Inequality of household consumption and PM$_{2.5}$ footprint across socioeconomic groups in China

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Abstract
The United Nations Sustainable Development Goals have highlighted the challenge posed by increasing air pollution. This study allocates PM$_{2.5}$ footprint to household consumption expenditure based on multi-regional input–output model and survey data collected from 30 000 households. The household indirect PM$_{2.5}$ footprint related to spending on food, hospital, electricity, and education rank as the top four items, plus direct PM$_{2.5}$ emissions, which in combination contribute more than 55% of total air pollution. Compared with the poor, the responsibilities for air pollution on the wealthy are more sensitive to changes in income, especially for high-end consumption categories, such as luxury goods and services, education and healthcare. Further, the wealthiest 20% of households cause 1.5 times the PM$_{2.5}$ footprint per capita than exposure to PM$_{2.5}$ emissions. The high-footprint household samples are concentrated in high-exposure areas. It is recommended that mitigation policies address inequality of PM$_{2.5}$ footprint by targeting the top 20% of footprint groups with tags of wealthy, urban resident, well-educated, small family, and apartment living.

1. Introduction
The United Nations Sustainable Development Goals have highlighted the challenges of increasing air pollution (Goals 11) (UN 2018). Chronic exposure to PM$_{2.5}$ (i.e. particulate matter with an aerodynamic diameter below 2.5 µm) has been shown to have detrimental effects on human health (Hou et al. 2019, Jin et al. 2019), which is inequitably distributed among demographic groups, including socioeconomic-status (Guan et al. 2014, Wang et al. 2021).

Given the severe consequences of air pollution, several directives and regulations have been issued by the Chinese government, such as the Technical Policy on the Prevention and Control of Pollution by PM$_{2.5}$ (MEE 2013) and the Air Pollution Prevention and Control Action Plan (CPG 2013). These directives/regulations have been mainly designed for application to industry and their production processes. However, the pollution generated by the industrial sector is ultimately driven by society’s demand for goods and services, and these consumption behaviors are largely ignored in these regulations (Martinez et al. 2019).

Households play an essential role in PM$_{2.5}$ emissions mitigation from a consumption perspective, and so are responsible for impacts on air pollution, both directly and indirectly (Nagashima et al. 2017, Chuai et al. 2021). Household emissions that...
contribute directly to PM$_{2.5}$ come mainly in the form of fossil fuel combustion for home cooking, heating, and private vehicles (Meng et al 2015). Also, indirect PM$_{2.5}$ emissions are embodied in goods and services consumed by households such as food and clothing production, and waste collection and disposal (Zhao et al 2015, Cheng et al 2020). Although indirect emissions from final consumers are of less concern than direct emissions, they are also an important part of emissions accounting and should not be ignored (Yang et al 2018b).

Several previous studies have made linkages between human end-use activities and PM$_{2.5}$ emissions, and found that interpersonal and intergroup differences in terms of race and income result in disproportionate emission and exposure (Tessum et al 2019, Zhao et al 2019). A detailed literature review is shown in the supplementary materials (SM) (available online at stacks.iop.org/ERL/17/044019/mmedia) (pp S1–S3). Findings from some of the recent literature indicates the heterogeneous nature of CO$_2$ footprint or energy footprint and income (Chancel 2018), e.g. around 4% of homes use significantly more electricity than the average, however, they have low household incomes (Nelson et al 2019). In addition to income, particular attention needs to be paid to household characteristics (Kialashaki and Reisel 2013), social economic status (Nair et al 2010) and individual characteristics (Vassileva et al 2012).

Similarly, we integrate the PM$_{2.5}$ emissions with a footprint idea, proposed by Rees (1992) and Wackernagel and Rees (1997). Household PM$_{2.5}$ footprint is defined as the PM$_{2.5}$ emissions produced directly and indirectly throughout the entire life cycle of a product/service or within a certain range (Yang et al 2018a). An analysis based on that evidence helps explore the key driving factors other than income for household PM$_{2.5}$ footprint.

