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Article

Direct and indirect consumption activities drive distinct urban-rural inequalities in air pollution-related mortality in China

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A B S T R A C T

Household consumption in China is associated with substantial $PM_{2.5}$ pollution, through activities directly (i.e., fuel use) and/or indirectly (i.e., consumption of goods and services) causing pollutant emissions. Urban and rural households exhibit different consumption preferences and living areas, thus their contributions to and suffering from air pollution could differ. Assessing this contrast is crucial for comprehending the environmental impacts of the nation's ongoing urbanization process. Here we quantify Chinese urban and rural households' contributions to ambient $PM_{2.5}$ pollution and the health risks they suffer from, by integrating economic, atmospheric, and health models and/or datasets. The national premature deaths related to long-term exposure to $PM_{2.5}$ pollution contributed by total household consumption are estimated to be 1.1 million cases in 2015, among which 56% are urban households and 44% are rural households. For pollution contributed indirectly, urban households, especially in developed provinces, tend to bear lower mortality risks compared with the portions of deaths or pollution they contribute. The opposite results are true for direct pollution. With China's rapid urbanization process, without adequate reduction in emission intensity, the increased indirect pollution-associated premature deaths could largely offset that avoided by reduced direct pollution, and the indirect pollution-associated urban–rural inequalities might become severer. Developing pollution mitigation strategies from both production and consumption sides could help with reducing pollution-related mortality and associated urban–rural inequality.

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1. Introduction

China's rapid economic development has been accompanied by substantial ambient $PM_{2.5}$ pollution and adverse health impacts [1–3]. The past decade has seen China's great efforts to mitigate $PM_{2.5}$ pollution [4,5], yet its annual average $PM_{2.5}$ concentration still significantly exceeds the World Health Organization (WHO) guideline (5 $\mu g/m^3$) [6]. Over the past decades, crowds of rural residents have swarmed into cities under the rapid urbanization process in China. This process has resulted in lessened emissions from household direct fuel use in activities like heating, cooking, and private vehicle driving. Hence, urbanization-induced population migration was estimated to have contributed to reductions in ambient $PM_{2.5}$ concentrations in China [7]. However, households, especially those living in urban areas, also contribute considerable $PM_{2.5}$ pollution indirectly, by causing pollutant emissions embedded in the supply chains to satisfy household-consumed products and services [8,9]. The indirect emissions attributable to a region could spill over to other regions through trade and atmospheric transport [10,11]. Thus the impacts of China's ongoing urbanization process on $PM_{2.5}$ pollution are more complicated with household indirect pollution contributions included. Yet the importance of such indirect pollution relative to the effect of household direct emissions remains unclear.

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Urban and rural households exhibit different consumption preferences and living areas [12]. Compared with rural households, urban households tend to have different consumption structures and higher affordabilities, and their direct energy consumption activities are dominated by cleaner fuel (e.g., gas). The living areas of urban and rural households are separated but usually interlaced, thus air pollution could affect both areas wherever it is emitted from, because of atmospheric transport. Furthermore, China is facing severe interprovincial social, economic, and demographic inequalities [12,13], so the urban and rural disparities could vary across different provinces. Given these disparities, urban and rural household contributions to and suffering from air pollution could be different. Assessment of this contrast is important to comprehensively understand the environmental impacts of China's urbanization process. Furthermore, it could help with emission responsibility assignment, emission mitigation, and inequality alleviation in China.

Previous studies have assessed the air pollution and health impacts attributable to urban and rural household consumption activities. Direct residential energy use for heating and cooking, especially by rural households, has been identified to be one of the leading drivers of air pollution in developing countries [14,15]. A study for India further revealed that transport and indirect emissions associated with household consumption contributed almost twice as much to ambient $PM_{2.5}$ as direct emissions from biomass cook stoves [16]. Zhu et al. [17] show that household indirect $PM_{2.5}$ emissions related to the top four items purchased, together with direct $PM_{2.5}$ emissions, could contribute more than 55% of total air pollution in China. It has been estimated that in China, urban and rural households each contribute to $\sim$0.25 million air pollution-related premature deaths through their consumption activities in 2012 [8]. The mortality calculation in Zhao et al. [8] was based on the Integrated Exposure-Response (IER) model [18], and newer epidemiological studies have suggested much severer sensitivity of human health to pollution exposure than represented in IER [19]. More importantly, previous studies have focused on urban and rural household contributions to air pollution (as a source), yet the contrast with their respective suffering from the pollution (as a receptor) has not been quantitatively evaluated.

Here, we evaluate urban and rural household contributions to and suffering from ambient $PM_{2.5}$ pollution, and assess the associated urban–rural inequalities in China. Our study is conducted for the year 2015, the latest year for which all necessary data are available. Anthropogenic emissions considered in our study include the major pollutants related to ambient $PM_{2.5}$, i.e., sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO), ammonia (NH_3), black carbon (BC), primary organic carbon (POC), and other primary $PM_{2.5}$ (excluding BC and POC). Household direct emissions are obtained from a customized emission inventory, and their indirect emissions are further estimated with a Multi-Regional Input-Output (MRIO) analysis (see Materials and methods). Then we use the GEOS-Chem atmospheric chemical transport model to simulate urban and rural household contributions to near-surface $PM_{2.5}$ mass concentrations. We further use the Global Exposure Mortality Model (GEMM) [19] to quantify the premature deaths attributable to long-term exposure to $PM_{2.5}$ pollution associated with household consumption activities. Through building a high-resolution (100 m) spatial distribution dataset for urban and rural population densities, we identify different household groups from all premature deaths. We only focus on the emissions and premature deaths contributed directly and indirectly by household consumption activities. Although part of government consumption and capital formation aims to provide public service to the whole society, its associated pollution is not considered here.

