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Environmental Justice Aspects of Exposure to $PM_{2.5}$ Emissions from Electric Vehicle Use in China

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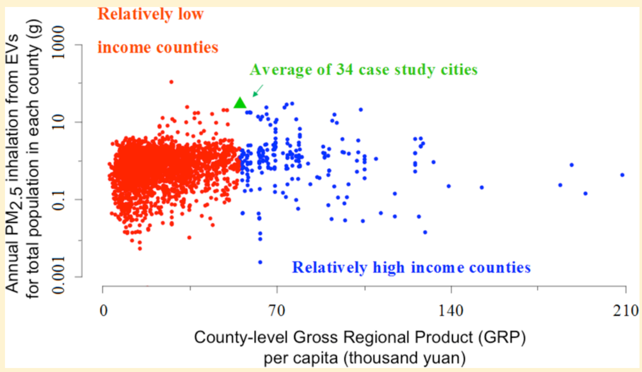
Supporting Information



ABSTRACT: Plug-in electric vehicles (EVs) in China aim to improve sustainability and reduce environmental health impacts of transport emissions. Urban use of EVs rather than conventional vehicles shifts transportation's air pollutant emissions from urban areas (tailpipes) to predominantly rural areas (power plants), changing the geographic distribution of health impacts. We model $PM_{2.5}$-related health impacts attributable to urban EV use for 34 major cities. Our investigation focuses on environmental justice (EJ) by comparing pollutant inhalation versus income among impacted counties. We find that EVs could increase EJ challenge in China: most (~77%, range: 41–96%) emission inhalation attributable to urban EVs use is distributed to predominately rural communities whose incomes are on average lower than the cities where EVs are used. Results vary dramatically across cities depending on urban income and geography. Discriminant analysis reveals that counties with low income and high inhalation of urban EV emissions have comparatively higher agricultural employment rates, higher mortality rates, more children in the population, and lower education levels. We find that low-emission electricity sources such as renewable energy can help mitigate EJ issues raised here. Findings here are not unique to EVs, but instead are relevant for nearly all electricity-consuming technologies in urban areas.

■ INTRODUCTION

Sustainable development aims to address economic development, social equity, and environmental protection.[1] Plug-in electric vehicles (EVs) are often considered as a technology to support sustainable development in the transportation sector.[2,3] Several prior studies have focused on environmental sustainability of EVs, focusing on greenhouse gas (GHG) emissions[4−8] or local air pollution,[9] and public health.[2,10−12] For conventional vehicles (CVs), use-phase emissions occur where vehicles are used; for urban EVs, use-phase emissions instead occur at (for fossil fuels) the power plant where electricity is generated. This shift remedies some intraurban environmental justice (EJ) challenges,[13−17] but potentially creates new challenges by exporting pollution to populations far from urban centers.

In China, EVs, including electric bikes (e-bikes) and electric cars (e-cars), are often considered an approach toward sustainable transportation, balancing mobility, energy security, GHG emissions, and air pollution. From 2011 to 2014, the annually estimated sales of e-bikes in China grew from 31.0 million units to 34.2 million units.[18] In the meantime, the annual sales of full plug-in e-cars in China increased from 5579 to 45 048 vehicles.[19,20] The Chinese central government also designed an ambitious plan to add 5 million pure e-cars and plug-in hybrid e-cars on the road by 2020.[21] In the short and medium term, EVs may not reduce GHG emissions or local air pollution due to reliance on coal electricity generation.[2,4,7,22,23] In the long term, EVs could reduce fossil fuel use and GHG emissions relative to CVs if electricity generation transitions to cleaner energy.[4,7] Especially, with the booming penetration of hydro, wind, solar, and other cleaner energy as well as supports from central and local governments in China,[24,25] a significant portion of future power may come from sustainable energy sources. At that time, EVs could improve relative to CVs.

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Despite significant research on environmental and economic sustainability aspects of EVs in China,[26−30] to our knowledge, no research has evaluated EJ aspects of EV's environmental health impacts across populations. This paper targets that gap. We focus on current distributional aspects of health impacts from fossil power plant emissions attributable to urban EVs (pure plug-in battery e-cars). The primary focus of the article is EVs, but the results are generalizable and would apply broadly to other examples of urban electricity consumption. In prior research,[2] we calculated health impacts of $PM_{2.5}$ from EVs and CVs using an intake fraction (iF) health assessment framework. Here, we extend the prior work to evaluate EJ. Specifically, using census data, we investigate demographic characteristics (e.g., income) of those who benefit from urban EVs (city dwellers) versus those who inhale pollution from electricity generation (predominantly, rural populations downwind of fossil power plants).

Environmental justice is an ethical concept related to the distributional fairness of impacts: which groups are more exposed or less exposed to environmental risks,[31−33] and are those risk-differences necessary, avoidable, or remediable.[34] Prior research has investigated EJ aspects of electricity generation. For example, Levy et al.[35] investigated particulate matter (PM) emission control strategies from power plants near Washington, DC. They found that half of the health benefits accrued among the 25% of the population with lower education level (below high school). Touché and Rogers reported that Texas power plants relying on more hazardous fossil fuels are located in lower socioeconomic communities.[36] Levy et al.[37,38] developed multiobjective frameworks to include EJ into U.S. air pollution management (focusing on $PM_{2.5}$ mortality) for fossil power plants.

