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Electric Vehicles in China: Emissions and Health Impacts

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Supporting Information

ABSTRACT: E-bikes in China are the single largest adoption of alternative fuel vehicles in history, with more than 100 million e-bikes purchased in the past decade and vehicle ownership about 2× larger for e-bikes as for conventional cars; e-car sales, too, are rapidly growing. We compare emissions (CO_2, $PM_{2.5}$, NO_X, HC) and environmental health impacts (primary $PM_{2.5}$) from the use of conventional vehicles (CVs) and electric vehicles (EVs) in 34 major cities in China. CO_2 emissions (g km^{-1}) vary and are an order of magnitude greater for e-cars (135−274) and CVs (150−180) than for e-bikes (14−27). $PM_{2.5}$ emission factors generally are lower for CVs (gasoline or diesel) than comparable EVs. However, intake fraction is often greater for CVs than for EVs because combustion emissions are generally closer to population centers for CVs (tailpipe emissions) than for EVs (power plant emissions). For most cities, the net result is that primary $PM_{2.5}$ environmental health impacts per passenger-km are greater for e-cars than for gasoline cars (3.6× on average), lower than for diesel cars (2.5× on average), and equal to diesel buses. In contrast, e-bikes yield lower environmental health impacts per passenger-km than the three CVs investigated: gasoline cars (2×), diesel cars (10×), and diesel buses (5×). Our findings highlight the importance of considering exposures, and especially the proximity of emissions to people, when evaluating environmental health impacts for EVs.

INTRODUCTION

China's rapid growth in income − annual GDP increases averaged 9−10% during 1978−2009[1] − has many impacts, including several with environmental health consequences. Outdoor air pollution causes ∼300,000 premature deaths in China each year.[2] For several pollutants, including fine particles ($PM_{2.5}$), transportation is a significant and growing source of emissions.[3] Automobile ownership increased more than an order of magnitude in one decade, from 3 cars per 1000 people in 1998 to at least 39 cars per 1000 people in 2009.[1,4] Encouraging motorized transportation is a national strategy for economic and social development in China.[5,6]

This article's focus on electric vehicles (EVs: electric cars [e-cars] and electric two-wheelers including electric bicycles and light electric scooters [e-bikes]) in China is motivated in part by their unprecedented rise in popularity (Figure 1). While conventional vehicle (CV) ownership and electricity consumption in China are both increasing rapidly − annual growth rates during the past decade were ∼25% and ∼10%, respectively − e-bike ownership is skyrocketing: 86% annual growth during the past decade (doubling time: ∼13 months). Ten years ago, e-bikes were nearly unheard of, with vehicle ownership rates 26× lower for e-bikes than for CVs. Today, e-bikes outnumber CVs 2:1. E-bikes in China are the single largest adoption of alternative fuel vehicles in history, with over 100 million vehicles purchased in the past decade, more than all other countries combined.[7,8]

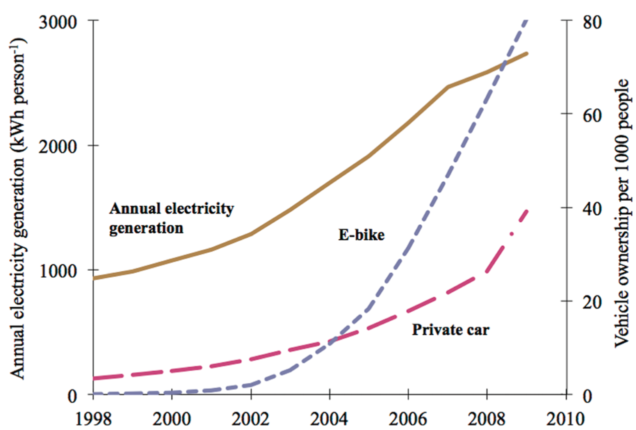

Figure 1. Motorization and electricity use in China normalized to population. During the past decade, e-bike ownership has grown from near-zero to ∼2× greater than CVs.

