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Reduced inequality in ambient and household $PM_{2.5}$ exposure in China

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ABSTRACT

The society has high concerns on the inequality that people are disproportionately exposed to ambient air pollution, but with more time spent indoors, the disparity in the total exposure considering both indoor and outdoor exposure has not been explored; and with the socioeconomical development and efforts in fighting against air pollution, it is unknown how the exposure inequality changed over time. Based on the city-level panel data, this study revealed the Concentration Index (***C***) in ambient $PM_{2.5}$ exposure inequality was positive, indicating the low-income group exposed to lower ambient $PM_{2.5}$; however, the total $PM_{2.5}$ exposure was negatively correlated with the income, showing a negative ***C*** value. The low-income population exposed to high $PM_{2.5}$ associated with larger contributions of indoor exposure from the residential emissions. The total $PM_{2.5}$ exposure caused 1.13 (0.63–1.73) million premature deaths in 2019, with only 14 % were high-income population. The toughest-ever air pollution countermeasures have reduced ambient $PM_{2.5}$ exposures effectively that, however, benefited the rich population more than the others. The transition to clean household energy sources significantly affected on indoor air quality improvements, as well as alleviation of ambient air pollution, resulting in notable reductions of the total $PM_{2.5}$ exposure and especially benefiting the low-income groups. The negative ***C*** values decreased from 2000 to 2019, indicating a significantly reducing trend in the total $PM_{2.5}$ exposure inequality over time.

1. Introduction

Clear air is a basic human right, but many people are exposed to poor air quality that adversely affect human health. Exposure to air pollution has been documented to be closely associated with various respiratory diseases, cardiovascular diseases, and mortality (Deng et al., 2021; Dong et al., 2020; Lim et al., 2012; Shi et al., 2016). Globally, approximately 6 million premature deaths were attributable to $PM_{2.5}$ (particles with aerodynamic diameters equal to or <2.5 μm) exposure, with high mortalities in densely populated developing countries such as China and India (GBD, 2019).

It has been concerned seriously that people expose to air pollution disproportionately (Jbaily et al., 2022; Mohai et al., 2009; Brulle and Pellow, 2006). Some studies found that the poor were more likely to work and/or live in places where the air quality was worse, for whom the exposure resulted in a high occurrence of many diseases and more premature deaths (Liu et al., 2017a; Jorgenson et al., 2021). Environmental inequality often discussed ambient exposure level or several specific health outcome disparities across the population of different race/ethnicity or socioeconomic status (e.g. income, occupation, and educational attainment). Early studies originated from field investigations of the dwelling environments of different races/ethnicities in the U.S. and many other developed countries (Jbaily et al., 2022; Colmer et al., 2020). Many of such studies pointed out that $PM_{2.5}$ exposures decreased with increasing incomes (Hajat et al., 2013, 2015; Milojevic et al., 2017), and the poorest were often subjected to the most serious environmental pollution, even though some studies showed a nonlinear relationship between air pollution and the income/deprivation index (Milojevic et al., 2017; Havard et al., 2009; Jiao et al., 2018; Keene and Deller, 2015). In recent years, environmental inequality in

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developing countries such as China, India, Peru, and Mexico have received increasing attention (Cao et al., 2019; Zhao et al., 2019; Chakraborty and Basu, 2021; Huang et al., 2019; Rao et al., 2021; Lome-Hurtado et al., 2020; Yao et al., 2018), for example, in India, the $PM_{2.5}$ levels were found to be higher in districts with higher percentages of households with poor residential conditions and without toilets (Chakraborty and Basu, 2021). The PM_{10} levels increased with an increase in the deprivation index in Mexico (Lome-Hurtado et al., 2020). Compared with that in developed countries, exposure inequality studies are much fewer in developing countries, and the inequality issue has been seriously underappreciated.

Available studies on $PM_{2.5}$ exposure inequality primarily relied on exposure estimations from ambient pollution levels. However, given the longer time spent indoors, when air pollution exposures were only based on the ambient concentrations, the exposure estimates would be substantially biased and significantly underestimated especially for the populations working and/or living in microenvironments with severe indoor air pollution (Ouyang et al., 2018; Huang et al., 2019). The relationship between exposure and income, which is one important indicator of socioeconomic status, would be rather different between ambient exposure and total exposure, as indoor exposure can contribute greatly to the total exposure (Huang et al., 2021; Li et al., 2016; Shen et al., 2021; Yun et al., 2020). But, this has not been investigated leading to probable mis-interpretation of the exposure inequality. Moreover, under the socioeconomic development, it is unknown how the exposure disparity has changed over time and which factors drove the trend.

In this study, we assessed the ambient and total exposure differences over the past two decades among populations with different income levels in China mainland. We demonstrated that the relationships between ambient $PM_{2.5}$ exposure and population income in China were different from those observed in many other countries, and the relationships were opposite when considering the total exposure that included both indoor and outdoor exposure. We further revealed that the spontaneous household energy transition from high reliance on traditional solid fuels to cleaner modern energies significantly reduced inequality in the total $PM_{2.5}$ exposure.

