, our findings demonstrate that a 10 μg m^{-3} increase in $PM_{2.5}$ is associated with higher healthcare expenditures. The greater effect may be attributed to our broader focus, which extends beyond the elderly and urban employee population to include all demographics such as children. We employed varying window times to investigate the lag effects of $PM_{2.5}$ on healthcare expenditures. Our findings indicate that our estimates tend to increase as the length of the time window extends marginally, while the confidence intervals of the effect size significantly widen (figure 1). This suggests that our results are not primarily influenced by short-term mortality displacement and boosts our confidence in the choice of a three-day specification to estimate the short-term impacts of air pollution.

3.2. Heavy and unequal physiological mortality burden and healthcare expenditures attributable to $PM_{2.5}$

Figure 2 shows the annual $PM_{2.5}$ concentration, $PM_{2.5}$-related deaths, $PM_{2.5}$-related healthcare transactions, and $PM_{2.5}$-related healthcare expenditures in 318 cities during the study period. The mortality due

Table 1. OLS and IV estimates of effect of daily $PM_{2.5}$ on healthcare transactions and healthcare expenditures.

	OLS		2SLS	
	Transactions	Expenditures	Transactions	Expenditures
$PM_{2.5}$ (10 $\mu g\ m^{-3}$)	0.452%***	0.323%***	0.723%***	0.674%***
	(0.000 017)	(0.000 021)	(0.000 081)	(0.000 10)
N	319 590	319 590	319 590	319 590
R^2	0.781	0.705	0.981	0.964
F statistics			300	300

Notes: Three-day total healthcare utilization outcomes (sums of current day and forward two days), based on the UnionPay from 2017 to 2019, are regressed on daily $PM_{2.5}$ levels (in10 $\mu g\ m^{-3}$). IV estimates are obtained using spatial spillovers of $PM_{2.5}$ as the instrument variables. All regressions control for time-fixed effects of holiday, year–month, day-of-week, and daily weather variables. The weather variables include maximum and minimum temperature bins (in 5 bins starting from −15), deciles of relative humidity and precipitation. Two leads of weather variables are also included as controls. The first-stage Cragg–Donald Wald F-statistic is reported for IV estimates. Standard errors are in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

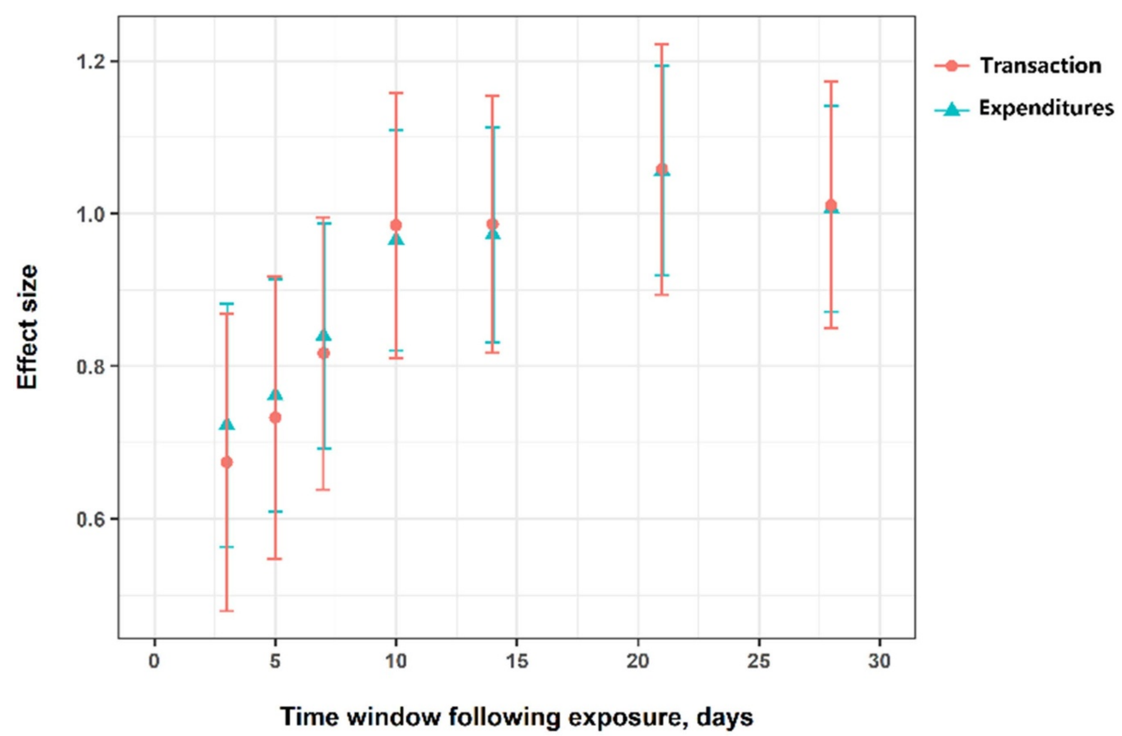

Figure 1. Effect of $PM_{2.5}$ on Healthcare Expenditures over Different Time windows.