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For EVs, combustion emissions occur where electricity is generated rather than where the vehicle is used.[9−11] In China, 85% of electricity production is from fossil fuels, of which ~90% is from coal. Most electricity generating units (EGUs) in China lack advanced pollution controls. Compared to typical vehicle emissions, EGUs are often located further from population centers; therefore, the exposure and health impacts per mass emitted tend to be lower for EGUs than for CVs.[12−15] The net result for China is that it is unclear a priori whether EVs are an environmental health benefit or disbenefit relative to CVs.

Prior research on environmental impacts of EVs in China[9,16] and elsewhere[17−21] generally compares emission factors or greenhouse gas emissions,[22−25] not exposures, intakes, or health effects. Our article works to address this important knowledge gap. We evaluate five vehicle types (gasoline and diesel cars, diesel buses, e-bikes, e-cars) and consider how environmental impacts (emissions, intakes, mortality risks) vary depending on the emission location. Our approach considers China's 34 largest cities and uses an intake-, rather than concentration-, based risk assessment for primary $PM_{2.5}$. Our results underscore differences among EVs (e-cars and e-bikes) and the importance of fuel type (here, mostly coal) when evaluating CO_2 and primary $PM_{2.5}$ health impacts of EVs and variability in EV impacts among locations (34 cities, 15 regional electricity grids).

METHODS

Our investigation follows a conventional risk assessment framework but is based on pollutant intake (mass inhaled) rather than concentration. Methods are summarized next, with details provided in the Supporting Information. Key steps are in Figure 2. We present emissions for several pollutants but focus

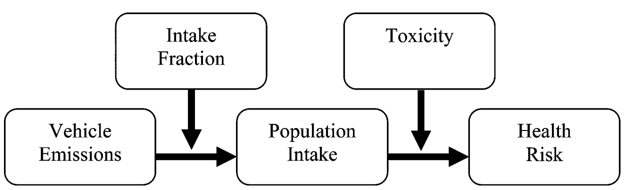

Figure 2. Summary of intake-based health risk assessment employed here.

on health effects of primary $PM_{2.5}$ because of the strong epidemiological evidence for that pollutant, because prior research suggests that $PM_{2.5}$ often dominates total air pollution health and economic impacts per mass emitted,[26] because primary $PM_{2.5}$ is relatively nonreactive, thereby simplifying the requirements for fate and transport modeling, and because peer-reviewed literature provides the information needed for analyses here. Secondary $PM_{2.5}$, also with important health effects, is explored briefly in the Results but is not a focus of this paper. Our health risk assessment only includes combustion emissions, though we discuss the relative magnitude of fuel life cycle emissions in the Results and Supporting Information. Our investigation considers five vehicle technologies and 34 vehicle-use locations covering all of China's urbanized provinces. We estimate exposure from emissions generated at more than 1000 fossil EGUs. Our primary results employ point estimates for input parameters. We then conduct a Monte Carlo simulation to identify the sensitivity of our results to variability and uncertainty. In the discussion, we illustrate an example of the policy significance of our research by considering a deployment scenario for one city (Shanghai). We explore distributional aspects in terms of urban/rural differences in exposures and health impacts attributable to urban use of EVs.

Emissions. In this study, we focus on station-to-wheel emissions and their health impacts. We also present well-to-station emission (coal mining and processing for EVs; oil extraction and refining for CVs). Here, a station is a fueling station (CV) or an EGU (EV). We do not estimate health impacts from well-to-station emissions since location and population information are unavailable for those activities.