2. Materials and methods

2.1. Ambient $PM_{2.5}$ concentration

The ambient $PM_{2.5}$ concentrations were modeled using the WRF/Chem model (v3.5) which couples the atmospheric chemical transport module with the Weather Research and Forecasting (WRF) model in Kinetic framework and microphysical processes. The meteorological field data as model inputs were from the National Centers for Environmental Prediction Final Operational Global Analysis data and WRF-modeled meteorological fields were evaluated by observations (The National Center for Atmospheric Research, 2020; National Meteorological Information Center, 2013). The simulation area covered China and its surrounding areas (latitude ranges 13–56°N, longitude ranges 67–143°E) with a spatial resolution of 50 × 50 km^2 and a time step of 300 s. Emission inventories of major air pollutants including primary $PM_{2.5}$, black carbon, organic carbon, NOx, CO, SO_2, and NH_3 were from PKU-FUEL inventory (http://inventory.pku.edu.cn/). VOCs (volatile organic compounds) and non-residential NH_3 emissions were from EDGAR-HTAP data set (Emission Database for Global Atmospheric Research-Hemispheric Transport of Air Pollution) (EDGAR, 2017; Janssens-Maenhout et al., 2015). Simulations were conducted for five-year intervals from 2000 to 2019. Based on wind fields and high-resolution emission inventories, the Gaussian downscaling approach was adopted to downscale the calculated $PM_{2.5}$ concentrations to 1/120° in both longitude and latitude (Meng et al., 2021). The modeled concentrations were validated against observation data from the Ministry of Environmental Protection (https://www.cnemc.cn/) (**Fig. s1**) and a database developed from visibility records for those when ground monitoring was not available (**Fig. s2**) (Liu et al., 2017b; Shen et al., 2019). Normalized mean bias (NMB) and normalized mean error (NME) were calculated to quantitatively assess the model performance. The NME values were 57.8 %, 49.0 %, 46.8 %, and 75.3 % for 2000, 2010, 2014, and 2019, respectively. It appears that the model overestimated ambient $PM_{2.5}$ with the relative differences within 2 times for most sites. The differences are attributed to complex factors such as uncertainties and potential biases in model inputs like inventory and meteorology parameters, atmospheric chemistry in the model, and uncertainties in the AOD-retrieved data in which, for example, it often had lower estimates in high pollution areas. The spatial variations in ambient $PM_{2.5}$ were generally captured by the model, as seen from the comparison of spatially resolved model outputs to the Aerosol Optical Depth (AOD) retrieved data (https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V4.NA.03) (**Fig. s3**) and the ground observation concentrations (**Fig. s4**). **Fig s5** further compared with time series of daily $PM_{2.5}$ in Beijing and Shanghai, as examples of northern and southern cities, respectively. Daily variations in the ambient $PM_{2.5}$ were also captured by the model simulation even though the NME values were 58.3 % and 49.8 %, respectively. To address the overestimation of model outputs, we then calibrated the model $PM_{2.5}$ against the ground observation data for 2014 and 2019 when the ground observation data were available, and the visibility inversed data for year 2000 and 2010 when the ground observation network of $PM_{2.5}$ was not built. The calibrated results were much closer to the monitoring results or visibility inversed data, with most data fell into the error range of 2.0 and few in the error range of 5.0 (**Fig. s6**). The NME values were 44.2 %, 40.6 %, 26.2 %, and 30.9 %, respectively. The slopes were 0.71, 0.77, 0.91, and 0.87, respectively. The calibrated ambient $PM_{2.5}$ was used in the follow-up analysis of exposure, health outcomes, and inequality.

2.2. Indoor $PM_{2.5}$ concentration

A database of indoor $PM_{2.5}$, at the county level in China, was built based on the updated household fuel and stove information (Tao et al., 2018) and summarized results, including means, deviations, and ranges, of indoor $PM_{2.5}$ for different households using dirty solid fuels or relatively clean fuels during the heating and non-heating seasons. For households burning solid fuels in indoor stoves, internal combustion source dominated the indoor air pollution, while for households using relatively clean fuels or where the stoves were located outdoors, indoor concentrations were mainly influenced by the outdoor air concentrations and infiltration factors (Xiang et al., 2019). The United Nations Environment Programme and World Health Organization had a similar database, and our database for China was updated from it by considering more recent data from available publications and field-based fuel and stove information from recent surveys in rural China (Tao et al., 2018; Shen et al., 2022). More details on the indoor $PM_{2.5}$ database can be found in Chen et al., (2018) and Meng et al., (2021). Annual average values were used and analyzed in the present study.

2.3. Integrated total exposure

A database of the average annual ambient and indoor $PM_{2.5}$ concentrations in mainland China until 2019 was built at an interval of every 5 years (2000, 2010, 2014 and 2019), to reflect the historical changes in air pollution exposure throughout the country. The $PM_{2.5}$ issue in China received worldwide concern in 2013, when several extremely high-pollution episodes were widely discussed. Since then, the central and local governments have taken a series of strict air pollution prevention and control measures to control the ambient $PM_{2.5}$ concentrations, which resulted in a significant turning point in 2014 (Zhu et al., 2019; Zhang et al., 2019). Ambient $PM_{2.5}$ data in 2020 and beyond are available, but the indoor pollution characteristics are not yet available when we started this study; thus, 2019 was the most recent year here.

The integrated total exposure was calculated as: $C_{in} \times T_{in} + C_{am} \times T_{am}$, Where C_{in} and C_{am} are the indoor and ambient $PM_{2.5}$ concentration, respectively. T_{in} and T_{am} are indoor and ambient residence time, respectively. Time-activity data for urban and rural residents in different regions are from Exposure Factors Handbook of Chinese Population (Duan, 2013).