China is facing similar EJ challenges. Brajer et al.[39] found that in China, between-city income inequity increased from 1990 to 2004 and that air pollution impacts are correlated with the inequity. Schoolman and Ma,[40] analyzing locations of air and water emissions in Jiangsu, reported that communities with a higher proportion of rural migrants were likely to live near to industrial emission sources. They concluded that the environmental health impact of power plant emissions depends on their location, the locations of population centers, and the transport of emissions from source to receptor. Ji et al.[2,23] estimated emission intake in urban and rural areas in China from urban use of EVs. They found that, on average, nonurban populations inhale approximately 52% (range: 19−64%) of emissions from urban use of EVs. An important context for those findings is the large and growing disparity between urban and rural incomes: the rural-urban difference in average income per person increased from 2.8× in 2000 (2253 RMB [US$338] rural versus 6280 RMB [US$941] urban) to 3.1× in 2011 (6977 RMB [US$1,046] rural versus 21 810 RMB [US$3,270] urban).[41]

A shortcoming of the rural/urban comparison is that it does not distinguish impacts based on traditional indicators of social status (e.g., income, education). Here, we focus on EJ implications of urban EVs, using two methods: investigating disparities between income and inhalation among the exposed populations; and applying discriminant analysis on multiple population groups exposed to air pollution.

■ MATERIALS AND METHODS

We extend the methods employed in Ji et al.[2,23] to estimate $PM_{2.5}$ pollution intake, focusing on locations of emissions (coal power plants) and where they are inhaled. In this paper, "inhalation" refers to total $PM_{2.5}$ emission inhalation attributable to urban EVs use. We employ an iF framework to estimate inhalation of $PM_{2.5}$ in China. Intake fraction is defined as the proportion of a pollutant that is inhaled relative to the amount emitted. Intake fraction can be calculated in multiple ways, based on data or models. It is an intuitive method to compare inhalation and health impacts across locations, technologies, fuels, and populations. Further information about estimating and using iF is available elsewhere.[42] For conserved primary pollutants in global cities, the reported intraurban iF range is 0.6−260 ppm (population-weighted values: median: 26 ppm, mean: 39 ppm, interquartile range: 14−52 ppm).[43] Intake fractions are higher for Chinese cities than for the global average (population-weighted values for China: median: 34 ppm, mean: 45 ppm, interquartile range: 21−64 ppm).[43,44]

Concentration-based estimates of iF would require fine resolution pollutant emissions and concentrations. A simplified regression approach developed for China by Zhou et al.[45] uses pollutant transport models from a sample of fossil power plants to estimate iF; then they regress iF against population data surrounding fossil power plants to obtain a predictive iF model (R^2 = 0.86−0.95). We use that model to estimate iF from coal power plants emissions throughout China. The model inputs are population living in the radii of 100km, 500 km, 1000 km, and farther than 1000 km from 2640 coal power plants in China. County population data are from the 2010 census.[46] The database of coal power plants in China applied here was previously derived by researchers at Tsinghua University[47] based on plant-level information (name, address, capacity, generation) from the China Electricity Council (CEC)[48] and emission factor information from Zhao et al.[49] The emission factor for each coal power plant is averaged to reflect coal and noncoal generation in that region. Additional details on the emission data set are in the Supporting Information (SI). We assume an arbitrary vehicle-travel distance as the basis for our comparisons: specifically, we evaluate the impact if 10^9 vehicle kilometers traveled by CVs were substituted by equivalent EVs in each city. If average energy efficiency of an e-car is 180 Wh km^{-1} and electricity transmission and in-plant use loss in China is 14%,[2] the energy demand from 10^9 vehicle kilometers traveled by EVs in each city will be 205.2 GWh. This energy demand would represent 0.2−4.7% of the total annual urban electricity use in each city we investigated, a small but likely growing percentage of total urban electricity consumption. Because of little available data on vehicle kilometers traveled by EVs in China, the assumption of 10^9 vehicle-kilometers traveled is based on fleet size, percentage of EVs, and annual vehicle kilometers traveled by light duty vehicles in Beijing (e.g., Beijing had ∼5 million CVs in 2010.[50] If 1% were replaced by EVs, each traveling ∼20 000 km y^{-1},[51] that shift would be 10^9 vehicle-kilometers y^{-1} by EVs.). Our results could easily be scaled up or down for alternative bases. We calculate $PM_{2.5}$ emissions from the corresponding power grid, then apply iF values to estimate county-level inhalation of $PM_{2.5}$ emissions. This approach is most useful to evaluate EJ aspects of replacing CVs with EVs in an urban area where most urban CV emission are inhaled by those dwelling in the city.[52] We investigate total inhalation attributable to EVs for the 34 cities analyzed in Ji et al.[2] We employ per capita gross regional product (GRP per capita) as our measure of county-level average income, and investigate whether exposures are greater for higher- or lower-income counties, relative to the city where the EV is used. We