2. Materials and methods

2.1. Customized emission inventory based on MEIC and GAINS

We derive a sector-, province-, and pollutant-specific emission inventory by combining two well-developed emission inventories, i.e., the Multi-resolution Emission Inventory for China (MEIC: http://www.meicmodel.org) and Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS: https://iiasa.ac.at/models-tools-data/gains). Air pollutants considered in this study include gaseous pollutants (SO_2, NO_x, CO, and NH_3) and primary aerosols (BC, POC, and other primary $PM_{2.5}$). MEIC is developed by Tsinghua University, and publicly provides anthropogenic emissions for 30 provinces in the Chinese mainland. We get all pollutants' emissions from MEIC except for NH_3, which is gotten from Huang et al. [20] and converted to the same sectors of MEIC. However, the publicly accessible emission inventory of MEIC only includes 5 integrated sectors, lacking sectorally detailed information for further consumption-based emission accounting. Thus we also incorporate another emission inventory, GAINS, which publicly provides emissions of 56 sectors for each province. For each province, we apply sectoral proportions in GAINS data to the total emissions in MEIC and obtain a customized emission inventory. We first separate the 56 sectors in GAINS into 5 groups according to the 5 integrated sectors in MEIC (see Table S2 online for sector mapping). For each sector group, the detailed sectoral proportions in GAINS are then applied to the emission amount in MEIC. We eliminate emissions from several minor sectors in GAINS which are not included in all provinces or not included in MEIC; these sectors together contribute less than 5% of the national total emissions for most pollutants.

For road-transportation sectors, we further separate emissions associated with commercial vehicles from emissions associated with private vehicles. Private transport does not participate in the supply chain and produces no economic output. The separation procedure follows our previous study [21], based on vehicle emission data from GAINS. Private transport includes passenger cars, and mopeds and motorcycles, and the rest are taken as commercial transport. Emissions from private transport and the residential sector are taken together as household direct emissions.

We get a customized Chinese emission inventory for 2015, including 30 provinces, 50 sectors (including one direct emission sector and 49 other sectors), and 7 pollutants. This customized emission inventory, except the direct emission sector, is then re-mapped from 49 sectors to 30 sectors to match the MRIO table (see Table S2 online for sector mapping).

2.2. Household consumption-based emission

Household direct emissions are obtained from the customized emission inventory. Indirect emissions driven by household purchases are estimated via a MRIO analysis [22]. The MRIO analysis has been widely used to trace emissions embedded in traded products [23–27]. In this study, we apply China's provincial MRIO table [28] in 2015 to calculate the indirect emissions.

A basic MRIO analysis can be simplified as

$$\boldsymbol{X} = \boldsymbol{AX} + \boldsymbol{Y}. \tag{1}$$

Here, $\boldsymbol{X}$ indicates the total economic output matrix, and its element x_i^r is the total economic output of sector i (i = 1, 2, ⋯, n) in region r (r = 1, 2, ⋯, m); $\boldsymbol{Y}$ is the final monetary consumption matrix, and its element y_{ij}^{rs} indicates the output produced in sector i of region r to supply final consumption in sector j (j = 1, 2, ⋯, n) of region s (s = 1, 2, ⋯, m); $\boldsymbol{A}$ is the direct requirement coefficient matrix, and its element a_{ij}^{rs} reflects the input required from sector i in region r

to support the production of one unit of output from sector j in region s.

Here, $\boldsymbol{A}$ is defined as

$$\boldsymbol{A} = \boldsymbol{Z}/\boldsymbol{X}, \quad (2)$$

in which $\boldsymbol{Z}$ is the intermediate monetary consumption matrix and its element z_{ij}^{rs} refers to the input required from sector i in region r to produce intermediate products from sector j in region s.

Eq. (1) can be further transformed as

$$\boldsymbol{X} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{Y}. \quad (3)$$

Here, $\boldsymbol{I}$ represents the identity matrix, and $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the Leontief inverse matrix.

Therefore, economic output triggered by household consumption activities can be calculated as

$$\boldsymbol{X}^{\mathrm{h}} = \boldsymbol{X}^{\mathrm{u}} + \boldsymbol{X}^{\mathrm{r}} = (\boldsymbol{I} - \boldsymbol{A})^{-\mathbf{1}} \cdot \boldsymbol{Y}^{\mathrm{u}} + (\boldsymbol{I} - \boldsymbol{A})^{-\mathbf{1}} \cdot \boldsymbol{Y}^{\mathrm{r}}. \quad (4)$$

Here, $\boldsymbol{X}^{\mathrm{h}}$ refers to the matrix of total economic output triggered by urban ($\boldsymbol{X}^{\mathrm{u}}$) and rural ($\boldsymbol{X}^{\mathrm{r}}$) household consumption. $\boldsymbol{Y}^{\mathrm{u}}$ and $\boldsymbol{Y}^{\mathrm{r}}$ represent the final consumption of urban and rural households respectively.

With the customized emission inventory, indirect emissions of pollutant k driven by household consumption activities can be calculated as

$$\boldsymbol{E}_{c,k} = \boldsymbol{f}_k \cdot \boldsymbol{X}^{\mathrm{h}}. \quad (5)$$

Here, $\boldsymbol{f}_k$ is the emission intensity matrix of pollutant k, and its element $f_{k,i}^{r}$ depicts the emission intensity of pollutant k in sector i in region r, and can be calculated as

$$f_{k,\ \ i}^{r} = P_{k,i}^{r}/x_i^{r}, \quad (6)$$

in which $P_{k,i}^{r}$ refers to the production-based emission of pollutant k in sector i in region r, which is obtained from the customized emission inventory.

Thus, urban and rural households' indirect contributions to emissions of pollutant k are calculated as Eqs. (7) and (8) respectively:

$$\boldsymbol{E}_{c,k}^{\mathrm{u}} = \boldsymbol{f}_k \cdot \boldsymbol{X}^{\mathrm{u}}, \quad (7)$$

$$\boldsymbol{E}_{c,k}^{\mathrm{r}} = \boldsymbol{f}_k \cdot \boldsymbol{X}^{\mathrm{r}}. \quad (8)$$

To facilitate subsequent GEOS-Chem simulations, household consumption-based emissions are then gridded with the spatial distribution information in 2015 from MEIC at 0.25° longitude × 0.25° latitude for 5 integrated sectors, i.e., agriculture, power, industry, transportation, and residential. Prior to the gridding, household direct and indirect emissions are aggregated to 5 integrated sectors according to the classification of MEIC.

For each province, to quantify the household comprehensive pollution contribution by considering emissions of all pollutants, we use the index named "atmospheric pollutant equivalent" (APE) designed by China's Ministry of Environmental Protection (MEP). The APE method has been used in many previous studies [9,29–31]. It allows the aggregation of different air pollutants based on their environmental and health impacts. APE gives us access to represent the integrated severity of air pollution caused by different air pollutants, which is to some extent similar to the use of carbon dioxide equivalent to measure all greenhouse gases and their global warming potential [32].