For CVs, combustion emission factors are taken from the literature and emission standards.[16,27−31] For EVs, EGU emission factors are estimated based on electricity generation rates[32] and modeled total EGU emissions.[33] Power-sector EGU emission factors vary by an order of magnitude among regional electricity grids in China (Figures S1 and S2; Table S4),[34] owing to differences in fuels (fossil versus renewable), fuel quality, combustion conditions, and emission controls. On average, EGU emission factors are higher in the Northeast and lower in the South. Our EV emission factors incorporate loss rates from electricity transmission and distribution.[4] Average well-to-station emissions are taken from the literature for CVs and EVs.[35−37]

Intake fraction. Intake fraction (iF) is the proportion of an emitted pollutant inhaled by the population:[12]

$$\mathrm{iF} = \frac{\text{Total intake}}{\text{Total emissions}} \tag{1}$$

We use a dynamic one-compartment model to estimate iF of emissions in urban areas. The one-compartment model estimates concentrations based on a mass-balance, assuming that the air is well mixed within the urban area and is vertically mixed up to the atmospheric mixing height. Prior research for urban areas in the US[13] and Mexico[38] suggests that the one-compartment model yields similar results as more detailed models. Main input variables for the one-compartment model are urban population and land area, average breathing rate, atmospheric mixing height, and average wind speed over the mixing height. Population and land-area data for urban areas are from the Chinese Bureau of Statistics.[1] Meteorological data (wind speed, mixing height; years 2005−2007) are from NASA's Global Modeling and Assimilation Office (http://disc.sci.gsfc.nasa.gov/daac-bin/DataHoldings.pl). The meteorological data set provides hourly estimates at 0.5°−0.667° spatial resolution; our one-compartment model simulates three years of air dispersion, using 0.1-min time steps. To avoid discontinuities in modeled meteorological data, we linearly interpolated the hourly raw data to 0.1-min increments. A merit of the dynamic one-compartment model is fine-scale temporal resolution; a weakness is lack of information about within-urban spatial variability. The one-compartment model is a screening approach and typically more reliable for relative comparisons (e.g., as applied here, for multiple technologies and locations) rather than for absolute values. As a result, our findings should be considered suggestive rather than definitive.

For EGU iFs, we employ the regression approach of Zhou et al.[39] This model was developed specifically for iF of EGU emissions in China. Intake fraction is estimated based on the population within specific radii of EGUs. We apply the regression models on all known EGUs (~1000 EGUs) in China.[32]

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Dose−Response (Toxicity). We employ a mortality dose−response function based on the American Cancer Society (ACS) cohort.[40] We convert the published concentration-based toxicity (average 4% increase in mortality per 10 $\mu g\ m^{-3}$) into an intake-based toxicity (5.3 deaths per kilogram inhaled), by assuming a population-average breathing rate[41] of 14.5 $m^3\ d^{-1}$ $person^{-1}$ and Chinese baseline annual mortality of 7 deaths per 1,000 persons.[42] Details are in the Supporting Information. Our approach applies the ACS finding that $PM_{2.5}$ exhibits, at the population level, a linear no-threshold dose response.

RESULTS

Emissions. Emission factors (Figure 3 and S2; Tables S3 and S4) vary by vehicle, fuel, and region. We not only focus on station-to-wheel emission factors but also report average well-to-station emissions in the Supporting Information. Figure 3 compares emission between vehicle types.

The order-of-magnitude variability in EGU emission factors by region (Figures S1 and S2) yields the same degree of variability in EV emission factors and with the same spatial pattern (highest in the Northeast because of heavy reliance on coal). EV emission factors vary by the city they are in (Table S4); we estimate that an e-car (180 Wh km^{-1})[43] in Beijing emits 220 $gCO_2\ km^{-1}$, equivalent to a gasoline car with a fuel economy of 9 L $(100\text{-km})^{-1}$ (or 26 mi gal^{-1} [mpg]), whereas in Chengdu the same e-car would emit only 135 $gCO_2\ km^{-1}$, equivalent to a gasoline car with a fuel economy of 5.6 L $(100\text{-km})^{-1}$ (or 42 mpg).

Compared to a new (Euro IV) gasoline car, average e-car emission factors are about the same for CO_2 and 19× greater for $PM_{2.5}$. That finding reflects, in part, China's heavy reliance on coal. E-bikes outperform cars, motorcycles, and buses on most emission metrics. That finding reflects, in part, the lighter weight and therefore lower energy requirements for e-bikes as for other passenger vehicles. Well-to-station emissions represent a larger proportion of total emissions for CVs relative to EVs for many pollutants.