to daily air pollution was 77.8 (34.5–121.1) thousand, with the total number of healthcare transactions and healthcare expenditures attributed to daily air pollution being 80.4 (65.2–95.6) million and 93.7 (69.1–118.3) billion Yuan per year, respectively. The healthcare expenditures attributed to $PM_{2.5}$ accounted for 8.47% of the total healthcare expenditures. A study estimating county-specific non-linear $PM_{2.5}$-mortality relationships found a total of 169 862 additional deaths from short-term $PM_{2.5}$ exposure in China in 2015 [27]. Although we employed a different exposure-response relationship at the province level, our results are comparable. Given the ongoing improvements in air quality in China and the reduction in the number of days with severe pollution, our relatively low number of deaths attributed to short-term $PM_{2.5}$ exposure remains reliable. The attributable hospital admission cases for lower respiratory infections, coronary heart disease, and stroke were associated with 3.68 billion CNY (US$550 million) in the entire urban employee population in China during 2016–2017 [28]. The higher attributable healthcare expenditure related to $PM_{2.5}$ exposure may be attributed to our wider range of healthcare expenses, including other non-hospital expenditures. Moreover, our study covers not only

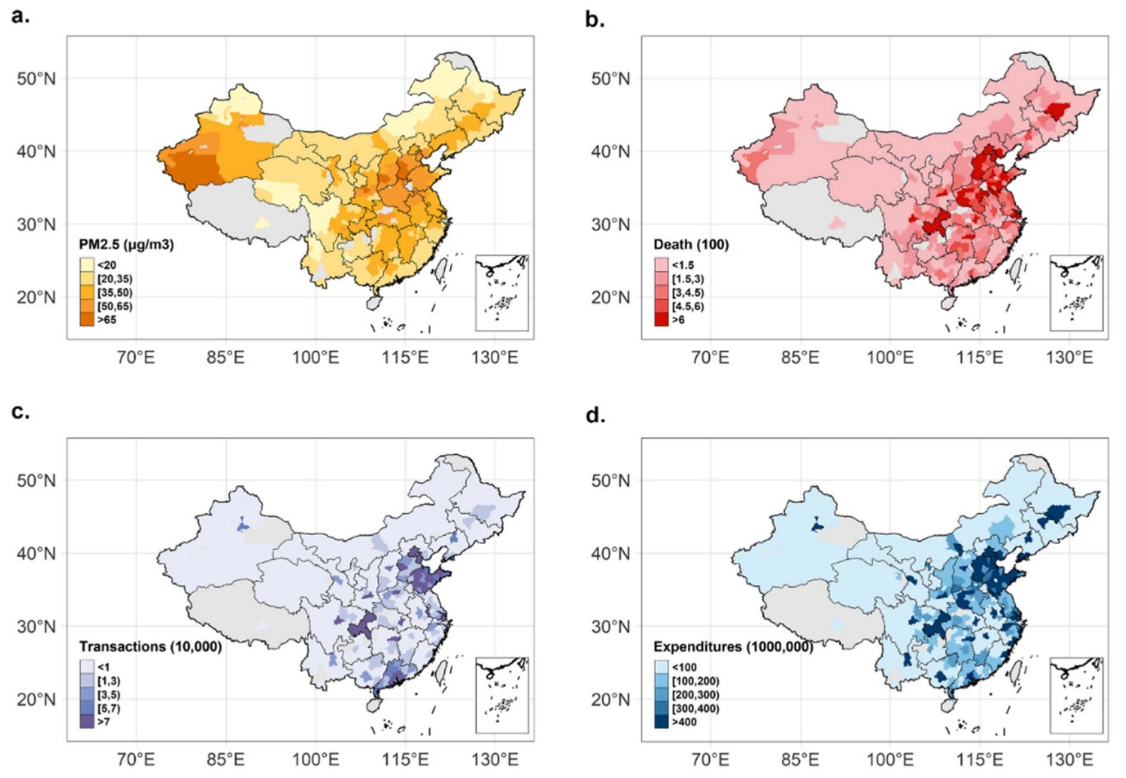

Figure 2. Annual $PM_{2.5}$ concentration, annual deaths, annual healthcare transactions and annual healthcare expenditures related to daily $PM_{2.5}$ in 318 cities during the study period. (a) Annual $PM_{2.5}$ concentration. (b) Annual deaths related to daily $PM_{2.5}$. (c) Annual healthcare transactions related to daily $PM_{2.5}$. (d) Annual healthcare expenditures related to daily $PM_{2.5}$.