In order to explore the inequality of the PM$_{2.5}$ footprint across socio-economic groups from household consumption, this study firstly accounts for household PM$_{2.5}$ footprint based on the multiregional input–output (MROI) model and household surveys at a micro-scale level. The distribution of the PM$_{2.5}$ footprint with categorical details is presented. Further, we estimate the elasticity of the PM$_{2.5}$ footprint with respect to consumption of products/services and compare the responsibilities for the PM$_{2.5}$ footprint by analyzing the socio-economic dimension. Shapley decomposition has been further employed to identify the key individual characteristics other than income for household air pollution.

2. Materials and methods

From a demand-side perspective, we provide a framework based on the environmental extended input–output (EEIO) model and household survey data—the China Family Panel Studies 2012 (The Institute of Social Science Survey 2014), which were derived from a national survey of China, which focused on household expenditure with eight categories (26 sub-categories) of different daily consumption items (SM, pp S4 and S5). These will be used to establish a link between embodied PM$_{2.5}$ footprint and household daily consumption (figure 1).

2.1. Scope of research

2.1.1. Primary PM$_{2.5}$ versus secondary PM$_{2.5}$

The secondary sources also contribute to PM$_{2.5}$ concentration, but their production is strongly dependent on the nonlinear chemistry of atmospheric oxidants, making it difficult to precisely trace the origin of PM$_{2.5}$ (Kolb and Worsnop 2012, Zheng and Xu 2020). And oxidation of gas-phase pollutants is on a timescale from hours to days, leading to a larger spatial mismatch between the precursors’ emission site and the formation of secondary PM$_{2.5}$ aerosols, when compared with primary PM$_{2.5}$ (Liu et al 2013, He et al 2014). Also, Guan et al (2014) and Yun et al (2021) both indicate that emissions of primary PM$_{2.5}$ have a greater contribution than secondary aerosol precursors in terms of PM$_{2.5}$ concentration. Hence, in this study, we focus only on the primary PM$_{2.5}$ emissions.

2.1.2. Ambient air pollution versus indoor air pollution

Households cooking with coal/wood generates indoor air pollution. Ignoring this part will underestimate the PM$_{2.5}$ footprint of residents. However, due to a lack of necessary basic data of indoor energy usage for accounting indoor air pollution at micro-level, if indoor PM$_{2.5}$ emissions are distributed to households evenly based on the macro data, the result will be biased. Thus, this study focuses on household ambient PM$_{2.5}$ emissions from consumption perspectives (Archer-Nicholls et al 2016, Xiang et al 2019).

2.2. Embodied PM$_{2.5}$ footprint accounting

The EEIO model was adopted to account for the consumption-based PM$_{2.5}$ and the PM$_{2.5}$ footprint, which are attributed to households via household expenditure, which is also known as input–output energy analysis combined with household expenditure data (IO-EA-expenditure) (Wiedenhofer et al 2013):

\[ Q = fL + D \]  

where Q is the consumption based PM$_{2.5}$ allocated to goods and services in a certain region from other regions, f is the direct PM$_{2.5}$ intensities that have been diagonalized, L is the MROI Leontief Inverse, and y represents the expenditure extracted via the household survey data. D indicates the PM$_{2.5}$ produced by the direct energy consumption of household’s car, cooking, heating, etc.
We adopted the Chinese MRIO table from our previous research (Chen et al 2019). Applying the equation (1), PM$_{2.5}$ relate to the certain expenditure category of individual samples, which were calculated. The PM$_{2.5}$ caused by the direct energy consumption of household was also calculated separately.

### 2.3. Income elasticity of PM$_{2.5}$ footprint

The traditional income elasticity of demand are the function describing how consumer’s expenditure on some goods or services related to the consumer’s income, with the price fixed (Lewbel 2008). This study builds on the income elasticity of PM$_{2.5}$ footprint to describe the relationship between household income and its contribution to PM$_{2.5}$ emissions, everything else being equal. The econometric estimation of the parameters is based on the log-linear form:

$$\ln (PM_j) = \ln (A) + \beta \ln (Income) + \gamma \text{Control} + \varepsilon$$  \hspace{1cm} (2)

where $PM_j$ is the household PM$_{2.5}$ footprint induced by consumption item $j$, income is individual income in 2012, $A$ is a constant, and $\beta$ is the elasticity of footprint increase with respect to income. Control is a set of control variables, such as age, gender, education, etc and $\varepsilon$ is a random error term. Thus, when individual income increases by 1%, PM$_{2.5}$ footprint of consumption item $j$ increased by $\beta\%$, holding other factors fixed.