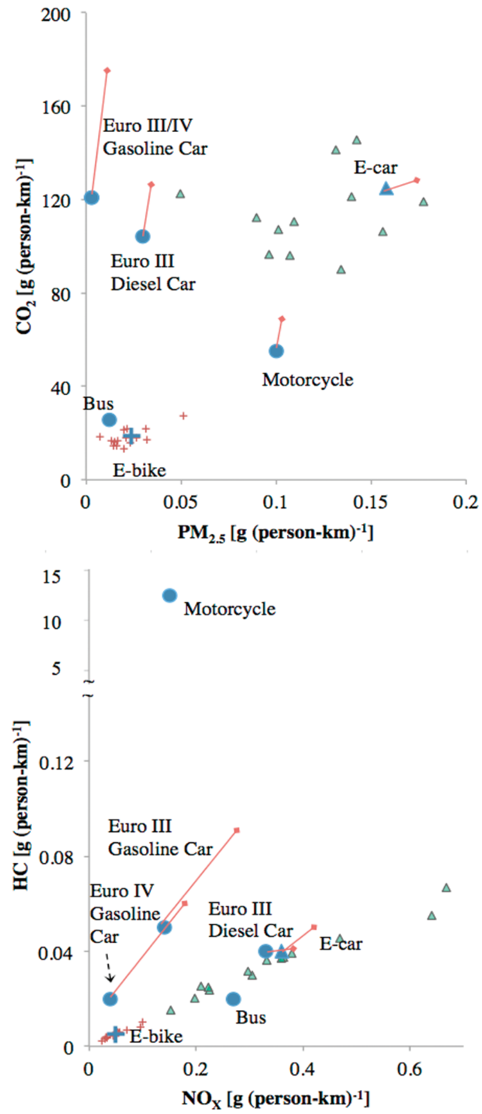

Figure 3. Emission factors for EVs and CVs (g person-km^{-1}), for four pollutants. Large circle icons indicate CVs. Small noncircle icons indicate EVs (e-car: triangle-icon; e-bike: plus-icon), with emission factors that vary among the 15 electricity grids. Large noncircle icons indicate the arithmetic mean of the 15 values per EV. Lines from icons indicate magnitude of well-to-station emissions; diamond end points of lines indicate well-to-wheel emission factors. (Missing lines indicate indistinguishable impacts.) Assumed average passenger load factors are car: 1.5, bus: 50, motorcycle: 1, e-bike: 1.

Intake Fraction. Estimated iFs for $PM_{2.5}$ (Figure 4) are 6−117 per million for urban emissions (CVs) and 4−8 per million for EGU emissions (EVs). For $PM_{2.5}$, urban iF values range from less than the EGU iF to more than an order of magnitude greater than the EGU iF, with a population-weighted mean difference of 5× (for unweighted median: 2.4×) greater iF for urban emissions than EGUs. (For comparison, the mean urban-rural iF difference in the US is about an order of magnitude,[44,45] which is consistent with the proportion of the population that is rural being greater in China than in the US.) For $PM_{2.5}$, spatial variability is greater for urban iFs (maximum:minimum ratio, 19:1) than for regionally aggregated EGU iFs (maximum:minimum ratio, 2:1).

Health Impacts. Table 1 provides example calculation and results of health impacts from station-to-wheel primary $PM_{2.5}$ emissions, based on parameter point estimates, for one city (Shanghai). In this example, emissions are greater for e-cars than gasoline cars, but the reverse holds for iF values; the net result for Shanghai is a higher $PM_{2.5}$ environmental health impact for e-cars than for gasoline cars. Here and below, comparisons employ a basis of 10^{10} km y^{-1} (e.g., 10^6 vehicles, each traveling 10^4 km y^{-1}) and employ units of ppm (parts per million) for iF.