2.4. Calculation of $PM_{2.5}$-related premature deaths and uncertainty

Premature deaths associated with $PM_{2.5}$ exposure were calculated based on background premature deaths and the corresponding population attribution fractions (PAFs). Five diseases including acute lower respiratory infections for children, lung cancer, ischemic heart disease, cerebrovascular disease (stroke), and chronic obstructive pulmonary disease were considered. Background premature deaths for different age (<5, 5–14, 15–65 and > 65 years), and gender groups were obtained from Global Burden of Disease (GBD) data (https://ghdx.healthdata.org/gbd-results-tool) (Wang et al.,2018; India S.L.D.B., 2019). The relative risk (RR) incorporated the latest integrated exposure–response (IER) function (Cohen et al. 2017). RR was calculated as follows

$$RR = \begin{cases} 1, z < z_{cf} \\ 1 + \alpha \times (1 - e^{\beta(z - z_{cf})^{\gamma}}), z \geq z_{cf} \end{cases}$$

where z is the $PM_{2.5}$ exposure concentration, z_{cf} is the minimum exposure concentration which follows a uniform distribution between 2.4 and 5.9 μg/m^3, and α, β, and γ are IER parameters with different values for different ages and genders. The corresponding health risk arises when $PM_{2.5}$ exposure is above the z_{cf} value. z_{cf} shows a uniform distribution between 2.4 and 5.9 μg/m^3. The GBD database provides referred values of α, β, γ, and z_{cf} from 1000 sets of Monte Carlo simulations (Cohen et al., 2017), which were adopted in the calculation of RR and its uncertainty. PAF calculation formula is as follows:

$$PAF = \frac{\sum_{I} P_i (RR_i - 1)}{\sum_{I} P_i (RR_i - 1) + 1}$$

where Pi is the population of each gender, age, year and cause, RRi is the corresponding relative risk of the population.

2.5. Calculation of the concentration index and its variations

We calculated the concentration index (C) with 95 % confidence interval to quantitatively evaluate the level of inequality in $PM_{2.5}$ exposures and followed the method recommended by the World Bank (O'Donnell et al., 2008). C was derived as follows:

$$C = \frac{2}{N\mu} \sum_{i=1}^{n} e_i r_i - 1 - 1/N$$

where e_i is the $PM_{2.5}$ exposure, μ is $PM_{2.5}$ exposure mean, and $r_i = i / N$ is the fractional rank of individual i in the per capita disposable income distribution (weighted by city population), with i = 1 for the lowest and i = N for the highest. The concentration curves (CC) are usually matched with the C value to graphically represent inequality. In the CCs, the x-axis is the cumulative percentages of the population ranking by income, and the y-axis is the cumulative percentages of exposure for the corresponding populations. The absolute valve of C is twice the area between the CC and the 1:1 equality line. When the CC and the 1:1 equality line coincide, the C value equals zero, indicating that there is an absolute equality that an entire population experience equal $PM_{2.5}$ exposure. When the CCs are above (below) the equality line, the C values are less (greater) than 0, suggesting that the exposures are concentrated among the poor (rich). Therefore, the C values range from −1 to 1. The greater the absolute valve of C or the farther away from the equality line, the greater the inequality of exposure.

2.6. Uncertainty analysis

To address uncertainty in the estimates, we run 1000 times Monte Carlo simulations from emission estimations to premature deaths. The coefficients of variation (CVs) for activity intensities and EFs (log-transformed) for emissions were obtained from the PKU inventories. CVs of 5 % were used to calculate the amount of time people spent indoors. Chen et al. (2018) calculated the CVs of log-transformed $PM_{2.5}$ concentrations in households using solid fuels, and the mean and standard deviation of the CVs for various fuels-microenvironment-season combinations were 14 ± 16 %, implying that the overall uncertainty of the calculated indoor $PM_{2.5}$ concentrations. CVs of 20 % for gridded ambient air $PM_{2.5}$ were adopted, based on the comparison of re-calibrated model outputs and observation data. The IER provided the parameter distributions in the dose–response curves of premature death models.

2.7. Other materials and data statistical analysis

The socioeconomic status is represented by the per capita disposable income data that were collected from Chinese statistical yearbooks (China Statistical Yearbook, 2020). Per capita disposable income is the sum of final consumption expenditure and savings available to the surveyed household during the survey period. Per capita disposable income = wage income + net business income + net property income + net transfer income (China Statistical Yearbook, 2020). It is necessary to note that the income data in this study were obtained from the census and might not be as precise as those obtained from individual questionnaires in exposure assessments and socioeconomic status analyses. Although survey data can usually cover more detailed information that is important for analyzing exposure inequality and its potential influencing factors, census data have advantages in their representativeness and wide coverage of entire target populations. To examine the overall situation in China, prefecture-level data were analyzed here, but there could be different equalities within the prefecture cities (Guo et al., 2020; Yao et al., 2018). It would be interesting to use microdata to validate this country-level exposure equality to support well-directed strategies in reducing inequality. The population was divided into five quintiles according to the per capita disposable income from low to high (e.g., low, low-middle, middle, upper-middle, and high). The medians along with the interquartile ranges (IQR) of incomes and exposures were calculated.