### 2.4. Key characteristics profiling

For the detailed key characteristics of individual profiling, we decompose the goodness of fit into contributions of regression variables according to the Shapley value (Owen 1977, Huettner and Sunder 2012). Based on the log-linear regression equation (2)—full model, we consider additional regressions for every combination of variables:

$$\ln (PM_j) = \ln (A) + \sum \alpha_p x_p + \varepsilon$$  \hspace{1cm} (3)

where $x_p$ is one of the regressor variables ($p = 1, 2, ..., k$), $\alpha_p$ is the coefficient of each variable. Each of these sub-regressions is associated with a worth of respective goodness-of-fit, e.g. $R^2(S)$.

The Shapley value of a variable equals the variable’s average marginal contribution over all possible permutations (Huettner and Sunder 2012), shown as:

$$\text{Sh} (x_p) = \frac{1}{k!} \sum \text{MC} (x_p)$$  \hspace{1cm} (4)

where $\text{MC}(x_p)$ is the $x_p$’s marginal contribution in a particular ordering of the regressors. Thus, the individuals’ key characteristics can be profiled with the top share of goodness-of-fit into contributions by individual regressor variables.
3. Results

3.1. Household PM$_{2.5}$ footprint in 2012
The total household PM$_{2.5}$ footprint ranged from 0.50 to 3.07 Mt and the average total household PM$_{2.5}$ footprint per capita ranged from 17.82 to 54.48 kg across 25 provinces. The average direct PM$_{2.5}$ emissions per capita in 2012 were 1.68 kg. The result is within the interval of previous studies, e.g. direct PM$_{2.5}$ emissions are 0.4 kg cap$^{-1}$ for urban residents and 5.8 kg cap$^{-1}$ for rural residents in China for 2010 (Guan et al 2014). The indirect household PM$_{2.5}$ footprint contributed about 95% of the total household PM$_{2.5}$ footprint, which is slightly lower than the results published by Yang et al (2018a) where PM$_{2.5}$ pollution was driven by Beijing residents, which indirectly accounted for 99.96% of the total.

The household indirect PM$_{2.5}$ footprint related to spending on food, hospital, electricity, and education rank as the top four items, plus direct PM$_{2.5}$ emissions, which in combination contribute more than 55% of total air pollution (figure 2). ‘Food’ was found to be the largest household expenditure (3226.33 CNY per capita in 2012), which is associated with multiple upstream industries, especially agricultural production. PM$_{2.5}$ emissions from agricultural sources constitute an important portion of PM$_{2.5}$ concentrations (Wu et al 2016, Pozzer et al 2017). In terms of ‘Electricity’, the thermal power sector generated 80% of the total electricity in China, and coal-fired thermal power generation accounted for over 70% of the total electricity generation of the thermal power sector (Peng et al 2018, Eguchi et al 2021). From the perspective of ‘Hospital’ and ‘Education’, the household indirect PM$_{2.5}$ emissions per capita of them are 4.79 kg and 2.70 kg, respectively. These emission intensities of the two categories are relatively low among the 26 sub-categories. However, households spent 897.38 CNY on hospital and 755.84 CNY on education per capita in 2012, which were ranked 2nd and 5th among 26 sub-categories. High expenditure on these two sub-categories leads to significant indirect PM$_{2.5}$ emissions, which have been largely overlooked in the previous literature.

As for direct emissions, a great amount of scattered coal directly consumed by residents and catering services for heating and cooking, vehicle fuel, natural gas, and liquefied petroleum gas (Meng et al 2015, Yang et al 2018a). It should be noted that the data of direct consumption of per capita residents in different regions comes from the macro level, and the current micro survey does not support us to carry out household-level PM$_{2.5}$ direct emission accounting. Allocating average direct PM$_{2.5}$ emissions from electricity/cooking/heating to all households is inaccurate. Therefore, in the following analysis, the direct emissions are omitted, but it is a minor issue due to their overall low contribution to overall ambient PM$_{2.5}$ (<5%).