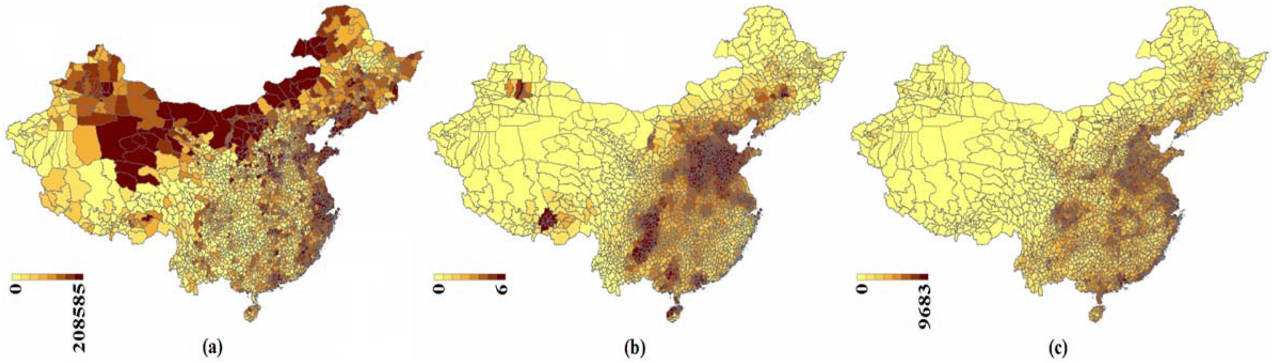

Figure 1. (a) Per capita gross regional product (in RMB) by county in China (darker color corresponds to higher values); (b) Per capita inhalation from coal power plants (μg $PM_{2.5}$ from 10^9 vehicle kilometers traveled by EVs in each of 16 power grids); (c) Population density (people km^{-2}).

apply discriminant analysis to investigate demographic factors that are correlated with emission inhalations.

Income and Inhalation Disparity Analysis. We conduct individual case studies for 34 cities, covering all of China's urbanized provinces. Using ArcGIS, each of China's counties (n = 2872) are assigned by distance to each coal power plant (n = 2640). We use the iF methods described above to assess iF from each coal power plant to each county (i.e., each county represents a proportion of the total iF from a coal power plant, related to county population and distance from the coal power plant). Applying coal power plant emission factors for each grid to urban EV use, weighted in proportion to the relative capacity of the coal power plant, we estimate total inhalation of emissions at the county level from an arbitrary urban power demand. Our approach is described in eqs 1 and (2).

$$\text{total inhalation}_{\text{county}x} = \sum_{j=1}^{n} iF_j^x \times E_j \tag{1}$$

$$\text{total inhalation}_{\text{county}x} = \sum_{j=1}^{n}\left[\left(\sum_{i=1}^{4} \alpha_i \delta_i^j P_x\right) \times \left(\frac{G_j}{\sum_{k=1}^{m} G_k} ED_l\right) EF_j\right] \tag{2}$$

Total inhalation in county x (eq 1) is equal to the sum over all coal power plants (j = 1 to n) of the county's proportional iF (iF_j^x) from each coal power plant j times the total emissions from an individual coal power plant j (E_j). Equation 1 can be decomposed (see eq 2) using the sum of the regression coefficients α_i times a binary (1 or 0) indicator variable (δ_i^j) to determine which distance bin county x falls in from coal power plant j, times the population of the county (P_x). The total emissions from an individual coal power plant is estimated by allocating the total electricity demands from coal power plants in power grid l (ED_l) to the attributable coal power plants in proportion to their relative generation ($G_j/(\sum_{k=1}^{m} G_k)$), where G_j is the generation of coal power plant j and $\sum_{k=1}^{m} G_k$ is the sum of electricity generations of all coal power plants in its power grid k. Total emissions from each coal power plant is estimated by multiplying the electricity demands allocated to each coal power plant by the average emission factor (EF_j) of each power plant. Inhalation values for each coal power plant are summed over total emissions from arbitrary energy demands in each power grid (EV use in this case), to estimate the impact per energy production. We include 14% generation and transmission losses, China's average.[41,53] Total inhalation in county x is the sum of incremental inhalation from emissions from all coal power plants.

Figure 1a illustrates GRP per capita at the county level in China based on 2010 census data, the most recent data available.[46] Much of the wealth is on the coast or northern borders. Figure 1b illustrates corresponding per capita inhalation of emissions from coal power plants for each county based on EV use in 34 Chinese cities throughout China. Using Huai River-Qin Mountain line as dividing line between northern and southern China, most of the inhalation per capita occurs in the northern portion of China; and less of the inhalation per capita occurs in the southern interior portion of China, with the exception of the band of power plants and population centers in the Chengdu and Chongqing regions. The higher per capita inhalation also corresponds to higher population densities (Figure 1c) resulting in much higher total inhalation.

Emissions from electricity generation from EV recharging in a city could potentially be inhaled over a wide area, including in the city where the EVs are operated. For EV inhalation, we attribute inhalation of $PM_{2.5}$ (from coal power plants serving urban EV charging) to counties with higher or lower income, relative to the city where the EV is operated. This contrasts CV emissions, where nearly all exposure and inhalation occurs in the city where the CV is operated. Inhalation of primary $PM_{2.5}$ emissions from EVs is classified into four groups:

- Group A, lower-income, lower-inhalation: the county has lower income and lower inhalation than the city where the urban EV is operated.
- Group B, lower-income, higher-inhalation: the county has lower income and higher inhalation than the city where the urban EV is operated.
- Group C, higher-income, lower-inhalation: the county has higher income and lower inhalation than the city where the urban EV is operated.
- Group D, higher-income, higher-inhalation: the county has higher income and higher inhalation than the city where the urban EV is operated.