government medical insurance but also commercial insurance and out-of-pocket expenses, and it is conducted on a national scale. Our findings show a more comprehensive assessment of residents' protective behaviors during short-term $PM_{2.5}$ exposure, such as buying masks, over-the-counter medications, and health supplements from pharmacies, as well as consultations at health service stations. These differences imply that protective actions beyond hospital visits also merit consideration. We believe that protective measures extending beyond hospital visits are significant and substantial, and the resulting economic burden should not be overlooked. The cities with high $PM_{2.5}$-related mortality are mainly located in eastern and central China, including the Beijing–Tianjin–Hebei (BTH), the Henan Plain, the Shandong Peninsula, the Yangtze River Delta, and the Sichuan Basin. The cities with high $PM_{2.5}$-related healthcare expenditures are mainly located in coastal areas of China and provincial capitals characterized by economic prosperity, dense population concentrations, and a concentration of healthcare resources.

Figure 3 further shows the inequality of $PM_{2.5}$-related deaths and healthcare expenditures. Compared with $PM_{2.5}$-related deaths, the distribution of healthcare expenditures is more skewed, indicating that the inequality in $PM_{2.5}$-related healthcare expenditures among cities is greater than that of $PM_{2.5}$-related deaths. The inequality coefficient of $PM_{2.5}$-related healthcare expenditures was 0.53 (figure 3(b)), which is 1.4 times that of $PM_{2.5}$-related deaths (0.13) (figure 3(a)). In 2019, China's income Gini coefficient was 0.47, indicating that the inequality in $PM_{2.5}$-related healthcare expenditures to $PM_{2.5}$ is greater than the inequality in income. It is worth noting that the distribution of $PM_{2.5}$-related healthcare expenditures at the city level shows a stronger correlation with per capita GDP compared to $PM_{2.5}$-related deaths. As depicted in figure 3, the Lorenz curves for $PM_{2.5}$-related healthcare expenditures exhibits a more uniform color distribution than that of $PM_{2.5}$-related deaths, indicating that cities with higher per capita GDP tend to concentrate in the higher brackets of $PM_{2.5}$-related healthcare expenditure. High-GDP cities contribute a higher percentage of $PM_{2.5}$-related healthcare expenditure relative to their contributions to $PM_{2.5}$-related deaths. The wealthiest 10% of cities were responsible for 15% of $PM_{2.5}$-related deaths, 40% of $PM_{2.5}$-related health transactions, and 36% of $PM_{2.5}$-related healthcare expenditures. The poorest 10% of cities suffered 5% of $PM_{2.5}$-related deaths, 1% of $PM_{2.5}$-related health transactions, and 1% of $PM_{2.5}$-related healthcare expenditures. The substantial disparity observed in $PM_{2.5}$-related healthcare expenditures underscores that the lack of affordable healthcare resources further exacerbated the health inequality of $PM_{2.5}$.

3.3. Cities with mismatched $PM_{2.5}$ attributed mortality burden and healthcare expenditures

Figure 4 illustrates the relationship between $PM_{2.5}$-related mortality and healthcare expenditure in each city. The X-axis represents the normalized $PM_{2.5}$-related death, the Y-axis represents normalized logarithmically transformed $PM_{2.5}$-related healthcare expenditure, and the size and color of the dot show the economic development level and air quality. We found that healthcare expenditures to address pollution challenges did not necessarily increase with an increase in deaths attributable to pollution. To better understand the mismatch between $PM_{2.5}$-related mortality and healthcare expenditures in cities, we further conducted a clustering analysis based on their $PM_{2.5}$-related death per capita, $PM_{2.5}$-related healthcare expenditures per capita, annual $PM_{2.5}$ concentration, and GDP per capita. According to K-Means clustering results, the 318 cities in China can be categorized into four distinct groups. The first cluster consists of 91 cities, including Linfen City, Handan City, and Kaifeng City. This cluster reports the highest $PM_{2.5}$-related death per capita (0.075%), the low $PM_{2.5}$-related healthcare expenditures per capita (48.1 Yuan), the highest annual $PM_{2.5}$ concentration (53.6 μg m^{-3}) and the lowest GDP per capita (64.8 thousand Yuan) (table 2). In terms of spatial distribution, these cities are primarily concentrated in central China, specifically in Shanxi, Hebei, Henan, and Shandong provinces (figure 5). For the first-cluster cities, healthcare expenditures are disproportionate to the number of deaths, suggesting that individuals may not seek medical care even when faced with significant physiological health burdens. There is also another cluster of cities (the fourth cluster) that reports medium $PM_{2.5}$-related death per capita (0.057%), the highest $PM_{2.5}$-related healthcare expenditures per capita (165.3 Yuan), comparatively high $PM_{2.5}$ concentration (42.9 μg m^{-3}) and the highest GDP per capita (120.6 thousand Yuan) (table 2). In terms of spatial distribution, these cities are mainly distributed in the Yangtze River Delta and the Pearl River Delta regions, as well as provincial capitals and municipalities (figure 5). The residents in the fourth cluster exhibit a heightened responsiveness to the physiological health impacts of $PM_{2.5}$, which may be advantageous at the individual level but poses challenges to the stability of city healthcare systems.