Results for all cities are in Figure 5. The bus/e-bike plot (Figure 5f) may provide a useful counterfactual for individuals who do not own a car; for all cities considered, e-bikes yield lower impacts than buses. The car/e-car plots (Figure 5a,b) may provide a useful counterfactual for car owners.

In general, based on Figure 5, e-cars typically perform better than diesel cars, worse than gasoline cars, and comparably to diesel buses; e-bikes perform much better than diesel cars and buses but are comparable to or slightly better than gasoline cars. Available surveys indicate that many e-bike users would switch to bus (50−65%) or car-based modes (20−25%) if the e-bike became unavailable.[46]

A useful aspect of Figure 5 is investigation of the variability among cities and therefore of the robustness of the comparisons to spatial differences. In some cases (Figure 5e,f), comparisons yield the same results for all cities. In other cases, variability among cities is large: in Figure 5c,d, the cities are

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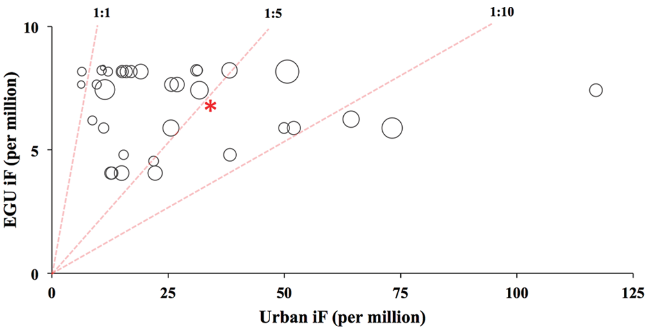

Figure 4. Intake fraction for primary $PM_{2.5}$ in the 34 urban areas considered here. The area of each icon is proportional to population. The population-weighted average value is indicated with an asterisk. For reference, dashed lines show constant urban/EGU iF ratios.

Table 1. Example Calculation: Health Effects of $PM_{2.5}$ in Shanghai[a]

	gasoline car	diesel car	bus	e-car	e-bike
emission factor (mg [person-km]$^{-1}$)	3	30	12	58	9
kilometers traveled (km y^{-1})	10^{10}	10^{10}	10^{10}	10^{10}	10^{10}
intake fraction (ppm)	51	51	51	8.2	8.2
unit dose (g death^{-1})	188	188	188	188	188
total excess deaths per year	9	90	32	26	3
	(8, 10)	(70, 111)	(15, 67)	(11, 38)	(2, 5)

[a]Load factors are listed in the caption for Figure 3. The values in parentheses are the 5th and 95th percentiles of Monte Carlo simulation results.

split roughly evenly (60/40) as to which vehicle-type has lower public health impacts. Figure 5 compares total health impacts but without consideration for *who* is exposed (see urban-rural comparison in the Discussion).

Sensitivity Analysis. In the previous sections, analyses employed point estimates for input variables. Here we develop a Monte Carlo simulation to explore variability and uncertainty in input variables (Table S2) and their propagation through our analyses to a range of outcomes (Figure S3). The shapes of the regions in Figure S3 are similar to Figure 5, though the range is larger. The proportion "P" (for which EVs have lower mortality risk than CVs) is similar (on average, higher) in the sensitivity analysis (Figure S3) than in Figure 5. Figure S3 simulates each city individually. A similar analysis (Figure S4) simulating the population-weighted average (the asterisk in Figure 5) reveals similar results but with less variance because of averaging; in that analysis, impacts for e-cars are always higher than for gasoline cars and lower than for diesel cars.