We analyzed the data by using Microsoft Excel 2019 and IBM SPSS Statistics 26 at a significance level of 0.05. We used Python 3.8 to create the figures.

3. Results and discussion

3.1. Inequality in ambient and total $PM_{2.5}$ exposure

The national average population-weighted ambient $PM_{2.5}$ exposure was 23.1 μg/m^3 in 2019. In comparison with the WHO Interim Target-1 (IT-1, 35 μg/m^3) (WHO, 2021), which was also the Chinese National Standard, nearly 210 million (16 % of the total population) people in 2019 were exposed to ambient $PM_{2.5}$ pollution levels that exceeded 35 μg/m^3 (Fig. 1). Compared to that in 2000, ambient $PM_{2.5}$ exposure was slightly higher in 2019. However, total exposure in 2019 was much lower than that in 2000, resulting from significant reductions in indoor air pollution associated with transitions to cleaner household energy mix especially in rural areas. The annual income for these people, whose ambient $PM_{2.5}$ exposure exceeded 35 μg/m^3, was 42,600 (IQR: 37,900–46,600) RMB/capita in 2019, which was higher than the national average of 33,400 (IQR: 16,900–42,100) RMB/capita. If comparing to the 10 μg/m^3 or new AQG of 5 μg/m^3, nearly the entire population of the country was exposed to severe ambient air pollution that exceeded the criteria (98.3 % exceeding 5 μg/m^3 and 89.3 % exceeding 10 μg/m^3).

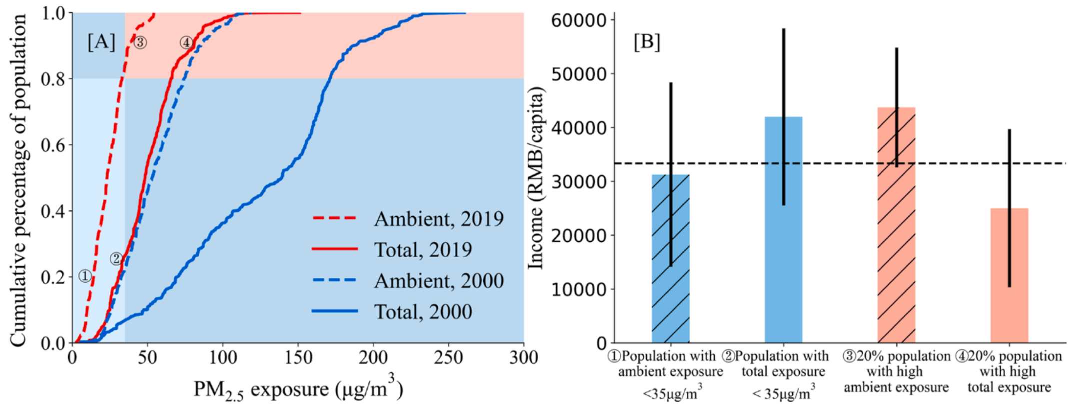

Fig. 1. Cumulative percentage of population of the ambient and total $PM_{2.5}$ exposure in 2000 and 2019 in China (A), and the income levels for the population with low $PM_{2.5}$ exposure <35 μg/m^3 or the 20 % population with the highest exposure levels (B). Note that data for Hong Kong, Macao, and Taiwan province are not available in this study.

The positive Concentration Index (***C***) value of ambient $PM_{2.5}$ exposure (0.099, and 0.080–0.118 as 95 % confidence interval) indicated more concentrated ambient $PM_{2.5}$ exposure among the rich. As seen in Fig. 2, the poorest group had the lowest exposure of 19.5 (IQR: 13.0–24.2) μg/m^3. The upper-middle group had the highest ambient $PM_{2.5}$ exposure, which was significantly higher than the exposure level in the richest group ($p < 0.05$). The urban population with higher income was unsurprisingly exposed to higher ambient $PM_{2.5}$ levels than the rural population (**Fig. s7**). The relative difference in ambient $PM_{2.5}$ exposures between the urban and rural populations was statistically significant, at 7.5 μg/m^3. Within the urban population, an apparently inverted V relationship was also observed, with the richest group (22.3, 16.3–34.7 μg/m^3) and the poorest group (22.1, 13.7–28.0 μg/m^3) being exposed to lower ambient $PM_{2.5}$, but the highest exposure (31.7, 17.6–37.1 μg/m^3) occurring for the upper-middle group. For the rural population, the subgroup analysis revealed that the low-income population was exposed to the lowest ambient $PM_{2.5}$ pollution levels, while the exposure levels for the other four groups were similar.

As most people spend more time indoors, ambient exposure accounts for only a small part of the air pollution exposure. By taking both indoor and outdoor exposures into the consideration, the national-average total exposure of 48.4 (33.9–62.5) μg/m^3 was much higher than the ambient exposure of 23.1 (15.5–31.2) μg/m^3. 74 % of the population (nearly 1.0 billion) in 2019 suffered from severe air pollution above 35 μg/m^3. Differences between the total and ambient exposure was much smaller for high-income populations, as relative contributions of indoor exposure became small when clean household energies were used. Indoor exposure accounted for a significant portion of the total exposure, ranging from 80 % to 95 % (**Fig. s8**), owing to high levels of indoor air pollution and lengthy periods of time spent indoors. Indoor exposure contribution exhibited a generally declining trend with the increase in income level. Relatively high contributions from indoor exposure for the low- and low-middle income groups were explained by the much more severe indoor air pollution associated with a high reliance on low-efficient burning of traditional solid fuels. Household fuel choices and switching to cleaner fuels are significantly affected by family income levels (Zhu et al., 2019; Shen et al., 2015; Stoner et al., 2021). Household energy sources are expected to be cleaner with increasing income (Sovacool 2011; Shen et al., 2022).