4. Discussion

Previous studies have separately examined mortality and healthcare expenditure attributable to short-term $PM_{2.5}$ exposure, demonstrating the substantial burden of $PM_{2.5}$ in China. Our research represents the mismatch of $PM_{2.5}$-related mortality and healthcare expenditure for the first time. Our results suggest that protective prompt response and protective actions beyond hospital care call for attention. Our findings reveal that alongside the existing inequality in $PM_{2.5}$-related mortality, economic conditions and the accessibility of healthcare resources exacerbated the inequality. Our finding highlights the vulnerable cities with high $PM_{2.5}$-related physiological burdens yet limited healthcare resources against it. It also underscores the potential environmental health justice issues that should be addressed by policy design.

The spatial distributions of city-level $PM_{2.5}$-related deaths and healthcare expenditures are uneven and disproportionate, which hampers progress toward SDGs. The mismatch implies that some cities lack the necessary affordable healthcare resources to protect their residents effectively against adverse health consequences of $PM_{2.5}$ pollution. In disadvantaged cities, there is limited access to medical services, inadequate healthcare infrastructure, and a lack of preventive measures to mitigate the impact of air pollution on public health. They face higher levels of $PM_{2.5}$ pollution and associated health risks yet bear the brunt of environmental hazards without adequate healthcare support. The inadequate healthcare support in these cities poses a substantial barrier to advancing SDG 3 (Good Health and Well-being). Furthermore, insufficient healthcare support may contribute to inequalities, hindering progress toward SDG 10 (Reduced Inequality). Conversely, residents in more advantaged cities benefit from readily available healthcare resources. When confronted with comparable levels of $PM_{2.5}$ concentration, they implement more timely and proactive responses to mitigate the associated health impacts. However, excessive response measures beyond corresponding physiological needs may result in overmedicalization and inefficient use of healthcare resources. While individual health is assured, the sustainability of the city's development remains a critical challenge, particularly in the context of the SDGs. The disproportionate pollutants and healthcare resources not only harm public health but also hinder progress toward SDG 11 (Sustainable Cities and Communities).

We also emphasize the additional amplifying effect of socioeconomic status on environmental health inequality. Prior research has highlighted how socioeconomic factors modify the relationship between environmental exposures and health outcomes. For instance, studies have shown that urban populations have a lower risk of mortality compared to rural areas for the same unit change of $PM_{2.5}$,

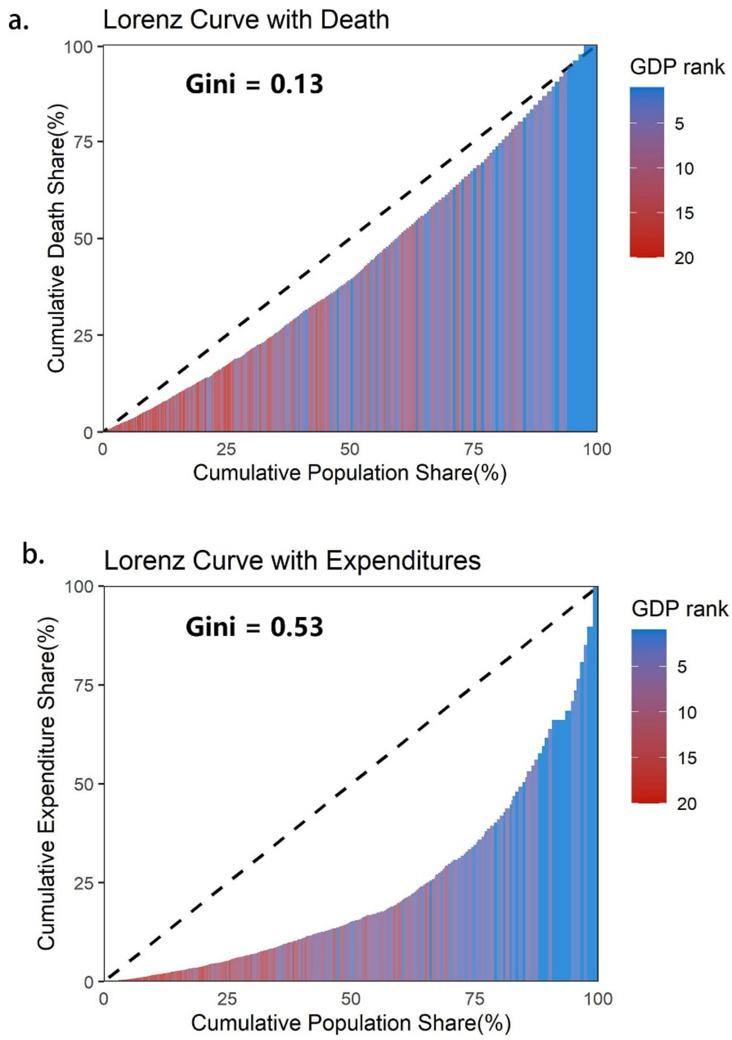

Figure 3. Lorenz curves for daily $PM_{2.5}$-related death and healthcare expenditures. (a) Lorenz curves for daily $PM_{2.5}$-related death. (b) Lorenz curves for daily $PM_{2.5}$-related healthcare expenditures.