Secondary $PM_{2.5}$. Results above investigate primary $PM_{2.5}$ (i.e., emissions). As a sensitivity analysis, we also explored two types of secondary $PM_{2.5}$: ammonium nitrate (from NO_x emissions) and ammonium sulfate (from SO_2 emissions). Formation rates depend on emissions from CVs or EVs, plus environmental conditions such as temperature and extant ambient concentrations. For both types of secondary $PM_{2.5}$, we employ two approaches. First, we apply the Zhou et al.[39] model to emissions from EVs and CVs. A main limitation of this approach is that it applies an EGU model to ground-level (vehicle) emissions. Second, we used recently published global-average iF values for archetypal urban, rural, and remote environments;[47] a main limitation is the use of global-average, rather than China-specific, values. Results (not shown), though preliminary, suggest that for some locations and mode comparisons, secondary $PM_{2.5}$ may be equally or more important than primary $PM_{2.5}$ for estimating environmental health impacts. We conclude that, while this article focuses on primary PM, robust exploration of secondary PM is warranted.

DISCUSSION

Electric vehicles are often proposed as a "sustainable" approach for increasing urban mobility and economic development.

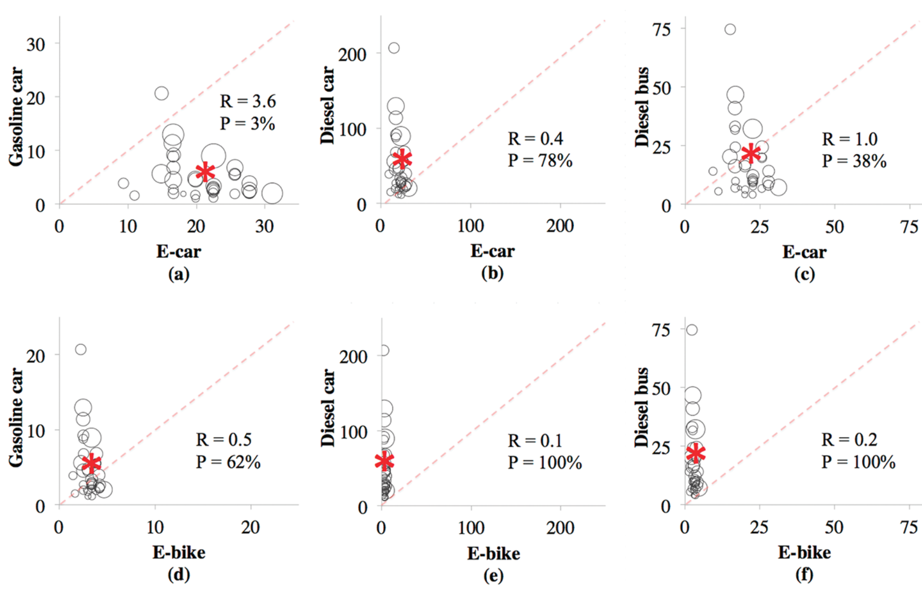

Figure 5. $PM_{2.5}$ mortality risk per 10^{10} passenger-km, for the 34 cities considered. Icon size is proportional to city population. In each plot, "R" is the population-weighted average ratio between x- and y-axes, "P" is the proportion of the population (among the 34 cities) for which the mortality risk is lower for EVs than for CVs. For reference, dashed lines are 1:1 lines. The population-weighted average value is indicated with an asterisk. Passenger load factors are listed in the caption for Figure 3.