For the total $PM_{2.5}$ exposure across different income groups, different from that in the ambient $PM_{2.5}$ exposure, the low-income population was exposed to higher total $PM_{2.5}$ pollution levels (Fig. 2**A)**. The total $PM_{2.5}$ exposure level for the poorest population was 63.8 (56.2–79.6) μg/m^3, approximately 2 times of the richest group at 33.0 (26.5–48.4) μg/m^3. The negative ***C*** value of −0.091 (95 %CI: −0.110 to −0.072) indicated that the total $PM_{2.5}$ exposure concentrated in the poor. The urban population had significantly lower total $PM_{2.5}$ exposure compared to the rural population ($p < 0.05$), with $PM_{2.5}$ exposure levels of 44.7 (30.1–53.0) μg/m^3 for urban population and 60.0 (44.4–73.9) μg/m^3 for rural population, respectively. This is inextricably associated with the widespread use of solid fuels in rural areas. For the rural population (**Fig. s8**), the poorest group had the highest total $PM_{2.5}$ exposure, and

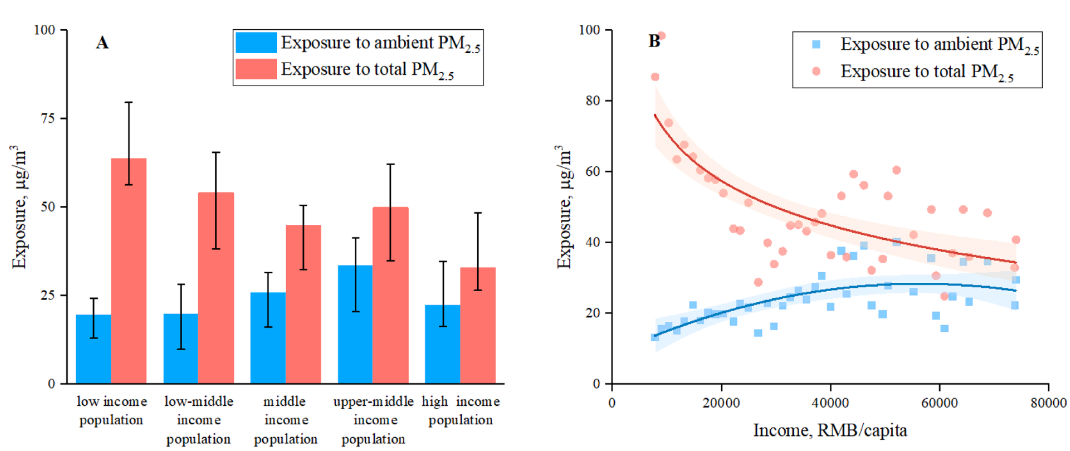

Fig. 2. Exposure to ambient $PM_{2.5}$ and total $PM_{2.5}$ for populations with different income levels for the Chinese population in 2019 (A), exposure to ambient $PM_{2.5}$ and total $PM_{2.5}$ for population with different incomes (B). Note that data for Hong Kong, Macao, and Taiwan province are not available in this study. The dot is for different income groups which was from the county level statistics and divided by the 1500 RMB/capita equal intervals.

the exposure decreased with increasing income, attributable to increasing use of cleaner household energy. The total $PM_{2.5}$ exposures for the urban population across different income groups revealed a likely inverted U shape with the highest exposure for the low-middle income group (48.0, 37.6–53.8 μg/m^3) and low exposure levels for the low- (42.9, 29.2–48.1 μg/m^3) and high-income groups (33.9, 26.5–48.4 μg/m^3). The indoor exposure contribution for the urban population was approximately 90 %, which was lower than that for the rural population (92–95 %). High-income urban population were mostly living in the relatively developed eastern and coastal areas, where effective ambient air pollution controls efficiently reduced outdoor pollution, and consequently the total exposure. However, the middle-income urban population are largely from the less-developed or developing western areas, and did not receive such high benefits of reducing the ambient and total $PM_{2.5}$ exposures.

3.2. More $PM_{2.5}$-associated premature deaths among the low-income population

In 2019, the total exposure to $PM_{2.5}$ was estimated to be responsible for ~1.13 (95 %CI: 0.63–1.73) million premature deaths nationally. The latest Global Burden of Disease (GBD) estimated that in China $PM_{2.5}$ exposure was associated with about 1.78 (95 %CI: 1.51–2.09) million premature deaths in 2019, and the number varied a little in the past two decades, resulting from the decrease in the HAP-associated mortality but an increase in the ambient $PM_{2.5}$-induced deaths (GBD, 2019). This estimate was higher than our present result partly due to an update estimate in the GBD, which for example used to be 1.12 million in 2014 but now re-estimated at 1.79 million (Yun et al., 2020). Zhao et al. (2018) estimated that $PM_{2.5}$-related premature deaths in 2015 was about 1.22 million. For only ambient exposure, Li et al. (2020) estimated 1.30 (95 % CI: 0.66–1.79) million premature deaths in 2016, and Wang et al. (2019) estimated 0.95 and 1.04 million in 2010 and 2020, respectively. Because of different methods (e.g. exposure-dose relationship and with or without indoor exposure considered) and basic datasets (e.g. pollutant concentration, activity data and mortality rates), the absolute number of premature deaths due to air pollution reported differed in literature (Yun et al., 2020; Li et al., 2020; Wang et al., 2019). Our results are generally within these estimates giving methodology differences and uncertainties into the consideration.