ozone, and temperature [14, 15, 20]. Our study further demonstrates that socioeconomic factors not only exacerbate environmental health inequalities by modifying the exposure-response relationship but also amplify these inequalities by influencing prompt responses and protective behaviors. High-GDP cities often boast superior healthcare facilities, and their residents have easier access to healthcare resources against adverse health effects of $PM_{2.5}$ [29, 30] as they are more likely to seek medical attention promptly. In contrast, due to limited access to quality healthcare services, individuals in less affluent areas may experience low healthcare expenditures despite suffering significant health risks [31]. In addition, wealthier individuals often invest more in measures, such as regular check-ups, consultations, and specialized medical interventions, to prevent themselves from air pollution-related health risks [21, 22]. While beneficial for health, these excessive preventive measures may occupy healthcare resources that could have been used to safeguard the health of individuals with lower socioeconomic status. This underscores the need for equitable healthcare resource allocation to safeguard the health of all individuals, irrespective of their socioeconomic status.

In China, environmental health inequality related to air pollution depends not only on the physiological health burdens caused by air pollution but also on healthcare affordability associated with economic development. In disadvantaged cities, individuals confront higher mortality risks but lack affordable healthcare resources. On the other hand, in advantaged cities, people tend to spend a significant amount of money, even facing relatively low mortality risks. This phenomenon underscores the complexity of environmental health equity, which involves the equitable distribution of environmental benefits and burdens and a range of strategies to rectify existing impacts [32]. Hence, to alleviate the environmental health inequality caused by air pollution, China should pay special attention to cities where individuals face elevated physiological burdens yet lack the financial means to access healthcare services.

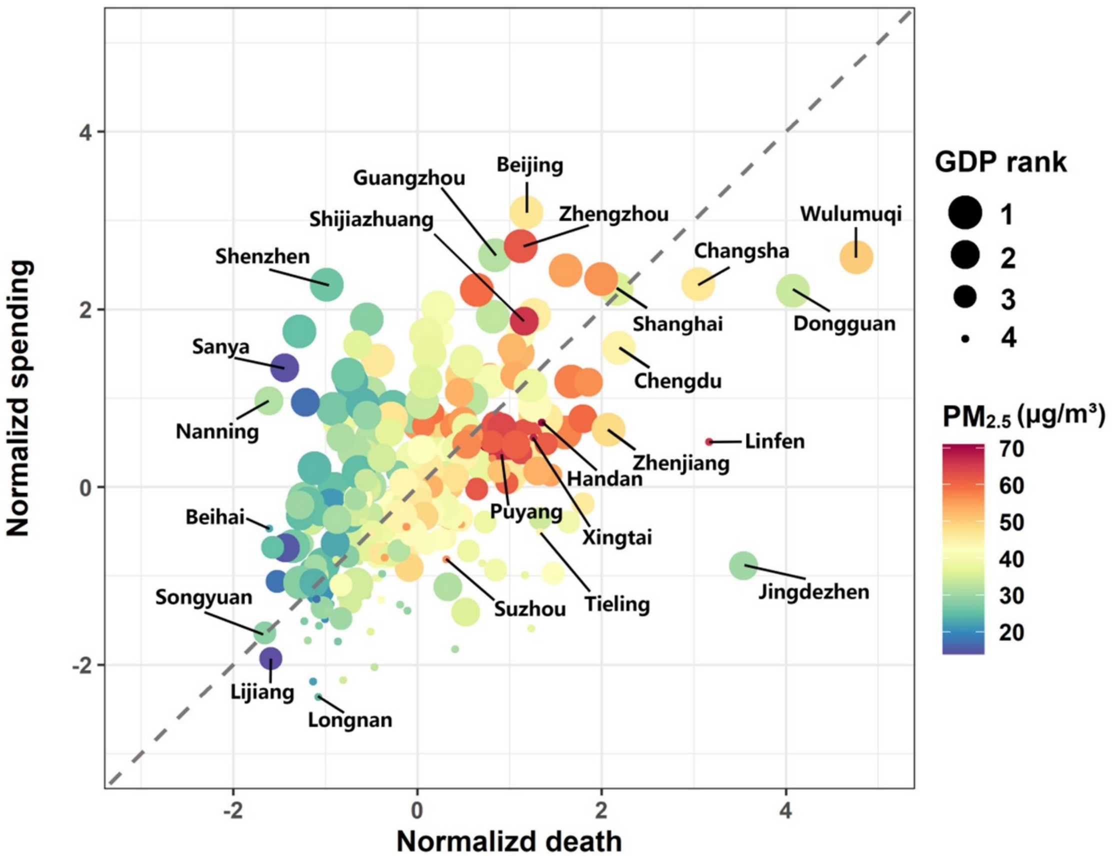

Figure 4. Relationship between daily $PM_{2.5}$-related mortality and healthcare expenditure in each city. The X-axis represents the normalized daily $PM_{2.5}$-related death, the Y-axis represents normalized logarithmically transformed $PM_{2.5}$-related healthcare expenditure, and the size and color of the dot show the economic development level and air quality.