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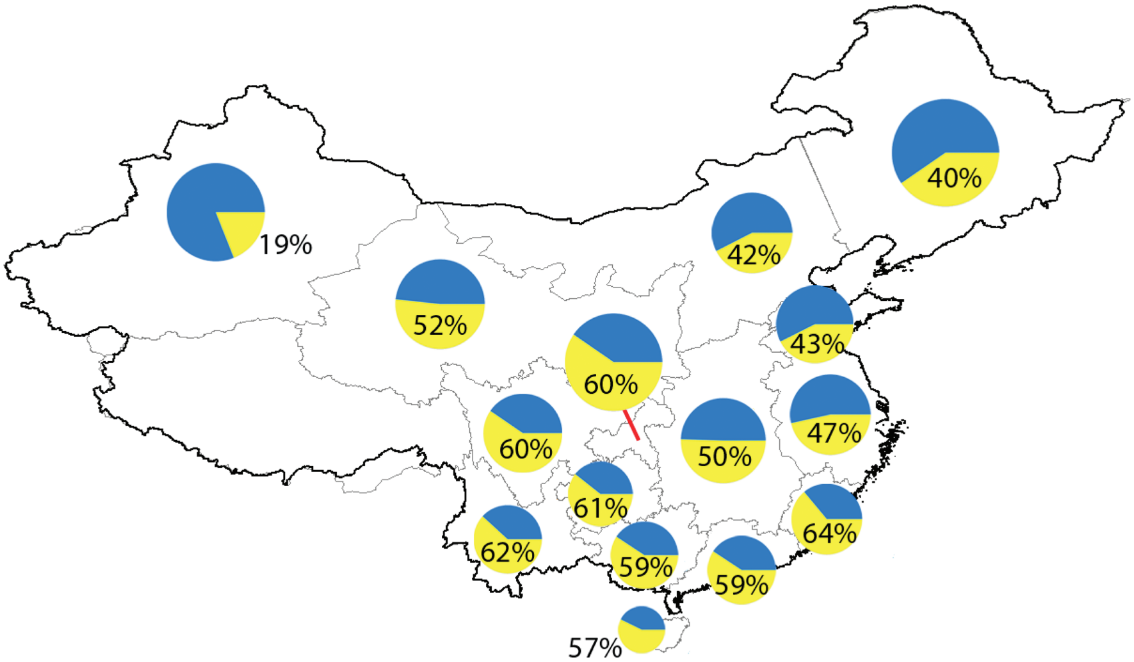

Figure 6. Portion of primary $PM_{2.5}$ health impacts from EGUs experienced by rural versus urban populations. Icon area is proportional to $PM_{2.5}$ emission factor (g km^{-1}) for an EV in that power grid. Numbers identify nonurban mortality impact proportions, i.e., of the total mortality impacts attributable to primary $PM_{2.5}$ from electricity generation − here, owing to urban use of EVs. Urban use of EVs rather than CVs typically moves the emissions (and, exposures and health impacts) to more rural locations. In general, a substantial proportion − on average, about half − of the emissions from urban use of EVs are inhaled by nonurban populations.

An implicit assumption is that air quality and health impacts are lower for EVs than for CVs. Our research aims to test that assumption for primary $PM_{2.5}$.

In several cases, our findings (Figure 5) exhibit strong spatial variability among locations. We find that using emission factors rather than intakes to compare vehicle-types is suboptimal for health comparisons: because electricity generation typically occurs farther from people than do tailpipe emissions, iF values are often lower for EVs than for CVs. For example, comparing $PM_{2.5}$ averages per passenger-km, emissions are 5× higher for an e-car than for a bus, but health impacts from primary $PM_{2.5}$ are about equal between the two modes. Comparing averages for e-bikes and buses, based on $PM_{2.5}$ emissions the two modes are similar (30% higher for buses) but based on $PM_{2.5}$ mortality rates, impacts are 7× greater for buses as for e-bikes. E-bikes perform well compared to CVs in terms of $PM_{2.5}$ emissions *and* health impacts.

For the first time at such a large scale, vehicle emissions are being transferred to power plants, potentially yielding dramatic exposure reduction. In some but not all cases, this transfer of emissions is expected to improve overall public health. However, this shift also transfers impacts to nonusers of the urban EVs, including potentially to low-income rural populations. Specifically, CV emissions and intakes generally occur within the urban area where the vehicle is used. With CVs, urban residents produce emissions and also bear the impacts (though causing within-urban distributional impacts).[48−50]