Based on the MEP calculation method, different types of pollutants are combined as

$$N_{\mathrm{APE}} = \sum_k \frac{E_k}{C_k}. \quad (9)$$

Here, N_{APE} denotes the number of APE. E_k depicts the emission of pollutant k. C_k denotes the pollutant equivalent coefficients (see Table S3 online) for pollutant k, which considers each pollutant's impact upon an ecological system, toxicity on organisms, and the technical feasibility for removal. As there are no official pollutant equivalent coefficients for the pollutants BC, POC, and other primary $PM_{2.5}$, we use the coefficient of soot as a reference.

2.3. $PM_{2.5}$ concentration simulation

With the gridded household consumption-based emission data, we further simulate urban and rural household contributions to China's ambient $PM_{2.5}$ concentration in 2015 with GEOS-Chem v11-01. GEOS-Chem is an atmospheric transport chemical model, and its $PM_{2.5}$ simulation has been evaluated extensively by previous studies [21,23,33,34]. $PM_{2.5}$ species analyzed in this study include sulfate, nitrate, ammonium, black carbon (BC), and primary organic aerosol (POA). Here, modeled POA is converted from modeled POC with a POA/POC ratio of 2.1 recommended by GEOS-Chem Wiki (https://wiki.seas.harvard.edu/geos-chem/index.php/Particulate_matter_in_GEOS-Chem). Our study conducts a total of six nested simulations, including one control case and five sensitivity simulations. The sensitivity simulations are designed for different pollution contribution cases, and the detailed definition can be found in Table S4 (online). $PM_{2.5}$ concentrations attributable to each pollution contribution case are derived from the differences between the all-emission simulation and each sensitivity simulation.

All simulations are driven by the assimilated meteorological field GEOS-FP and performed with the resolution of 0.3125° longitude × 0.25° latitude. Boundary conditions are provided by GEOS-Chem global simulations at a resolution of 2.5° longitude × 2° latitude and updated every 3 h. Each simulation is run from June 2014 through December 2015, with the first seven months in 2014 used for model spin-up. Other model setups, including natural emissions, meteorology, and physical schemes, can be found elsewhere [21,35]. The standard GEOS-Chem simulation can well reproduce $PM_{2.5}$ concentrations, but show certain biases in simulating $PM_{2.5}$ components. For instance, GEOS-Chem tends to underestimate sulfate (normalized mean bias (NMB) ∼ –40%) and overestimate nitrate (NMB ∼ 80%) [36]. To account for these issues and better simulate $PM_{2.5}$ over China, we make several model improvements. Firstly, we add the chemical mechanism of aqueous-phase oxidation of S(IV) (the sum of dissolved SO_2, HSO_3^-, and SO_3^{2-}) by dissolved nitrogen dioxide (NO_2) in GEOS-Chem's chemistry module to enhance sulfate formation by following Zhang et al. [34]. Secondly, we consider the heterogeneous uptake of SO_2 on deliquesced aerosols under high-relative humidity conditions by taking suggestions from Wang et al. [37]. Finally, we follow Heald et al. [38] that reduce surface HNO_3 concentration by 25% when using ISOROPIA II to simulate inorganic aerosols, to minimize the potential impact of the overestimated surface HNO_3 due to the weak wet deposition in the model on nitrate and ammonium simulations.

To obtain a more accurate health impact estimate, the simulated surface $PM_{2.5}$ concentrations are further downscaled to a finer resolution of 0.1° longitude × 0.1° latitude by applying the spatial distribution of the satellite-derived $PM_{2.5}$ data from Hammer et al. [39]. To achieve the scaling, we perform the following steps according to our previous work [21]. We first regrid the simulated $PM_{2.5}$ concentrations from the resolution of 0.3125° longitude × 0.25° latitude to the resolution of 0.1° longitude × 0.1° latitude. We then calculate the ratio of satellite-derived $PM_{2.5}$ concentrations in each grid to the simulated $PM_{2.5}$ concentrations in the control case. Finally, we apply this grid-level ratio to all simulations.

Both the model-simulated surface $PM_{2.5}$ and the satellite-scaled surface $PM_{2.5}$ are evaluated by comparison with air quality monitoring station observations, and are shown in Fig. S1 (online). The spatial distribution of the observation stations is shown in Fig. S2 (online). Here, each data point represents a model grid cell. Prior to the scaling, the model simulation already shows a good performance in spatial distribution of surface $PM_{2.5}$ (r = 0.94, NMB = 21%), especially in densely populated areas (r = 0.97, NMB = 15%). However, the model tends to overestimate $PM_{2.5}$ with a relatively large bias in concentrations. After scaling with satellite retrieval data, the bias is remarkably reduced (all stations: r = 0.96, NMB = −2.9%; population-dense stations: r = 0.97, NMB = −4.6%).

We further evaluate the modeled $PM_{2.5}$ compositions, including sulfate, nitrate, ammonium, POA and BC. Due to the absence of publicly available time-continuous observational $PM_{2.5}$ composition data, we collected the composition observation data from the literature (see Table S5 online for the observational composition data details). Fig. S3 (online) shows that nitrate (NMB = 5.5%) and sulfate (NMB = −17.8%) simulations exhibit much lower biases than shown in the previous study [36]. Ammonium, POA and BC are also well reproduced with NMB of 7.0%, −16.4% and 5.1%, respectively. The model-simulated $PM_{2.5}$ compositions exhibit low-to-modest spatial correlation with observations (R = 0.22–0.40 for these compositions). This relatively low correlation is partly because the observation time for each sample does not completely match the simulation time. Additionally, the observation stations for each $PM_{2.5}$ composition are limited in number and spatially dispersed, thus the model performance is largely dependent on the selected stations. Moreover, the differences in observation approaches across various studies [40,41], from which we collect the observational data, could also explain the relatively low correlation to some extent.

2.4. Premature deaths caused by $PM_{2.5}$ exposure

In this study, we employ the GEMM exposure–response model [19] to estimate $PM_{2.5}$-related premature deaths. The GEMM model represents an update upon the IER model used in GBD studies [42]. Our estimates are based on the GEMM NCD + LRI method which considers all deaths due to non-communicable diseases (NCDs) and lower respiratory infections (LRIs) associated with long-term ambient $PM_{2.5}$ exposure. We consider the health responses of 15 different age groups to ambient $PM_{2.5}$ pollution.

The premature deaths due to $PM_{2.5}$ exposure can be calculated as

$$\Delta M = MR \times Pop \times \frac{HR - 1}{HR}. \tag{10}$$

Here, MR is the basic mortality ratio; Pop represents the total population; HR represents the hazard ratio and the detailed calculation can be found in Burnett et al. [19]. The country-based baseline mortality data for each disease and the gridded population data on a 0.1° longitude × 0.1° latitude spatial resolution are both from GBD 2016 [42].