Group B especially reflects a potential EJ concern.

Discriminant Analysis. Beyond income, other metrics can also be used to quantify EJ concerns. Discriminant analysis can extract information from large quantities of socioeconomic data. Before conducting discriminant analysis, we aggregate the inhalation for each county in China by assuming 10^9 vehicle kilometers traveled by EVs in each power grid. The per capita inhalation for all counties is compared with census data. Our

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data set provides 167 attributes (e.g., age, industry, and education levels) for all (n = 2872) counties in China. Discriminant analysis requires grouping of data. Based on income and total inhalation, we classify different counties into one of three mutually exclusive groups. (The prior section ("Income and Inhalation Disparity Analysis") employed four groups (Groups A–D). The three groups employed here for discriminant analysis are entirely distinct, and bear no direct relation, to those four groups.) Thresholds were chosen such that these three groups are mutually exclusive (inhalation per capita greater than or less than 3 ug per capita; GRP per capita greater than or less than 65 000 RMB [US$10,484]). We employ the labels "advantaged" for the higher-income, lower-inhalation counties; "disadvantaged" for lower-income, higher-inhalation counties; and, "unclassified" to reflect all other counties. Here "advantaged" means a higher-income county that gains health outcomes (i.e., experiences a reduction in environmental risk) via a policy or a technology (in this case, increased use of EVs), potentially at the expense of others. A "disadvantaged" county is lower-income and bears comparatively larger incremental health costs from the policy/technology. The data, showing how we classified counties, are in Figure 2; this figure highlight the spread of data and differences between the advantaged and disadvantaged counties. The 34 cities we investigate (brown triangles) generally fall in the advantaged (38%) or unclassified (56%) groups; only two cities (6% of the 34 cities, representing 14% of the total population of the 34 cities) are in the disadvantaged group. After grouping, we compare the counties in the advantaged and disadvantaged group to investigate socio-economic differences across multiple variables.

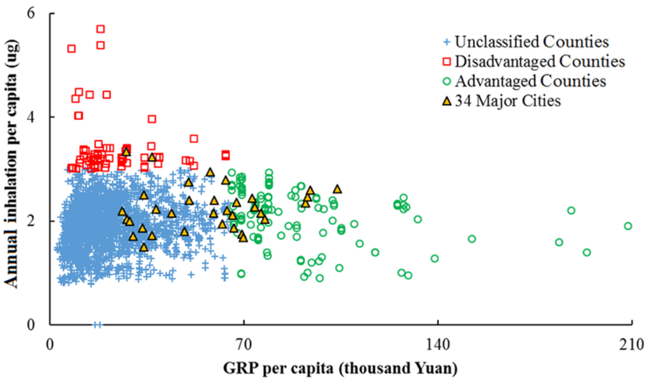

Figure 2. Bivariate scatter plot of pollution inhalation and income. Green circles represent advantaged counties (130 counties; total population >86 million people). Red squares represent disadvantaged counties (70 counties; total population >45 million people). Brown triangles represent 34 major cities in the case study (total population >256 million people). Blue pluses represent unclassified counties (2672 counties; total population >1.2 billion people). "Advantaged", "disadvantaged", and "unclassified" are defined in the text.

RESULTS AND DISCUSSION

Income and Inhalation Disparity Analysis. We evaluate conditions for 34 specific cities where EVs are likely to operate. In each case, we compare within-urban emissions and inhalations attributable to urban CV use, versus total emissions and inhalation (disaggregated by county) attributable to urban EV use. In both cases (EVs and CVs), we consider the income of each county where the inhalation occurs.

Figure 3 presents, for all n = 2,872 counties, inhalation and income distributions attributable to EV used in 12 representative cities. (Results for all 34 major cities are in SI Figure S1.) In these figures, each county is represented by a dot and the city where the EVs are operated is located at the intersection of the red lines. In high-income cities such as Beijing, Dalian, Shanghai, and Guangzhou, a large portion of primary $PM_{2.5}$ emissions are inhaled by populations (bottom/left) who have lower income compared to the populations in these cities. In contrast, lower-income cities (e.g., Chongqing, Shijiazhuang, and Harbin) have a substantially higher inhalation compared to some higher income counties. SI Table S1 reports the detailed proportion of inhalation of primary $PM_{2.5}$ emissions from EV use in four groups: lower income with lower inhalation (bottom/left of SI Figure S1 quadrant), lower income with higher inhalation (top/left of the quadrant), higher income with lower inhalation (bottom/right of the quadrant), and higher income with higher inhalation (top/right of the quadrant) compared with the income and inhalation level of the city adopting EVs.