Table 2. Mean of different clusters based on k-means.

	$PM_{2.5}$-related mortality (‰)	$PM_{2.5}$-related healthcare expenditures per capita (Yuan)	$PM_{2.5}$ (μg m^{-3})	GDP per capita (thousand Yuan)
Cluster 1	0.075	46.3	53.6	64.8
Cluster 2	0.042	48.1	31.8	114.2
Cluster 3	0.035	32.8	30.2	66.2
Cluster 4	0.057	165.3	42.9	120.6

Categorize cities into four clusters based on their daily $PM_{2.5}$-related mortality, $PM_{2.5}$-related healthcare expenditures per capita, $PM_{2.5}$ concentration and GDP per capita using K-means.

Reducing pollution concerns in these cities is imperative as it serves as the foundation for safeguarding public health by alleviating various physiological burdens. Additionally, it is crucial to adopt a balanced approach that prioritizes both economic growth and environmental protection [33]. As China advances its industrialization and pursues economic reforms, it should simultaneously invest in green technologies and renewable energy sources to reduce emissions [34]. Government subsidies and support programs should be implemented to ensure that residents have access to affordable and clean energy alternatives [35]. By promoting energy efficiency and transitioning to sustainable energy sources, the government can address both environmental and socioeconomic challenges. Furthermore, in the pursuit of environmental health equity, economically accessible healthcare resources are critical. Sustainable economic development provides financial support for investing in healthcare infrastructure in underserved areas, expanding healthcare insurance coverage, and reducing healthcare expenses associated with the treatment of air pollution-related diseases. Promoting public health awareness is equally vital; through education, individuals can better understand how to protect their health during pollution events and utilize healthcare resources effectively. By prioritizing public health and environmental sustainability, the government can create a healthier and more prosperous society for all.

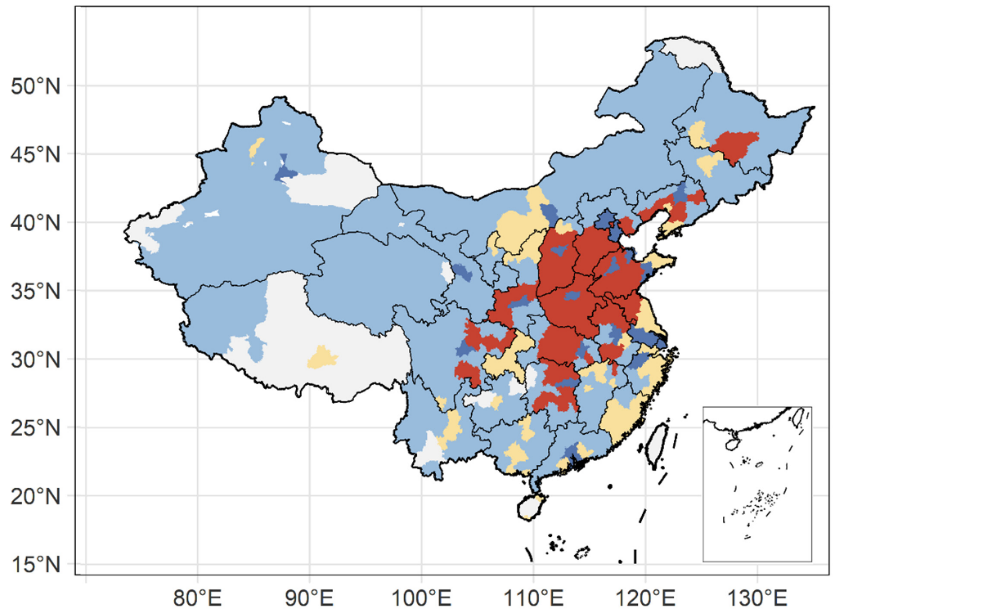

Figure 5. Spatial distribution of cities with different characteristics in daily $PM_{2.5}$-related mortality, per capita $PM_{2.5}$-related healthcare expenditures, annual $PM_{2.5}$ concentration, and GDP per capita.