A positive relationship between income and indirect PM$_{2.5}$ footprint was found (figure 3), which is in line with the previous studies (Luo et al 2018, Cao et al 2019). The wealthiest 5% of residents were responsible for 63.81 kg cap$^{-1}$, whereas the poorest 5% of residents were responsible for 20.78 kg cap$^{-1}$. Levels of inequality with regards to PM$_{2.5}$ footprint is also significant at a categorial level, especially for ‘Transport and Communications’ and ‘Household Equipment, Furnishings and Services’. The wealthiest 5% of residents for the two sectors are 4.50 and 4.53 times higher in terms of what they contribute to PM$_{2.5}$ footprint when compared with the poorest 5% of residents. Among the eight categories, ‘Transport and Communications’ and ‘Household Equipment, Furnishings and Services’ have the fastest average growth rate (8.28% and 8.24%) with the increase of income. The growth rates for the remaining seven sectors range from 3.00% to 7.50%.

3.2. Household PM$_{2.5}$ footprint across socioeconomic groups
Public policy decision-makers and air pollution researchers (as indicated by the large body of literature on the topic) are focused on socioeconomic responsibility inequalities induced by PM$_{2.5}$ footprint. In this part, we will compare the responsibilities for PM$_{2.5}$ footprint by analyzing the socioeconomic dimension.

3.2.1. Income elasticity of PM$_{2.5}$ footprint analysis
This study extends on the traditional elasticity as income elasticity of PM$_{2.5}$ footprint to reveal how patterns of air pollution change with income, which can also be disaggregated into categorial details (figure 4) by connecting these with household lifestyles (Hasan and Mozumder 2017). For the wealthy, increases in income come with increases in demand for high-end consumer goods and services. Whereas for the poor, increases in income follow a different script, where demand for essential goods and services such as food, clothing and basic household products increase (Meyer and Sullivan 2003). High-end consumption and services are not directly related to high PM$_{2.5}$ intensity, but may have lower PM$_{2.5}$ intensity than traditional products such as clothes, food, and basic household products. Varying in consumption propensity has led to a gap in consumption expenditure between the wealthy and the poor, causing differentiated PM$_{2.5}$ footprint.

For example, the elasticities of ‘Education, culture and recreation’ and ‘Health care and Medical services’ have the big difference between the poor and the wealthy. Although both of them do not belong to high PM$_{2.5}$-intensity categories, differences in households’ consumption preferences will also lead to varying degrees of PM$_{2.5}$ footprint. Given that education provides a direct benefit in terms of competitiveness in the labor market and
income, high-income households will tend to make high educational expenditures as a capital investment (Hashimoto and Heath 1995, Douglass 2018). In China, the rapid expansion of healthcare insurance coverage and the increasing investment in health facilities have led to an increased demand for their high-end medical services. It is very attractive to the wealthy. In addition, thanks to the extensive coverage of China’s basic medical insurance system, there’s a decrease in the percentage of total health expenditure borne by out-of-pocket spending, especially for the poor (Yip et al 2019). Thus, PM$_{2.5}$ footprint from those two categories have different sensitive to personal income between the wealthy and the poor.

Also, the elasticity of ‘Miscellaneous Goods and Services’ is ranked the top (0.69) for the wealthy. In other words, adding 1% to income will cause household PM$_{2.5}$ footprint of the category to increase by 0.69%. However, for the poor it is ranked at the bottom (−0.11). ‘Miscellaneous Goods and Services’ containing such as things as ‘luxury items’, which are PM$_{2.5}$ intensive and will boost PM$_{2.5}$ footprint as residents incomes increase (Tian et al 2016, Han et al 2020). The consumption of luxury items, often associated with lifestyles of excess, indulgence and waste, are in many ways antithetical to the concept of sustainability (Hennigs et al 2013). Existing studies suggest that industries which

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**Figure 2.** The embodied PM$_{2.5}$ footprint (kg cap$^{-1}$) induced by household consumption with sectoral details in 25 provinces (SM, pp S6 and S7).