To illustrate, if 10^9 vehicle kilometers are traveled by EVs (e-cars) in Shanghai, Shanghai residents will cumulatively inhale 14.8 g primary $PM_{2.5}$ emissions. Over 85% (i.e., 307 g, or 21× what Shanghai residents inhale) of primary $PM_{2.5}$ emissions from this switch will be inhaled by populations in counties with average income lower than in Shanghai; and ~3% of those emissions are inhaled by populations in the poorest 10th of the China's counties (i.e., in counties whose GRP per capita is in the bottom 10th percentile in China (<8673 RMB [US $1,400])). In contrast, under the same technology scenario (10^9 vehicle kilometers traveled by EVs) in Chongqing, the residents in Chongqing will cumulatively inhale 59.5 g of primary $PM_{2.5}$ emissions, which accounts for 27% of total inhalation (221 g). Counties that are poorer than Chongqing inhale 55% of total inhalation. The reason why the cumulative inhalation of primary $PM_{2.5}$ for residents in Chongqing is larger than other cities may be that the residents in Chongqing are close to coal power plants in the Chongqing power grid.

By averaging the results among 34 cities (using population-weighting), if EVs are used in urban areas, ~ 75% (range: 41–92%) of the total inhalation of the attributable coal power plant $PM_{2.5}$ emissions will occur in counties in China with lower income and lower inhalation level than the cities where EVs are used (Group A; bottom/left of scatter plots in Figure 3). On average, about ~3% (range: 0–14%) of the total inhalation of coal power plant emissions will occur in counties with lower income but higher inhalation level compared with cities where the EVs are used (Group B; top/left). More than ~77% of the total emissions from EV use are inhaled by residents of counties with lower average incomes (Groups A plus B) than the cities where the EV is operated; that aspect reflects potential EJ issues associated with electricity consumption. The remaining ~23% of inhalation will be in higher income counties and most have lower pollution inhalation compared with urban communities using EVs (Group C: bottom/right). On average, ~5% (range: 3–11%) of emissions from coal power plants are inhaled by the population from the poorest 10% of the China's counties. These analyses contrast the case of CVs, for which almost all tailpipe emissions are inhaled in the city where the CVs are used. These results demonstrate important EJ impacts associated with EVs in China. Results here, although developed to investigate EVs, would generally apply to nearly all urban use of electricity-demanding technologies.

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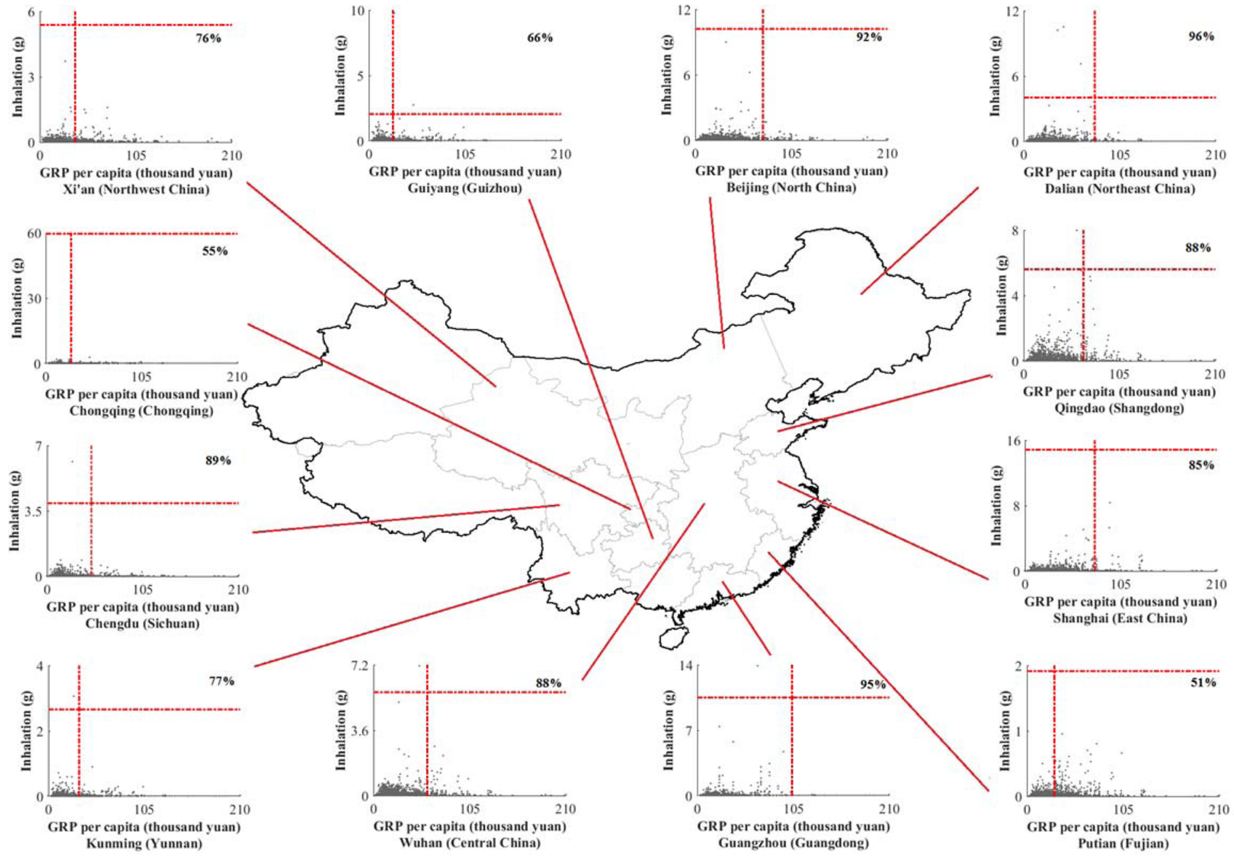