We then apply the widely-used direct proportion approach to assign the fraction of mortality contributed by household consumption-related $PM_{2.5}$ in each source region. The direct proportion approach assumes that the contribution of one source to the disease burden of air pollution is directly proportional to its share of the total $PM_{2.5}$ concentration. Then, the gridded mortality caused by the household consumption activities of a specific region can be calculated as

$$\Delta M' = \Delta M \times \frac{\Delta C}{C}, \tag{11}$$

in which ΔC is the gridded household consumption-related $PM_{2.5}$ concentration of a specific region; C is the gridded annual mean $PM_{2.5}$ concentration. Following this method, we also calculate the gridded premature deaths (0.1° longitude × 0.1° latitude) caused by urban/rural direct/indirect emission-related $PM_{2.5}$ exposure.

2.5. Identifying urban and rural households from the premature deaths

We attempt to identify urban and rural households from all premature deaths. This process is done with a high-resolution spatial distribution dataset of urban and rural population densities in China. The population dataset is built based on a hierarchical population spatialization model at 100 m resolution, by using the street blocks classification and ranks according to land use categories and VANUI index. The permanent resident demographic information of 2015, NPP/VIIRS nighttime lights data [43], land use [44], road network [45], and other auxiliary data are used as model inputs. The urban and rural population is allocated to the 100 m grid cells based on multi-source data and the hierarchical population spatialization model. To match the resolution of our gridded mortality data, the population data are re-projected to 0.1° longitude × 0.1° latitude. The overall and local pattern comparison, correlation analysis, and matching analysis of the existing population spatialization data suggest that the model's population spatialization data have higher accuracy. As shown in Fig. S4 (online), the spatial distribution of urban and rural population data are consistent with their land distribution supplied by the Geographical Information Monitoring Cloud Platform (GIM Cloud, http://www.dsac.cn).

With the urban and rural population spatial distribution dataset, the ratio of urban and rural population in each grid could be estimated. Through applying such a population ratio to the premature deaths data, we could separate the premature deaths in each grid into urban and rural households respectively.

2.6. Uncertainty analysis

There exist some limitations in this work due to uncertainties in the emission inventories, MRIO analysis, GEOS-Chem simulations, GEMM model, and population spatial distribution dataset. Firstly, emission inventories are subject to errors in the process of data collection and processing, such as production activities, technology distribution, and emission factors. The uncertainties for emissions of NO_x, SO_2, BC, and POC were estimated to be ±31%, ±12%, ±208%, and ±258%, respectively [46]. Secondly, the provincial MRIO table used here also contains uncertainties contributed by errors in data collection and economic relationship balancing. Thirdly, as discussed in previous studies, uncertainties of GEOS-Chem simulations are associated with multiple factors, such as errors in emission inventories and model representations of atmospheric chemical and physical processes [23,33]. A full evaluation of model uncertainties is computationally prohibitive. Nevertheless, many of GEOS-Chem errors are corrected by the satellite-based post-model scaling. Fourthly, the GEMM is subject to the internal validity and the generalizability of the health model [47,48]. According to the uncertainty estimates introduced by Burnett et al. [19], we calculate the 95% confidence intervals for the premature deaths estimated in this study. We do not consider the exposure–response functions associated with $PM_{2.5}$ sizes and types due to a lack of data. Finally, the uncertainties of the urban/rural population spatial distribution dataset are largely contributed by the precision of basic spatial data used in the model. By comparing the simulated population spatialization data with the population spatialization data supplied by GIM Cloud, we find that the average error at the county level is 1.43%. Previous work has tested the uncertainties of this dataset in Beijing, indicating that the model simulation error against China's published population data was less than 10% [49].

3. Results

3.1. Ambient $PM_{2.5}$ pollution driven by household consumption activities

On the basis of MRIO model analysis and GEOS-Chem simulations, we first estimate the contribution of household consumption to $PM_{2.5}$ pollution in China. As shown in Fig. 1, Chinese household consumption activities (direct + indirect) contribute 7.6 Tg NO_x, 6.9 Tg SO_2, 6.2 Tg NH_3, 87.4 Tg CO, 1.0 Tg BC, 2.2 Tg POC, and 1.6 Tg other primary $PM_{2.5}$ in 2015. Over half of carbonaceous pollutants emissions (e.g., CO, BC, POC, and other primary $PM_{2.5}$), which primarily result from incomplete combustion of fossil fuels and biomass, could be attributed to household consumption in China. Species like NO_x and SO_2 are usually emitted from the industrial (e.g., electricity, heating, and other industries, see Fig. S5 online) and/or transportation sectors. Thus, compared with consumption activities like government consumption and capital formation that are associated with massive industrial production, household consumption activities contribute much less NO_x and SO_2 emissions. Due to heavy reliance on agricultural products and processed food, households are responsible for 59% of NH_3 emissions, the majority of which are indirect emissions.

For urban households, their direct energy use for heating, cooking, and private vehicle driving accounts for only 10%, 18%, and 3% of household consumption-associated NO_x, SO_2, and NH_3 emissions, respectively (Fig. 1a–c). However, with indirect emissions included, these contribution rises to 71%, 62%, and 71%. This is because, compared with rural households, urban households have a larger population, a different consumption structure (e.g., types of goods), and higher consumption affordabilities on products and services; and they tend to use cleaner fuel types. On the contrary, rural households are more self-sufficient and more heavily rely on fossil fuels and biomass. Thus, via direct energy use, rural households contribute over half of the household consumption-associated carbonaceous emissions.

We further quantify ambient $PM_{2.5}$ concentrations contributed by household consumption. In 2015, the national annual average $PM_{2.5}$ concentration over China is estimated to be 31.1 $\mu g/m^3$ (Fig. S6 online), more than 6 times the guideline level of WHO (5 $\mu g/m^3$). Of the national annual average $PM_{2.5}$ concentration, 10.0 $\mu g/m^3$ is attributed to household activities (Fig. 2a). The rest results from natural sources and other anthropogenic consumption sources, including capital formation, government consumption, stock, and international exports. As shown in Fig. 2b, in Eastern China, over 40% of the $PM_{2.5}$ concentrations could be attributed to household consumption activities. The proportion even reaches 66% in Heilongjiang Province. In contrast, household consumption activities could explain less than 30% of $PM_{2.5}$ concentrations in Western China, where $PM_{2.5}$ pollution is dominated by natural dust. Household consumption-associated $PM_{2.5}$ concentration in a region is contributed by local household consumption, household consumption in other regions, and $PM_{2.5}$ pollution transported in the atmosphere from other regions.