**Figure 3.** The indirect PM$_{2.5}$ footprint (kg cap$^{-1}$) associated with 20 income levels. Household consumption was aggregated to eight categories from the original 26 sub-categories (SM, p S8).
produce luxury goods and services lag behind others in terms of sustainable commitments (Yang et al 2017).

3.2.2. The distribution of PM$_{2.5}$ footprint responsibility

The distribution of household PM$_{2.5}$ footprint presents a 'funnel' shape for income groups (figure 5). The unevenly distribution of PM$_{2.5}$ footprint resulted in inequality of pollution responsibility. From a national perspective, the wealthiest 20% of the population is responsible for 35.96% of the PM$_{2.5}$ footprint, while the poorest 40% of the population is responsible for 27.00% of the PM$_{2.5}$ footprint. The PM$_{2.5}$ footprint caused is 57.58 kg cap$^{-1}$ for the wealthiest 20%, and 21.62 kg cap$^{-1}$ for the poorest 40%, taking up only 37.54% of the wealthiest 20%. As for middle-income households (the 5th–8th deciles income), the footprint account for 8.00%, 8.44%, 9.34% and 11.27% respectively, and PM$_{2.5}$ footprint caused is 29.67 kg cap$^{-1}$.

From an individual perspective, the wealthiest 20% of households cause 1.53 times the PM$_{2.5}$ footprint than their exposure (figure 6). However, this average result does not apply to each province. A large number of coal production and related heavy industry sectors are concentrated in Hebei and Shan- dong. Households based in these areas live in heavily polluted environments, thus the final pollution exposure from consumption of households are 1.32 and 1.63 times the wealthiest 20% of emission households, respectively, and even are 3.10 and 2.96 times the poorest 20% of emission households. In other words, households in these areas, whether the wealthy or the poor, are exposed to air pollution per capita that have exceeded the PM$_{2.5}$ footprint induced by their consumption. On the contrary, by outsourcing the production of a large number of goods and services to the other regions, the per capita exposure of households based in Beijing and Shanghai, far less than the PM$_{2.5}$ footprint by daily consumption. The gap of PM$_{2.5}$ footprint and exposure risk, for the
wealthiest 20% of households, has widened by 6.41 and 4.57 times, respectively. And the gap, for the poorest 20% of households, has widened by 3.87 and 2.12 times, respectively. In some regions, the air pollution exposure suffered by households is between the responsibilities of PM$_{2.5}$ footprint of the wealthy and the poor. For example, the tertiary industries in Tianjin and Zhejiang are highly developed, and the exposure level of air pollution (35.66 kg cap$^{-1}$ and 43.50 kg cap$^{-1}$) is 62.59% and 29.43% lower the PM$_{2.5}$ footprint of the wealthiest 20%, but 18.93% and 7.31% higher than the PM$_{2.5}$ footprint of the poorest 20%. There are typical regions where the wealthy benefit but the poor lose.

From a total footprint perspective, the top 20% of PM$_{2.5}$ footprint groups are also concentrated in high-exposure areas, thus exposing their living to greater risk (figure 7). The distribution of purple color blocks on the map in figure 7 shows that the regions with the largest numbers of top 20% of footprint households are Jiangsu, Zhejiang, Shandong, Hebei, Guangdong and Hunan, each with more than 15 million. According to calculations, Hebei, Shandong, Hubei, Jiangsu, and Guangdong rank in the top 5 of the 25 regions in terms of total PM$_{2.5}$ pollution exposure, each with more than 2 million tons. The households in these five regions caused 15.42 million tons due to PM$_{2.5}$ exposure, accounting for 43.47% of the total pollution responsibility.

### 3.3. Influential factors decomposition and key characteristics profiling

This part begins by reporting the results of the stepwise regressions and proves the combination of the eight variables including urban/rural, family size, car, regions, income, house type, education and consumption level, are in the best fitness. As outlined in the methodology section, we carry out further analysis of PM$_{2.5}$ footprint influential factors for the top 20% footprint group and bottom 40% footprint group. The key characteristics of profiling are based on Shapley decomposition (SM, pp S10 and S11).