Figure 3. Inhalation of primary $PM_{2.5}$ emissions attributable to urban EV use, showing results for one city in each of the 16 regional electricity grids. Each scatterplot represents, for one urban area, the by-county inhalation of emissions attributable to EV use in that city. The red dash lines in each scatter-plot divide counties into four groups—lower-income with lower-inhalation (bottom/left), lower-income with higher-inhalation (top/left), higher-income with lower-inhalation (bottom/right), and higher-income with higher-inhalation (top/right). (The terms "lower" and "higher" refer to conditions in the county, relative to the city; for example, "lower-inhalation" means that a county's $PM_{2.5}$ inhalation attributable to urban EV use is lower than the $PM_{2.5}$ inhalation in the city attributable to urban CV use.) Note that *y*-axis scales vary among scatterplots. The cross point of dash lines represents urban use of EVs for that electricity grid. The percentage value given on each of the scatterplots shows the percentage of primary $PM_{2.5}$ emissions will be inhaled by populations who have lower income than residents in the urban area where EVs are used (range among cities shown here: 41−96%, population-weighted mean: 77%). In general, on average, urban use of EVs rather than CVs shifts inhalation of emissions to locations where income is lower than in the urban area.

Discriminant Analysis. Since per capita income and pollution inhalation are the key outcome measures we use here to study EJ, we segment counties by those two variables as shown in Figure 2. Most counties cluster on the lower left corner (lower income, lower inhalation), almost none on upper right corner (higher income, higher inhalation). Here, we focus on "Advantaged" and "Disadvantaged" counties in the income and inhalation distribution.

Figure 4 presents the distributions of EJ-related variables that distinguish the advantaged and disadvantaged counties. In each subfigure, the curves represent the smoothed density of the distribution. Statistical significance (two-sample *t* test) is represented in the subplots of Figure 4 and SI Table S2. In general, those results support the hypothesis that socio-economic differences between the disadvantaged and advantaged counties are tied to social fairness indicators. For example, the disadvantaged counties have a comparatively larger percentage of the population employed in the agricultural industry (also called "1st industry"), larger proportion of households with no tap water, lower average education level, fewer migrants from other counties, and higher death rate. In contrast, the advantaged counties on average have comparatively a larger percentage of the population employed in manufacturing ("2nd industry") and service ("3rd industry"), more migrants from other provinces, higher average education level, and lower death rate. Based on 2008 data (the most recent reported data)[41] for China overall, 40%, 27%, and 33% of the population work in agricultural, manufacturing, and service industry, respectively. The national average annual wage is 12 958 RMB [US$1,946] (range: unknown) for agriculture, 29 832 RMB [US$4,479] (range: US$3,232−US$5,886) for manufacturing, and 34 335 RMB [US$5,155] (range: US $2,925−US$9,285) for service. Counties with more agricultural industry are usually in rural areas with much lower wages. Results here illustrate that residents in those counties, not-likely EV adopters in the short term, bear a disproportionate level of primary $PM_{2.5}$ inhalation and health impacts if EVs are used in higher-income (e.g., urban) regions.

Overall, urban electricity use for EVs displaces emissions from the point of use (tailpipes for CVs) to the point of electricity generation (for EVs: typically, distant fossil power plants). Exposed populations (typically: rural, lower income), tend to inhale more of that pollution than urban energy users. In general, nearly all urban electricity consumption suffers from this same EJ challenge; this aspect is not unique to EVs. EVs are an interesting case because EV technology transfers formerly

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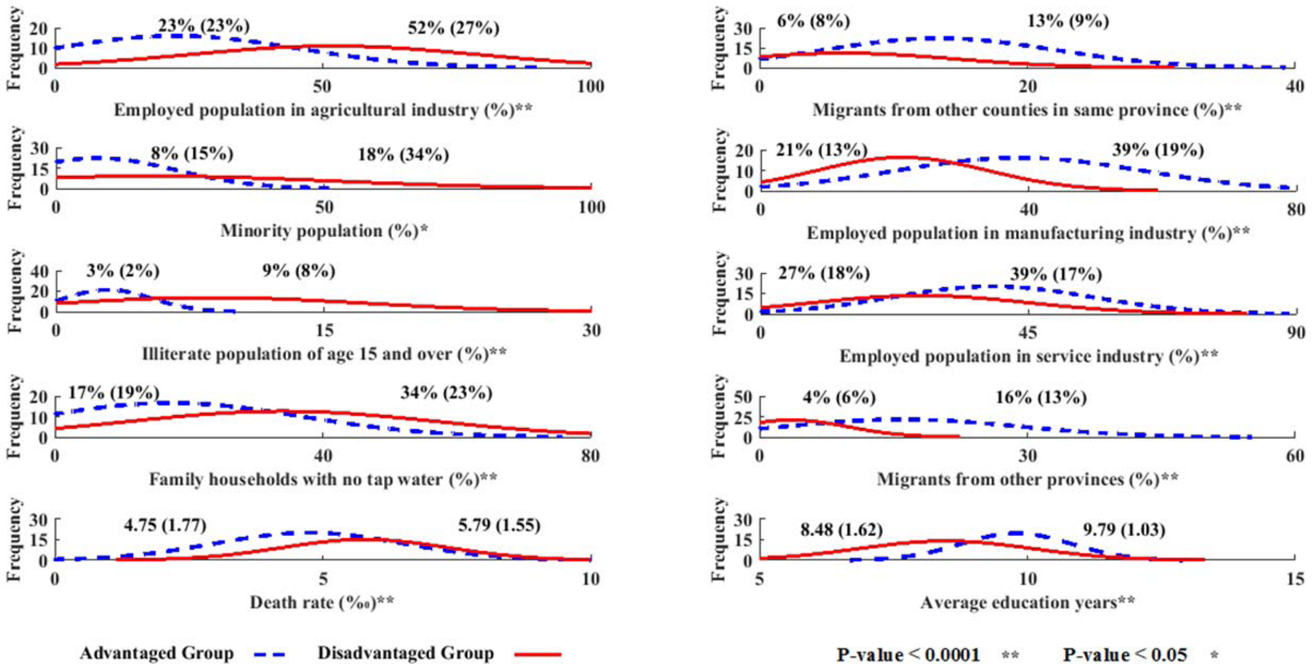