3.2. Who pollute and who suffer

Household consumption-associated $PM_{2.5}$ pollution could harm public health and even result in premature deaths. As estimated in Fig. 3, the ambient $PM_{2.5}$ pollution-related premature deaths in China are estimated to be 2.39 million cases (95% CI: 1.98–2.76 million cases) in 2015, of which 88% are due to anthropogenic activities. Our estimate based on the GEMM model is more than twice the estimate based on the IER model in Zhao et al. [8]. This corresponds with the difference revealed by Burnett et al. [19].

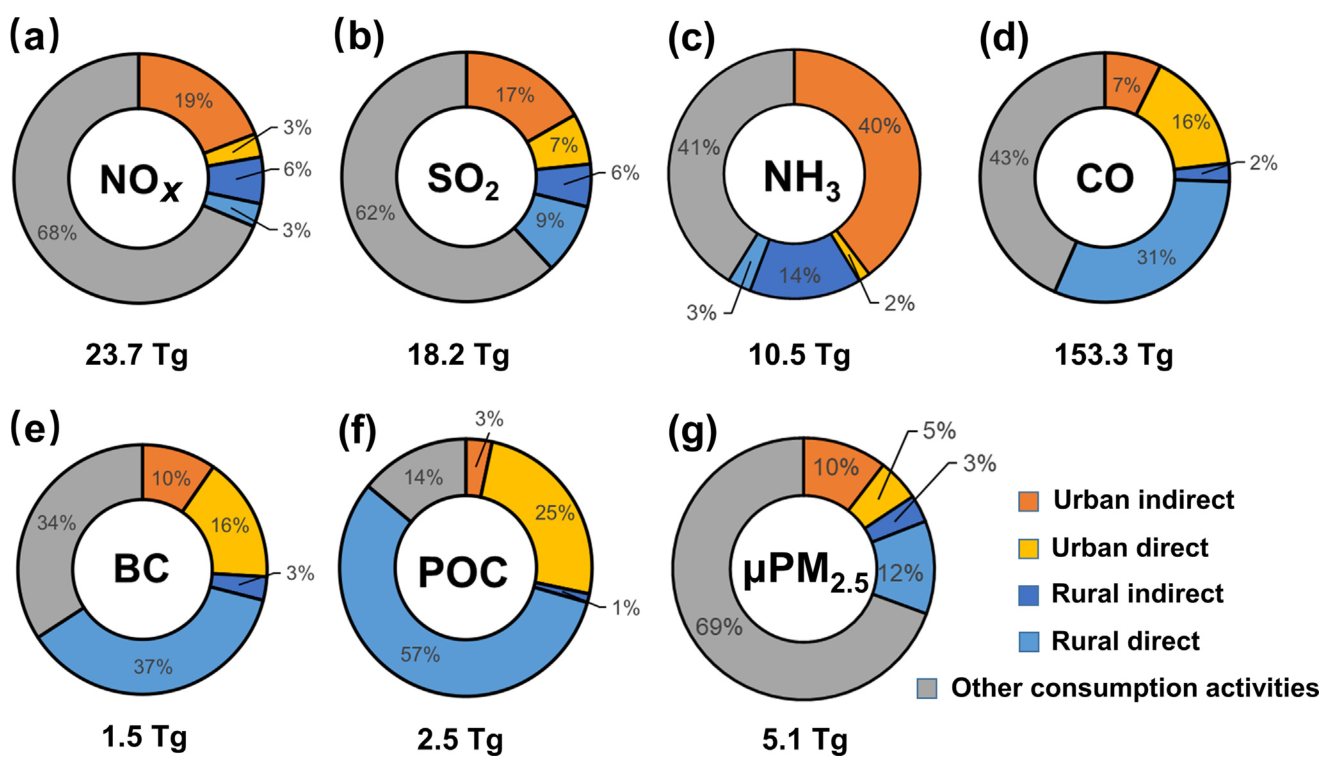

Fig. 1. Different consumption sources' contribution to China's $PM_{2.5}$-related emissions in 2015. The figure shows the emissions of NO_x, SO_2, NH_3, CO, BC, POC, and other primary $PM_{2.5}$ ($\mu PM_{2.5}$) with the number below each panel showing their annual emission totals. Other consumption activities include government consumption, capital formation, stock, and export.

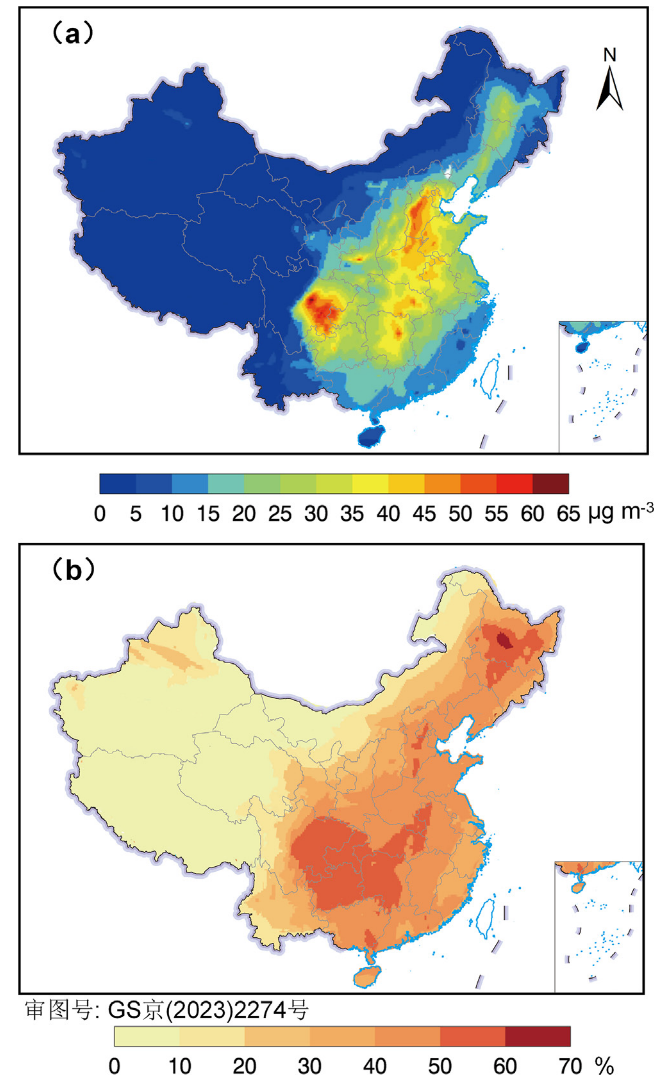

Fig. 2. Ambient $PM_{2.5}$ concentrations caused by Chinese household consumption (a) and their proportion in total ambient $PM_{2.5}$ concentrations (b) in 2015. The value of Taiwan Province is blank due to lack of data.