Our study has certain limitations that should be acknowledged. First, our healthcare expenditure data cannot include transactions outside the UnionPay network, such as cash payments or the portion of mobile payments, such as WeChat Pay and Alipay. While cash payments are increasingly rare in China, mobile payments are widespread and generally recorded by the UnionPay network. Even in cities with higher economic levels, where the proportion of mobile payments may be slightly higher, this would only underestimate the inequality of healthcare expenditures. Second, our study may face challenges in establishing causality due to concurrent exposure to other atmospheric pollutants and health outcomes not specific to diseases. However, we employed established methods from epidemiology and econometrics to enhance our analysis. Third, solely focusing on short-term mortality and healthcare expenditure may underestimate the health impacts of $PM_{2.5}$, since its risk primarily manifests in the long-term effect. Nevertheless, our conclusion regarding the amplification of healthcare resource accessibility to $PM_{2.5}$-related health inequities remains robust. Limited healthcare resources and insufficient awareness of prevention measures in underdeveloped cities may exacerbate the economic burden of chronic diseases. Thus, the amplifying effect of healthcare resource accessibility on the long-term impact of $PM_{2.5}$-related health inequities could be further pronounced. Last, due to the constraints in daily mortality data, we were unable to employ the same two-way fixed effects model to compute attributable deaths. However, we utilized epidemiological finding with same lag effect and controlling for meteorological factors and time effects to ensure the comparability.

5. Conclusion

In conclusion, our findings underscored the inequality in $PM_{2.5}$-related health, offering a basis for clean air policies that avoid and redress inequities. A nuanced understanding of the inequality in $PM_{2.5}$-related deaths and healthcare expenditures involves considering the intricate interplay between population dynamics, air quality, and healthcare resources. Policymakers need to formulate tailored strategies for sustainable, resilient, and equitable solutions, addressing not only the reduction of $PM_{2.5}$-related mortality but also the promotion of efficient healthcare services and environmental well-being.

Data availability statement

The data cannot be made publicly available upon publication due to legal restrictions preventing unrestricted public distribution. The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

The study was financially supported by The National Natural Science Foundation of China (Grant Nos. 72222012, 72174084, 72234003 and 71921003), Jiangsu Natural Science Foundation (Grant No. BK20220125), Jiangsu R&D Special Fund for Carbon Peaking and Carbon Neutrality (Grant No. BK20220014). The contents of this paper are solely the responsibility of the authors and do not necessarily represent the official views of the sponsors. The authors declare that they have no actual or potential competing financial interests.