Figure 4. Distributions of key demographic variables that distinguish advantaged and disadvantaged counties. Values show means (standard deviations). Values for the following demographic attributes are higher for the advantaged counties than for the disadvantaged counties: percentage of employed population in manufacturing industry, percentage of employed population in service industry, percentage of migrants from other counties in same province, percentage of migrants from other province, and average education years. Values for the following demographic attributes show the opposite pattern (higher for the disadvantaged counties than for the advantaged counties): percentage of employed population in agricultural industry, percentage of family households with no tap water, percentage of minority population, percentage of illiterate population of age 15 and over, and death rate. See text for definitions of "advantaged" and "disadvantaged".

local CV (tailpipe) emissions, to more rural areas. However, EV adoption could have strong net benefits over CVs, including improved urban air quality in cities with acute air quality challenges. This paper's results should focus attention on the importance of emission-reductions for electricity generation. EVs coupled with more renewable power generation could yield increased energy efficiency, improved air quality, reduced GHG emission, and improved EJ. EVs are again unique because the on-road fleet environmental performance can improve over time if power generation emissions are reduced. However, replacing CVs with EVs in China raises potential EJ concerns. If this shift takes place, most emissions will be distributed and inhaled in communities outside the city where EVs are used, which generally are in poorer counties. Most (~77% on average) primary $PM_{2.5}$ emissions from coal power plants will be inhaled by communities that have lower income than the city where EVs are used. Of the total increase in $PM_{2.5}$-inhalation caused by a shift to EVs in China, the poorest counties (the bottom 10th percentile counties representing 7.4% of the population) will inhale 8.7% while the richest counties (the top 10th percentile counties representing 12.5% of the population) will inhale 10.5%. Thus, we estimate that the average increase in exposure burden from EVs in China would be 40% greater for the poorest counties than for the richest counties. Low-income rural communities likely will not directly benefit from urban EV use. EVs, like with other examples of increased urban electricity consumption or rural electricity production, could represent new exposures for nonurban poor counties. The disadvantaged counties are primarily located in less development areas in China—areas that are primary agricultural. A policy implication of our research is the need to consider ways to avoid or remedy impacts to these lower-income communities; future policy relevant to EVs (and to urban electricity consumption in general) should aim to investigate and tackle this EJ challenge head on.

There are many benefits of EVs not described in this paper (e.g., noise pollution). A main benefit of widespread EV adoption is that parallel future improvements in power generation can have immediate impacts across the transportation sector—something impossible with a large fleet of aging CVs. This provides the government with more regulatory and economic control over transportation emissions that could result in reductions in total pollution and greenhouse gas emissions. As of 2014, China emerged as one of the world's largest producers and users of renewable energy.[54] From 2010 to 2014, the percentage of total electricity generated by nonfossil sources increased from 17% to 20% for wind and hydro power[55] and from 1.8% to 2.4% for nuclear power.[55] These increases in renewables and nuclear power can positively impact $PM_{2.5}$-related EJ in China. To illustrate, we use Beijing as a case study to investigate the EJ impacts of three renewable energy scenarios; in each case, 10% of electricity generation (69 TWh) is replaced with nonemitting sources, and we consider the same case as above (10^9 vehicle-kilometers traveled by CVs were substituted by EVs):

- Scenario I, replace the dirtiest 10th percentile of electricity generation with nonemitting sources.
- Scenario II, replace lowest capacity (i.e., smallest) 10th percentile electricity generation with nonemitting sources.
- Scenario III, replace 10th percentile electricity generation that is nearest to Beijing with nonemitting sources.

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The results (Table 1) show that more renewable energy on Northern China power grid does lead to lower overall inhalation and better EJ performance for electricity generation. All three strategies result in similar EJ outcomes, though the data reflects many small and high-polluting power plants make up the bulk of the top 10th percentile dirtiest generation. Scenarios I and II turn out to be similar, because small-capacity coal plants tend to be comparatively dirty plants. Scenarios I and II yield a ~10% drop in the proportion of inhalation occurring in lower-income counties, a 19−22% drop in total emissions, and 20−24% drop in total inhalation (and potentially in subsequent health effects). Scenario III reduces the proportion of inhalation by lower-income counties by 8%, corresponding to an 8% reduction in total emissions and 11% reduction in inhalation, but also results in replacement of comparatively larger and cleaner power plants, which is a suboptimal outcome. For the case considered, replacing the dirtiest (which are often the smallest) plants first would result in the greatest EJ and total health outcomes. For all cases, such improvements would improve EJ of emissions from EVs, but would also lead to dramatic improvements for total electricity generation from urban consumption.