Fig. 4a indicates that premature deaths are mostly concentrated in populous regions, such as Shandong, Hebei, Henan, Jiangsu, and Guangdong. Among all anthropogenic $PM_{2.5}$ pollution-related deaths, 45% (i.e., 1.06 million cases, 95% CI: 0.89–1.24 million cases) is attributed to household consumption activities. Deaths due to household direct emissions are 1.5 times as much as that due to indirect emissions.

For the deaths attributed to household direct emissions, the contribution from urban households is only half of that from rural households. However, for the deaths associated with household indirect emissions, the urban contribution is over triple that of the rural. Overall, urban and rural household total consumption-associated death contributions are comparable with each other. Comparing Fig. 4b with Fig. 2a, we find that the spatial distributions of household consumption-associated $PM_{2.5}$ concentrations and premature deaths show large differences. This is partly because the amount of premature deaths is affected not only by the severity of $PM_{2.5}$ pollution but also by population density.

We further explore who suffer from household consumption-associated $PM_{2.5}$ pollution, by identifying different household groups from all premature deaths. Among the 1.06 million household consumption-associated premature deaths, 56% are urban households and 44% are rural households, approximately equal to their proportion in the total population. For each province, urban and rural premature deaths are also proportional to their population (Figs. S7 and S8 online). Considering that $PM_{2.5}$ and its precursors can stay in the atmosphere for days, they can be transported to downwind areas at various distances. Urban and rural areas in China tend to be interlaced, so pollutants can be easily mixed between urban and rural areas no matter where it is produced. Therefore, the urban and rural deaths caused by either consumption source (direct or indirect) tend to follow their population proportion.

3.3. National and provincial urban–rural inequalities

At both national and provincial scales, we further analyze the urban–rural contrast in terms of their roles as pollution sources and receptors. We examine the ratio between the pollution contributed by each household type and the pollution-related mortality risk that household type suffers from. Here, we introduce several terms to simplify the discussion: (1) PDS, per capita death suffering (the proportion of deaths in the total population of a group). We use PDS to represent household mortality risk. Urban and rural PDS could be represented by UPDS and RPDS respectively, and this rule is also applied to the following terms; (2) PDC, per capita death contribution (deaths contributed by per capita consumption activities in a group). We use PDC to represent household pollution contribution at the country level; (3) PAC, per capita consumption-based APE contribution. We use PAC to represent household pollution contribution for each province. Using the provincial APE instead of explicitly modeling each province's contribution to $PM_{2.5}$ pollution is because the modeling would have required too many computational resources to do the calculations for the 30 individual provinces.

From a national level, we contrast urban and rural household PDC and PDS. In the direct emission case, compared with urban households, rural households have over twice the pollution contribution (UPDC: 2.7 cases/ten thousand people; RPDC: 7.1 cases/ten thousand people), but suffer from a lower mortality risk (UPDS: 4.6 cases/ten thousand people; RPDS: 4.5 cases/ten thousand people). In contrast, in the indirect emission case, urban and rural households suffer from comparable mortality risk (UPDS: 3.2 cases/ten thousand people; RPDS: 3.1 cases/ten thousand people), but urban households have almost triple pollution contribution (UPDC: 4.4 cases/ten thousand people; RPDC: 1.6 cases/ten thousand people).

Such urban–rural inequalities are also obvious in individual provinces (Fig. 5a, b). In the case of direct emission (Fig. 5a), UPAC is just half as much as RPAC on the national average, but their mortality risk (i.e., PDS) is almost at the same level. Such inequalities are severer (i.e., U-RPDS/U-RPAC is further from 1.0) in less developed provinces, because direct emissions in these provinces are dominantly contributed by rural households (Fig. S8 online). By comparison, the urban–rural inequalities are weaker (i.e., U-RPDS/U-RPAC is closer to 1.0) in the developed provinces with large urban populations, such as Shanghai, Beijing, Zhejiang, Guangdong, Tianjin and Fujian.

In the case of indirect emissions (Fig. 5b), the contrast between household PAC and PDS shows results opposite to those for direct emissions. Compared with rural households, urban households have more PAC by 0.4–2.2 times in each province. However, urban and rural households suffer from comparable mortality risks (i.e., PDS). This contrast is obvious in several affluent provinces like Shanghai and Guangdong. Although urban households in these provinces have very high values of per capita annual consumption expenditure, most of the emissions embedded in their consumption activities are outsourced to other provinces [9,29]. By comparison, Jiangsu is an affluent province, but its rural–urban contrast is