Inequality in the $PM_{2.5}$-relaetd premature deaths across different income group did exist. Of the 1.13 million premature deaths in 2019, about half (49.6 %) were the rural people, though the urbanization rate in China was 60.6 % (China Statistical Yearbook, 2020). The median value of per-capita income people died from $PM_{2.5}$ exposure was 28,400 RMB, lower than the national average income of 30,700 RMB/capita. Over half of people died from the $PM_{2.5}$ exposure was low and low-middle income population (Fig. 3**A**), whereas only 14 % of peopled died from $PM_{2.5}$ exposure were the high-income people. The premature death number per million people was significantly negatively correlated with the income per capita, as seen in Fig. 3**B** ($p < 0.001$), suggesting higher premature death fractions from the $PM_{2.5}$ exposure in the lower income group due to much higher exposure levels. As mentioned, the estimated absolute number of $PM_{2.5}$-related premature deaths may vary due to methodology difference, and the GBD updated global, regional, and country estimates using the latest exposure–response relationship, as well as updates on other parameters, resulting in a new estimated number. However, this is thought to less-likely affect the observed inequality issue in the $PM_{2.5}$-premature deaths among different income groups, that is, more premature deaths were from the low-income population. The concentration curves were above the line of equality, and the ***C*** value in $PM_{2.5}$-realetd death was negative, at −0.129 (95 %CI: −0.144 to −0.114) (**Fig. S9**).

3.3. Reduced inequality under spontaneous transition and intervention measures

Though exposure inequality was common and is not expected to be eliminated soon, it is found that the degree of inequality did change substantially over time. From 2000 to 2019, the national average exposure to ambient $PM_{2.5}$ increased firstly till 2013 attributed to increased air pollution problem in the country under rapid economic growth and industrialization, and then declined to 23.1 μg/m^3 in 2019. For all five income groups, the exposure to ambient $PM_{2.5}$ increased gradually from 2000 to 2010 (**Fig. s10**), but the increasing rates, ranging from 3 % to 19 %, were different across different income groups. Much greater increases were observed for the relatively high-income groups, in both urban and rural areas. Since the late 2013 and early 2014, a series of strict countermeasures to address $PM_{2.5}$ were efficiently implemented, especially in several heavily polluted regions, such as Jing-Jin-Ji in the North China Plain (NCP), Yangtze River Delta (YRD) in East China, and Pearl River Delta (PRD) in Southeast China, where the ambient air quality has improved significantly since then (Cheng et al., 2021; Jiang et al., 2015; Lu et al., 2020; Ma et al., 2019; Tong et al., 2019). Compared to 2014, the ambient $PM_{2.5}$ exposure levels in 2019 decreased by 34–50 %, but also varying in different income groups. The concentration curve clearly lies below the equality line and confirms a disproportionate exposure distribution across the population (Fig. 4**A**). The positive Concentration Index (***C***) values of ambient $PM_{2.5}$ exposures, namely 0.071 (0.053–0.090), 0.100 (0.083–0.117), 0.104 (0.084–0.124), and 0.099 (0.080–0.118) in 2000, 2010, 2014 and 2019, respectively, confirmed more concentrated ambient $PM_{2.5}$ exposure among the rich, and it is clearly evident that the exposure inequality in ambient $PM_{2.5}$ exposure reduced in 2019 compared to that in 2014 when the toughest-ever air pollution countermeasures were issued.

Meanwhile, the total $PM_{2.5}$ exposure decreased gradually from

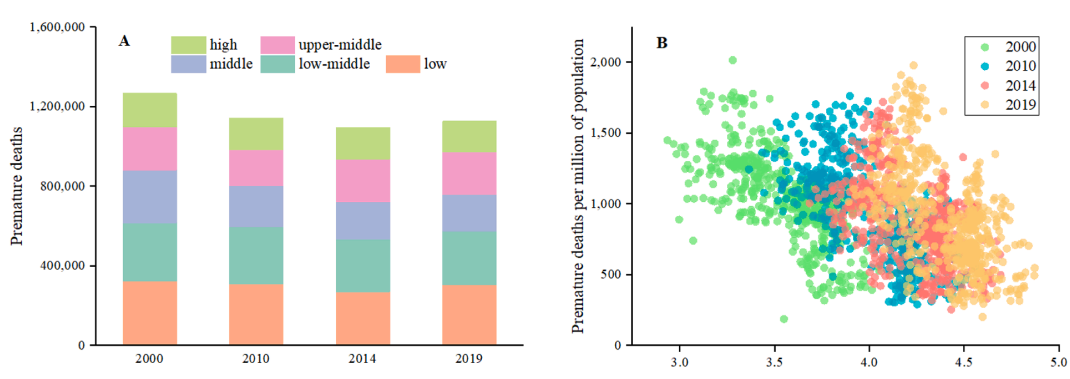

Fig. 3. The total $PM_{2.5}$-associated premature deaths and the proportions from different income groups in China (A), and the relationship between the premature deaths per million people and the per-capita income (B). Note that data for Hong Kong, Macao, and Taiwan province are not available in this study.