Table 1. Impact of Renewable Energy on EJ Aspect in Beijing

	current	scenario: I - dirtiest	II - smallest	III - closest
number of coal power plants in Northern China grid	438	177	126	404
electricity generation from coal power plants (TWh)	693	624	624	624
$PM_{2.5}$ emissions (metric ton)	38.0	29.6	30.8	34.9
$PM_{2.5}$ inhalations (g)	374	284	298	334
proportion of inhalation in four groups (%)[a]	(8; 0; 92; 0)	(18; 0; 82; 0)	(18; 0; 82; 0)	(13; 4; 80; 3)
proportion of inhalation in lower-income counties (%)	92	82	82	84

[a]The order of four groups is (higher income with lower inhalation; higher income with higher inhalation; lower income with lower inhalation, lower income with higher inhalation).

Key limitations of this study include the following. The most recent Census data available in the needed format are more than 4 years old. Intake fractions and emissions may change over time.[56] GDP per capita in China rose more than 60% from 2010 to 2014 (from ~30 000 RMB [$4,700] to ~46 500 RMB [$7,600]), which emphasizes the potential importance of continually monitoring and updating this analysis. Average annual income growth rates are 11% and 14% in urban and rural area, respectively.[41] These changes should cause the counties in Figure 3 to shift toward the right. Dots representing urban counties would shift slower than those representing rural counties. At the same time, urbanization in China increased from 50% urban population in 2010 to 55% urban population in 2014.[41] This urbanization has caused emission inhalation increases in urban areas and reduced the lower-income inhalation rates. This change should cause the dots representing urban counties to shift upward and the dots representing rural counties shift downward in Figure 3. Furthermore, unregistered migrants who work in urban area with rural *hukou* (thus counted as rural population in the census) might cause inaccuracies in the EJ analysis. On one hand, the potential increases in uncounted urban population could increase urban inhalation rates. This change should cause the dots representing urban counties shift upward in Figure 3. On the other hand, the unregistered migrants may cause reduction in estimated GRP per capita, because unregistered migrants contribute to urban GRP, but this GRP was divided by smaller registered populations (not including unregistered migrants). This change should cause the dots representing urban counties move toward the left in Figure 3. As a robustness check, we applied the same methods above to an earlier data set (2000 census data[57] and 2006 emissions data[58−60]). The results were similar (details in SI Tables S3 and S4), suggests that societal changes during a ~decade time-scale some of which were sizable (e.g., GDP per capita was 74% lower in 2000 than 2010, urbanization rate was 36% lower in 2000 than 2010) have not dramatically altered the broad findings given here.

The methods employed here rely on coarse spatial data inputs (counties and large buffers surrounding fossil power plants). The regression approach developed by Zhou et al.[45] used dispersion models to estimate regression relationships between air pollution concentrations and geographic and population parameters. They found that the regression approach was robust to different geographies within China (e.g., interior and coast), the results are generalizable across fossil power plants in China (especially for PM), and the results are most suited for policy analysis and support (e.g., as is presented here). Our main assumptions include uniform within-zone pollution and population concentrations. If better air dispersion modeling were available connecting emissions to inhalation for each fossil power plant, we could revise our approach. Each fossil power plant has different pollution technology and pollution dispersion characteristics across nonuniform populations; our study does not include those important sources of variability. As a result, our study is limited to informing electric utility policy, not making recommendations for specific fossil power plant pollution controls. We consider here only coal power plants and only primary $PM_{2.5}$. Consideration of additional fuels and pollutants (including secondary $PM_{2.5}$) is important for future research. Another limitation of this research is that within-urban EJ concerns are not considered;[17,61] investigating that issue would require a different air dispersion modeling approach to the one employed here.

Despite those limitations and the many changes in the past 4 years, the general findings of this study will likely hold as long as growth in income and consumption in urban areas outpace rural growth. Electric vehicles continue to be promising technologies for sustainable transportation, particularly if the power sector increases the use of non- and lower-emitting sources of electricity. Future increased reliance on electricity generation for the transportation sector calls to mind the need to address the increased health burden on the rural poor who are not likely early beneficiaries of EVs. This paper highlights an important step toward understanding a sustainable transportation energy policy that includes EJ and fairness as key values. As noted above, our general findings are not unique to EVs, but are common to nearly all electricity-demanding technologies consumed predominantly in urban areas.

■ ASSOCIATED CONTENT

Supporting Information

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Inhalation of primary $PM_{2.5}$ emissions from EV shift in 34 major cities (Figure S1 and Table S1) and outcomes of two sample t tests for equal means of selected census variables (Table S2). We also include main indicators from this method applied on earlier-year data (2000 census data and 2006 emissions data) in Table S3 and Table S4 (PDF)

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Notes

The authors declare no competing financial interest.

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