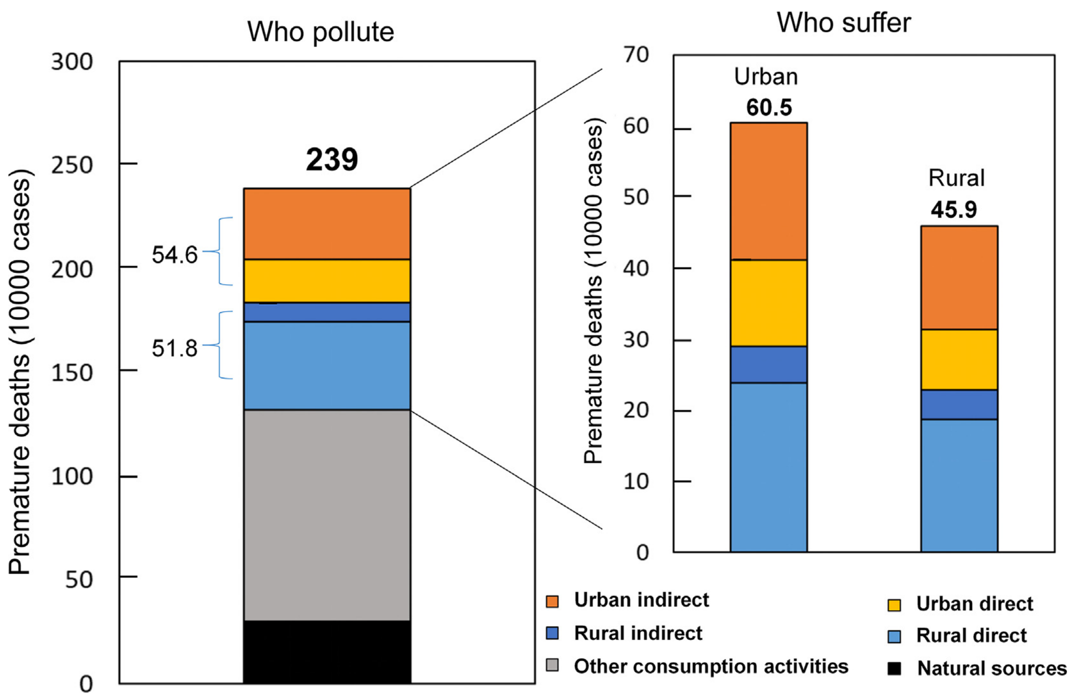

Fig. 3. Different consumption sources' contribution to China's $PM_{2.5}$-related premature deaths in 2015. Bar plots on the right show premature deaths in urban and rural households as a result of pollution exposure.

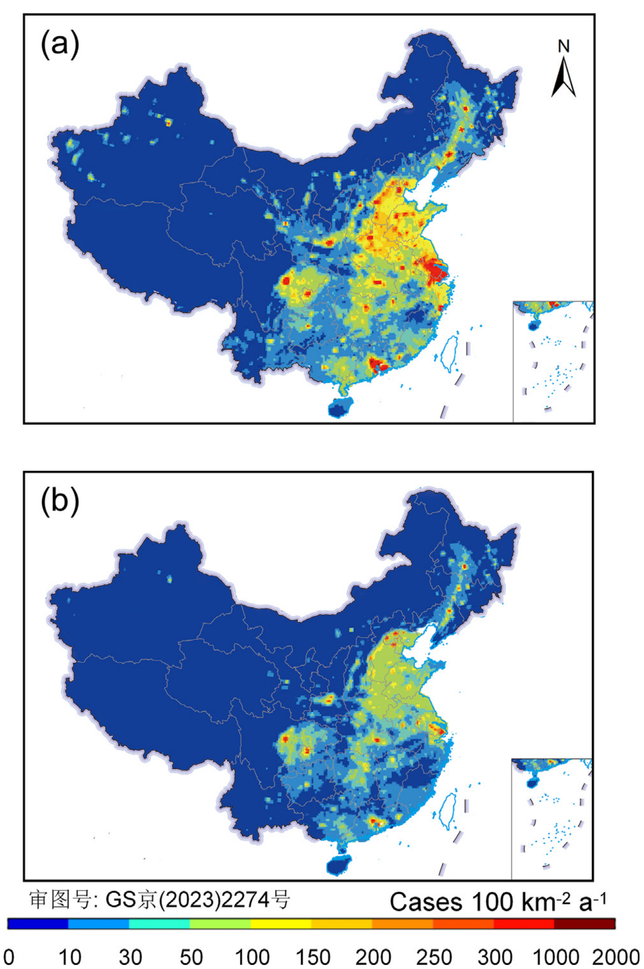

Fig. 4. Premature deaths caused by total (a) and household consumption related (b) ambient $PM_{2.5}$. The value of Taiwan Province is blank due to lack of data.

the weakest (i.e., U-RPDS/U-RPAC is closest to 1.0) among all provinces, resulted from the relatively small difference between its UPAC and RPAC. This is because rural households' per capita annual consumption expenditure in Jiangsu is the highest among 30 provinces and is comparable with Jiangsu's urban households.

For both direct and indirect emission, compared with urban households, rural households suffer from higher mortality risks in Beijing and Tianjin. This might be because a large portion of rural households in these two megacities live at the border with Hebei Province, thus would be largely affected by the pollution transported across the border. In Xinjiang, rural households suffer from twice the health risk of urban households in both cases. This might be because urban households in Xinjiang usually live in limited major cities which are relatively far from each other, thus would be less affected by the pollution contributed by industrial and residential processes in the suburban and rural areas.

4. Discussion and conclusions

Our results show that rural households contribute over 2/3 of the $PM_{2.5}$-related premature deaths associated with direct energy use, while urban households contribute over 3/4 of the $PM_{2.5}$-related premature deaths through indirect emissions related to purchase of products. Among all household consumption-associated premature deaths, 56% are urban households and 44% are rural households, approximately equal to their proportions in the total population. There exist notable urban–rural inequalities in terms of their roles as victims versus contributors of pollution. Although urban households contribute more indirect emissions and associated deaths, the corresponding mortality risk they suffer is relatively low at the provincial and national levels. The opposite results are true for direct emissions.

China's ongoing urbanization process has altered and will continue to alter households' living areas and consumption preferences. The nation's urban area fraction in 2030 is projected to reach almost 3%, equal to 7 times that in 1980 and 3 times that