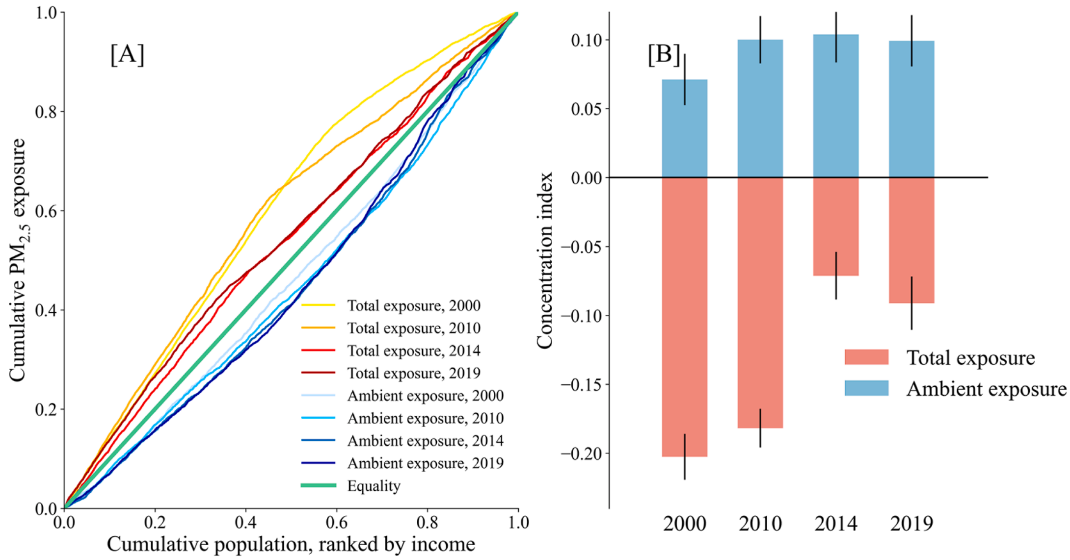

Fig. 4. Concentration curves for the ambient and total $PM_{2.5}$ exposure from 2000 to 2019 in China (A), and the calculation means of the Concentration Index values (B). Note that data for Hong Kong, Macao, and Taiwan province are not available in this study. If the concentration curve coincides with the 1:1 line, it indicates that $PM_{2.5}$ exposure is equal across different income levels and the concentration index is zero. If the concentration curve is below (above) the 1:1 line, it indicates that exposure is concentrated among the rich (poor) and the concentration index is positive (negative).

139.4 μg/m^3 in 2000 to 48.4 μg/m^3 in 2019. The total exposures dropped substantially, especially notable for the low and lower-middle income groups (**Fig. s11**). The concentration curves were above the line of equality, and negative ***C*** values of both the total $PM_{2.5}$ exposure and $PM_{2.5}$-associated premature deaths suggested that the total exposure and associated premature deaths concentrated among the poor (Fig. 4**A**). The ***C*** value of the total $PM_{2.5}$ exposure, namely −0.203 (-0.219 to −0.186), −0.182 (-0.196 to −0.168), −0.071 (0.088 to −0.054), and −0.091 (-0.110 to −0.072) in 2000, 2010, 2014, and 2019, respectively, indicated that the level of exposure inequality was declining (Fig. 4**B**). The rapid reduction in total $PM_{2.5}$ exposure (**Fig. s11**) was explained by the clean household energy transition, with more people utilizing clean energy sources such as gas and electricity to replace traditional solid fuels in their daily lives (Tonne et al., 2018; Stoner et al., 2021; Shen et al., 2022). Note that the ***C*** values of the $PM_{2.5}$-associated premature deaths, namely −0.120 (-0.132 to −0.108), −0.145 (-0.155 to −0.135), −0.099 (-0.111 to −0.086), and −0.129 (-0.144 to −0.114) in 2000, 2010, 2014, and 2019, respectively, were significantly different from zero, and did not show a decreasing trend as that in the total $PM_{2.5}$ exposure.

The decline in the total $PM_{2.5}$ exposure from 2000 to 2019 was much more apparent for the rural populations in all income groups (**Fig. s10**); while for the urban residents, the temporal changes had distinct characteristics for the different income groups. The total exposures were high in 2000 and low in 2019, but did not linearly decline. The high exposure levels in 2000 were attributed to high indoor exposures, while the high exposures in 2010 were mainly due to severe outdoor air pollution, as many urban residents already switched to clean household energy. For the high-income urban population, as the indoor exposures contributed less than outdoor exposures to the overall total, the total exposure increased from 2000 to 2014 and then declined, with the exposure level in 2019 being close to that in 2000.