In order to target the key influence characteristics, we developed word clouds based on the frequency of these. The method is useful for quickly understanding the most prominent terms of individual characteristics to determine their relative prominence in PM$_{2.5}$ footprint induced by consumption. The profiling was conducted for the top 20% of PM$_{2.5}$ footprint (figure 8(a)). In comparison, the bottom 40% of PM$_{2.5}$ footprint was also listed (figure 8(b)).
‘Urban’ and ‘rich’ (the two major tags) accounted for the top 20% of samples in the PM$_{2.5}$ footprint. 55.01% of the samples were urban residents, and 44.99% of them occupied the high-income group. Residents in this group tended to have smaller families and so lived in smaller households. As a result they typically produced less emissions compared to larger households, but with higher per-capita footprint (Zhou and Yang 2016). The samples with high footprint are influenced by house type. The figure suggests that they prefer living in apartments. Also, they are well-educated. Nearly 39.48% had completed high school or above. Most of them were concentrated in Jiangsu, Zhejiang, Guangdong and Hunan.

Rural residents (89.91%) made up a large number of those in the bottom 40% of samples in PM$_{2.5}$ footprint. The family has long been a key component within Chinese society; it is common that people, especially those living in a rural areas, prefer to have many generations of a family living under the same roof. Thus, big or upper medium-sized families led to the decrease in per capita PM$_{2.5}$ footprint. These...
families tended to be less educated or uneducated and tend to be more limited when it came to the consumption of products and services. Further, nearly 53.66% of this group occupied the low and lower middle-income groups. Their geographic distribution was found to be relatively scattered.

4. Conclusions
This study attributed responsibility for direct and indirect PM$_{2.5}$ emissions to socioeconomic groups, measured the inequality of the PM$_{2.5}$ footprint, and identified the key characteristics of the top 20% of PM$_{2.5}$ footprint groups.

By analyzing the income elasticity of the PM$_{2.5}$ footprint this study found that the responsibilities for air pollution on the wealthy are more sensitive to changes in income when compared to the poor. The rise in income between wealthy and poor leads to an increase of different spending categories, resulting in inequalities of PM$_{2.5}$ footprint. For the wealthy, there is a bigger increase in high-end consumption categories, such as the purchase of luxury goods and services, education and healthcare. Although these categories are not completely high PM$_{2.5}$ intensive, the wealthy spend a lot, which greatly increases the PM$_{2.5}$ footprint. In contrast, a rise in income for poor households is likely to be spent on essential needs such as food, clothing, and housing, which was found to be more PM$_{2.5}$ intensive than high-end consumption categories. However, the PM$_{2.5}$ footprint induced by their little increased consumption expenditure is far less than that of the wealthy. In order to create fairness in the system, mitigation policies need to be examined for separate footprint groups and specific consumption items (Büchs and Schnepf 2013).

The responsibilities for the PM$_{2.5}$ footprint are unevenly distributed among the population, resulting in inequality of pollution responsibility. From an individual perspective, the wealthiest 20% of households cause 1.53 times PM$_{2.5}$ footprint than exposure to PM$_{2.5}$ emissions, but this average result does not apply to each province. From a total perspective, the top 20% of emission groups are also concentrated in high-exposure areas. Further, we targeted the key influence characteristics for the top 20% and the bottom 40% of PM$_{2.5}$ footprint households. It was found that the household characteristics (e.g. rural/urban registration, family size, car ownership, regions and house type) have a greater influence on the PM$_{2.5}$ footprint induced by daily consumption than income, while income only ranks as the 5th most influential factor. This result further highlights a necessity to explore individual characteristics with detailed household surveys.

Also, the present study is not without its limitations, and the SM (pp S12–S14) presents the limitation discussion of the model. The SM (pp S15–S19) presents a discussion on health impacts from the PM$_{2.5}$ footprint and its uncertain analysis.

Data availability statement
All data that support the findings of this study are included within the article (and any supplementary files).

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