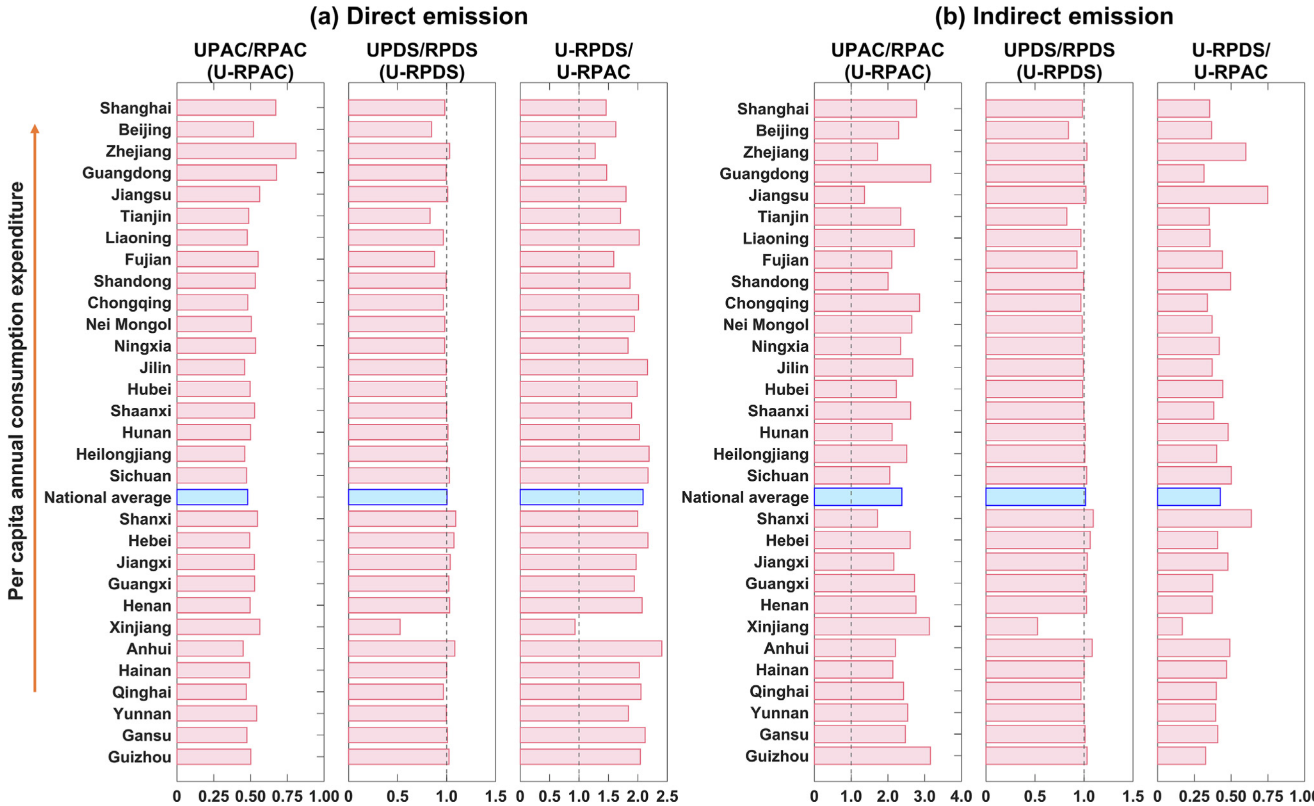

Fig. 5. Urban and rural household PAC versus PDS under direct (a) and indirect (b) emissions cases. PDS refers to per capita death suffering, that is, the proportion of deaths in the total population of a group. UPDS and RPDS refer to urban and rural PDS respectively. PAC refers to per capita consumption-based APE (i.e., air pollution equivalent) contribution. UPAC and RPAC refer to urban and rural PAC respectively. Provinces are ranked according to their per capita annual consumption expenditure (Fig. S9 online), reflecting provinces' affluence levels in this study.

in 2010 [7]. The ratio of the nation's urban population to rural population surged from 0.2 in 1980 to 1.8 in 2021 [12]. These changes brought by China's urbanization give rural-to-urban migrants more access to cleaner fuels, which will significantly reduce the pollution contributed by residential energy use and benefit human health in both areas [7]. At the same time, the rapid growth of urban population also increases household reliance on clean(er) energy resources. To maintain sustainable urban development, China should accelerate the energy mix transition and improve energy efficiency, taking the opportunity provided with the carbon neutrality pledge [50].

The urbanization process usually provides higher incomes to rural-to-urban migrants and changes their consumption preferences, resulting in an increase of indirect emissions if the nation's economic structure and emission intensities are fixed. Suppose rural-to-urban migrants perform the same consumption behaviours as urban households, China's urbanization process would nationally avoid direct pollution-associated premature deaths by 4 cases for every 10,000 migrants, but would increase indirect pollution-associated premature deaths by 3 cases per 10,000 migrants. Thus, during the urbanization process, the increased indirect pollution would largely offset the premature deaths avoided by reduced direct pollution. Different from the direct emissions from household energy use, the increased indirect emissions of any specific region could spread all over China along the supply chain [17,51]. The industry-intensive regions could receive more outsourced air pollution, affecting public health in their local and surrounding areas.

In addition, green products are usually at higher prices, thus many rural-to-urban migrants might still prefer to consume cheaper and more pollution-intensive products [52]. This could increase urban household per capita indirect pollution contribution, i.e., higher ratio of UPAC to RPAC. With China's urbanization ongoing, more people would be concentrated in several major cities. Thus urban households would be less affected by the pollution from industrial processes in suburban and rural areas, which is to a large extent indirectly driven by households' purchase of products, i.e., lower ratio of UPDS to RPDS. These factors could aggravate indirect emission-associated urban–rural health inequality.

Comprehensive environmental and socio-economic strategies could be developed to abate indirect pollution, diminish household exposure to pollution, and alleviate accompanying inequality. Firstly, companies, especially the leading ones in heavily polluting industries, could be regulated to report their direct and indirect (i.e., all upstream and downstream emissions arising from the firm's supply chain) emissions [53]. Disclosure of indirect emissions will contribute to reliable consumption-based emission accounting and promote the companies' green production. Secondly, an efficient cross-regional pollution abatement collaboration in China could be established to mitigate transboundary air pollution caused by interregional trade and atmospheric transport [10,54]. Thirdly, China's environmental pollution taxation could be imposed upon consumption (rather than production, as implemented currently) of pollution-intensive products [9,30]. The tax revenue could then be recycled as subsidies to less affluent rural and urban households to boost their transition to clean(er) energy [55,56]. These strategies will help reduce air pollution and associated urban–rural inequalities by incentivizing green consumption.

In China and other developing countries, urbanization is occurring at varying stages. Our findings shed new light on environmental policy formulation during this process that takes consumption activities and social-economic inequalities into consideration.

Effectively joint control actions would contribute to an urbanized country along with improved household life quality.

Conflict of interest

The authors declare that they have no conflict of interest.

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Author contributions

Jintai Lin and Jingxu Wang conceived the research and designed the research. Jingxu Wang, Ruijing Ni, and Lulu Chen performed simulations of health impacts. Yu Liu provided the Chinese provincial MRIO table. Feng Wu built the urban and rural population spatial distribution dataset. Fangxuan Ren compiled the $PM_{2.5}$ composition data. Zhongyi Li, Haoyu Zhang, and Zhengzhong Liu contributed to the data processing and figure polishing. Jingxu Wang, Jintai Lin, Ruijing Ni, and Mingxi Du led the analysis. Jingxu Wang and Jintai Lin wrote the paper. All authors commented on the manuscript.

Appendix A. Supplementary materials

Supplementary materials to this article can be found online at https://doi.org/10.1016/j.scib.2023.12.023.

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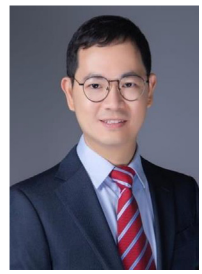

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