3.4. Discussion and implications

The present study found that in China, exposure to ambient $PM_{2.5}$ was generally high in the high-income group. This was different from many observations in developed countries (Tonne et al., 2018; Hajat et al., 2013; Milojevic et al., 2017). Poverty- and race-related environmental inequality studies in the U.S. have highlighted the severe exposure and adverse health impacts among low income or low socioeconomic status populations (Bell and Ebisu, 2012; Brochu et al., 2011; Jones et al., 2014; Paolella et al., 2018; Tessum et al., 2021). Hajat et al. (2013) showed that in the U.S., per unit increase in the ***z*** score of family income was associated with a drop of 0.03 μg/m^3 in the $PM_{2.5}$ concentrations. In China, the high-income population are mostly living in relatively developed regions, e.g. the eastern and coastal areas, where ambient air pollution was also serious. Consequently, high ambient $PM_{2.5}$ exposures, mainly from sources such as industry and transportation sectors, were observed for the high-income groups, especially before 2013 when a series of strict tough-ever $PM_{2.5}$ control countermeasures were taken (Tong et al., 2019; Jiang et al., 2015; Lu et al., 2020). A measure-by-measure evaluation showed that actions like upgrades on industrial boilers, phasing out outdated industrial capacities, strengthening emissions standards in power plants and emission-intensive industrial sectors effectively reduced ambient $PM_{2.5}$ (Zhang et al., 2019). However, the present study revealed that these control policies appeared to be more effective in reducing the ambient $PM_{2.5}$ exposure for the richest group. These populations are mostly located in central China and in the relatively developed urban areas in the west. The air pollution issues in these areas should be given more attention, in addition to the well-known NCP, YRD and PRD areas. People are disproportionately receiving benefits from the air pollution control policy. These areas should have a highly responsible spirit and use their wisdom to balance economic development with ambient air quality improvement.

Most people spend more time indoors. If impacts of indoor combustion emissions on ambient air and exposure were considered, relative contributions of indoor emissions would be more significant. For example, it was found that, on the national average, even though residential energy use (mainly solid fuels combustion) accounted for only 8 % of total energy consumption, residential emissions contributed to 23 % of outdoor $PM_{2.5}$ and 71 % of indoor $PM_{2.5}$, resulting in relative contributions to population-weighted exposure and premature deaths of ~70 % (Yun et al., 2020). By considering indoor exposure, our study for the first time clearly demonstrated a rather distinct inequality concern regarding the total $PM_{2.5}$ exposure relative to the ambient $PM_{2.5}$ exposure. Indoor exposure contributed to ~90 % of the total exposure, and because of the high reliance on traditional solid fuels, such as coal and biomass fuels for daily cooking and heating in the low-income groups, severe indoor air pollution results in high $PM_{2.5}$ exposure among them. The negative ***C*** values indicated concentrated total $PM_{2.5}$ exposure among the poor. The most past studies so far on exposure inequality on air pollutant primarily focused on ambient pollutants like particles and SO_2. Indoor exposure was ignored or simply assumed to be equal to that outdoor. With strong internal sources, indoor air pollutant concentrations in most cases are higher than the outdoor air pollution, therefore, ignoring indoor exposure would result in high underestimation of the total exposure. As the low-income population or those with relatively low social-economic statues, on the global scale, had high reliance on traditional solid fuels, and suffered from severe household air pollution, their exposure and consequently adverse health outcomes would be obviously underestimated, and the observation in exposure inequality might be biased.

The study highlighted that clean household energy transition effectively reduced the exposure equality. Changes in household fuels were identified to be a major driver in reducing $PM_{2.5}$ exposure and premature mortality associated with air pollution in China. A nearly spontaneous transition to clean energy has occurred in cooking activity during the past three decades, but for heating, the clean transition is not as significant as that for cooking, and official interventions can make notable progress in heating energy switching, especially in the northern areas. It was recently estimated that nearly-one in three people around the world still rely on traditional solid fuels, and residential emissions are a major source that contribute to air pollution-associated premature deaths (McDuffie et al., 2021). If the equality in $PM_{2.5}$ exposures and adverse health outcomes are high priority concerns, the poor suffering from high total $PM_{2.5}$ exposure and indoor air pollution should be addressed; but unfortunately, many studies and policies still have only discussed ambient air pollution.

The study revealed contrasting exposure disparities between the ambient and total $PM_{2.5}$ levels across the different income groups in China and the importance of indoor air pollution controls in protecting human health by reducing exposure to air pollution. There might be very similar issues in other developing countries, that is, the exposures concentrated among the poor, and household energy transition significantly reduced the exposure equality.

CRediT authorship contribution statement

Zhihan Luo: Methodology, Investigation, Validation, Formal analysis, Writing – original draft. **Guofeng Shen:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Funding acquisition. **Yatai Men:** Investigation, Validation, Formal analysis, Data curation, Writing – review & editing. **Wenxiao Zhang:** Methodology, Validation, Data curation, Writing – review & editing. **Wenjun Meng:** Methodology, Data curation, Writing – review & editing. **Wenyuan Zhu:** Investigation, Formal analysis, Writing – original draft. **Jing Meng:** Resources, Writing – review & editing. **Xinlei Liu:** Validation, Writing – review & editing. **Qin Cheng:** Investigation, Validation. **Ke Jiang:** Data curation, Writing – review & editing. **Xiao Yun:** Methodology, Resources, Data curation. **Hefa Cheng:** Writing – review & editing. **Tao Xue:** Methodology, Resources. **Huizhong Shen:** Methodology, Writing – review & editing. **Shu Tao:** Methodology, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

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