ORCID iD

Zongwei Ma https://orcid.org/0000-0003-0257-5695

References

[1] Friel S, Marmot M, McMichael A J, Kjellstrom T and Vågerö D 2008 Global health equity and climate stabilisation: a common agenda *Lancet* **372** 1677–83
[2] Sachs J D 2012 From millennium development goals to sustainable development goals *Lancet* **379** 2206–11
[3] Zhang J, Mauzerall D L, Zhu T, Liang S, Ezzati M and Remais J V 2010 Environmental health in China: progress towards clean air and safe water *Lancet* **375** 1110–9
[4] Yue H, He C, Huang Q, Yin D and Bryan B A 2020 Stronger policy required to substantially reduce deaths from $PM_{2.5}$ pollution in China *Nat. Commun.* **11** 1462
[5] Han C, Xu R, Gao C X, Yu W, Zhang Y, Han K, Yu P, Guo Y and Li S 2021 Socioeconomic disparity in the association between long-term exposure to $PM_{2.5}$ and mortality in 2640 Chinese counties *Environ. Int.* **146** 106241
[6] Wang S, Zhou C, Wang Z, Feng K and Hubacek K 2017 The characteristics and drivers of fine particulate matter ($PM_{2.5}$) distribution in China *J. Clean. Prod.* **142** 1800–9
[7] Jin H, Zhong R, Liu M, Ye C and Chen X 2022 Spatiotemporal distribution characteristics of $PM_{2.5}$ concentration in China from 2000 to 2018 and its impact on population *J. Environ. Manage.* **323** 116273
[8] Qingyue M, Anne M, Longde W and Qide H 2019 What can we learn from China's health system reform? *BMJ* **365** l2349
[9] Marten R, McIntyre D, Travassos C, Shishkin S, Longde W, Reddy S and Vega J 2014 An assessment of progress towards universal health coverage in Brazil, Russia, India, China, and South Africa (BRICS) *Lancet* **384** 2164–71
[10] Zhang Q *et al* 2017 Transboundary health impacts of transported global air pollution and international trade *Nature* **543** 705–9
[11] Lin J, Pan D, Davis S J, Zhang Q, He K, Wang C, Streets D G, Wuebbles D J and Guan D 2014 China's international trade and air pollution in the United States *Proc. Natl Acad. Sci.* **111** 1736–41
[12] Mikati I, Benson A F, Luben T J, Sacks J D and Richmond-Bryant J 2018 Disparities in distribution of particulate matter emission sources by race and poverty status *Am. J. Public Health* **108** 480–5
[13] Mackenbach J P *et al* 2019 Determinants of inequalities in life expectancy: an international comparative study of eight risk factors *Lancet Public Health* **4** e529–37
[14] Sun Z, Zhang X, Li Z, Liang Y, An X, Zhao Y, Miao S, Han L and Li D 2024 Heat exposure assessment based on high-resolution spatio-temporal data of population dynamics and temperature variations *J. Environ. Manage.* **349** 119576
[15] Xing Q, Sun Z, Tao Y, Zhang X, Miao S, Zheng C and Tong S 2020 Impacts of urbanization on the temperature-cardiovascular mortality relationship in Beijing, China *Environ. Res.* **191** 110234
[16] Barwick P J, Li S, Rao D and Zahur N B 2018 The healthcare cost of air pollution: evidence from the world's largest payment network *Natl. Bur. Econ. Res. Working Paper Ser.* 24688
[17] Lai W, Li S, Liu Y and Barwick P J 2022 Adaptation mitigates the negative effect of temperature shocks on household consumption *Nat. Hum. Behav.* **6** 837–46
[18] Barwick P J, Donaldson D, Li S, Lin Y and Rao D 2022 Improved transportation networks facilitate adaptation to pollution and temperature extremes *Natl Bur. Econ. Res. Working Paper Ser.* 30462
[19] Chen R *et al* 2017 Fine particulate air pollution and daily mortality. A nationwide analysis in 272 Chinese Cities *Am. J. Respir. Crit. Care Med.* **196** 73–81
[20] Han L, Qin T, Sun Z, Ren H, Zhao N, An X and Wang Z 2023 Influence of urbanization on the spatial distribution of associations between air pollution and mortality in Beijing, China *GeoHealth* **7** e2022GH000749
[21] Zhang J and Mu Q 2018 Air pollution and defensive expenditures: evidence from particulate-filtering facemasks *J. Environ. Econ. Manage.* **92** 517–36
[22] Freeman R, Liang W, Song R and Timmins C 2019 Willingness to pay for clean air in China *J. Environ. Econ. Manage.* **94** 188–216
[23] Deryugina T, Heutel G, Miller N H, Molitor D and Reif J 2019 The mortality and medical costs of air pollution: evidence from changes in wind direction *Am. Econ. Rev.* **109** 4178–219
[24] Xia F, Xing J, Xu J and Pan X 2022 The short-term impact of air pollution on medical expenditures: evidence from Beijing *J. Environ. Econ. Manage.* **114** 102680
[25] Yang J and Zhang B 2018 Air pollution and healthcare expenditure: implication for the benefit of air pollution control in China *Environ. Int.* **120** 443–55
[26] He P, Liang J, Qiu Y, Li Q and Xing B 2020 Increase in domestic electricity consumption from particulate air pollution *Nat. Energy* **5** 985–95
[27] Li T, Guo Y, Liu Y, Wang J, Wang Q, Sun Z, He M Z and Shi X 2019 Estimating mortality burden attributable to short-term $PM_{2.5}$ exposure: a national observational study in China *Environ. Int.* **125** 245–51
[28] Xie Y *et al* 2021 Short-term ambient particulate air pollution and hospitalization expenditures of cause-specific cardiorespiratory diseases in china: a multicity analysis *Lancet Reg. Health* **15** 100232
[29] Dunlop S, Coyte P C and McIsaac W 2000 Socio-economic status and the utilisation of physicians' services: results from the canadian national population health survey *Soc. Sci. Med.* **51** 123–33
[30] Zhao Y, Atun R, Oldenburg B, McPake B, Tang S, Mercer S W, Cowling T E, Sum G, Qin V M and Lee J T 2020 Physical multimorbidity, health service use, and catastrophic health expenditure by socioeconomic groups in China: an analysis of population-based panel data *Lancet Glob. Health* **8** e840–9
[31] Patel J A, Nielsen F B H, Badiani A A, Assi S, Unadkat V A, Patel B, Ravindrane R and Wardle H 2020 Poverty, inequality and COVID-19: the forgotten vulnerable *Public Health* **183** 110–1
[32] Northridge M E, Stover G N, Rosenthal J E and Sherard D 2003 Environmental equity and health: understanding complexity and moving forward *Am. J. Public Health* **93** 209–14

[33] Wang J, Wang K and Wei Y-M 2020 How to balance China's sustainable development goals through industrial restructuring: a multi-regional input–output optimization of the employment–energy–water–emissions nexus *Environ. Res. Lett.* **15** 034018

[34] Lu C, Zhang S, Tan C, Li Y, Liu Z, Morrissey K, Adger W N, Sun T, Yin H and Guo J 2022 Reduced health burden and economic benefits of cleaner fuel usage from household energy consumption across rural and urban China *Environ. Res. Lett.* **17** 014039

[35] Zhao J, Wang M and Zhu J 2022 Household energy transition and social status: evidence from large-scale heating renovation in China *Environ. Res. Lett.* **17** 115011