To explore the impact of EGUs on urban versus rural populations, we repeated the intake calculations above but distinguishing urban versus rural intakes of EGU primary $PM_{2.5}$ emissions using the population in China's 660 classified cities.[1] We find that, on average, ∼ half (52%) of urban EV emissions are inhaled by nonurban populations. Figure 6 and Figure S5 shows this parameter by electric grid (range: 19−64%). An important context underlying this shift (i.e., that pollution from urban activities is exported to rural locations) is the large and growing income disparity between urban and rural populations: the rural-urban difference in average income per person increased from 2.8× in 2000 (2240 RMB [$336] rural versus 6280 RMB [$941] urban) to 3.3× in 2009 (5200 RMB [$780] versus 17175 RMB [$2573]).[1]

An important aspect of any technology comparison is substitution: how the use of one technology impacts the use of other technologies. China's rapidly evolving motorization trends challenge traditional mode-substitution models. Here we provide an illustrative comparison based on available data; similar scenarios could be developed for other technologies or locations. In 2007, Shanghai had ∼1,000,000 registered e-bikes, each averaging ∼5,000 vehicle-km y^{-1}.[46] Calculations similar to those in Table 1 yield an estimate for air pollution excess mortality of 2 deaths y^{-1} from e-bike use. Surveys indicate that of e-bike users, about 70% are displaced bus riders, 20% are displaced bicycle riders, and 10% are displaced gasoline car drivers.[16,46] For this simple illustration, we assume a 1:1 relationship between mode choice and trip distance, which is close to stated mode/trip distance responses for urban trip-making in Shanghai (i.e., each 100 vehicle-km by an e-bike displaces 70 passenger-km by bus, 20 vehicle-km by bicycle, and 10 passenger-km by gasoline car),[46] and we restrict consideration to sufficiently large shifts that added bus demand would be met with added bus capacity. If e-bikes did not exist (for example if they were banned, as many cities have proposed) and e-bike riders redistributed to stated best alternative modes, the excess mortality would increase from 2 y^{-1} to 12 y^{-1}, most of which is a result of the shift toward the bus. This example highlights that in some cases banning e-bikes could worsen air pollution and environmental health.

Our research has several important limitations. As such, results should be considered suggestive rather than conclusive. We used a simple one-compartment model for urban iF, which provides excellent temporal resolution while capturing important meteorological variables but without incorporating within-urban variability in concentrations or accounting for reactive pollutants. Our iF estimates reflect ambient concentrations only and do not consider microenvironments.[51] Average EGU emission factors were employed here for EV charging; however, EV emissions can be sensitive to temporal (time-of-day; seasonal) charging patterns;[19,52,53] at present, this information is unavailable for China. Our approach implicitly assumes that $PM_{2.5}$ emissions from electricity generation and from CVs tailpipe exhaust are equally toxic. We focus on one pollutant (primary $PM_{2.5}$) and one outcome (mortality) and therefore have quantified only a fraction of total health impacts. Prior analyses considering multiple pollutants and health outcomes indicate that results of the pairing we employed ($PM_{2.5}$; mortality) generally dominates comparative analyses.[26,54]

For the electricity sector in China, future changes in emissions are uncertain. Zhao et al.[55] developed three emission control scenarios for coal power plants to predict future emissions changes: base (no improvement), normal (inefficient EGUs are decommissioned and replaced with efficient EGUs), and strict (aggressive emission abatement). Based on their scenarios, by 2020, total suspended particulate (TSP) emission intesity (g kWh^{-1}) could be reduced by 42% (base), 68% (normal), or 75% (strict) relative to current conditions. SO_2 and NO_X emission rates would also decrease under these scenarios. EV emission factors would follow EGU emission trends, improving over time (accounting for temporal charging patterns[19,52,53]). On-road vehicle emissions usually degrade as a car ages, though new-vehicle emissions will likely improve following adoption of tighter new-vehicle emission standards and cleaner fuels. Transitioning to a new bus fleet may reduce emission factors dramatically. For example, PM emissions from new (Euro III) buses will be 6× lower than on-road buses. Improved CV and EGU emission technology should reduce impacts per vehicle-km for both CVs and EVs; potential increases in total travel distance may also be important.

China provides a useful case study because of the large number of EVs (in 2009, 100 million EVs) and because of government policies aimed at increasing the number of EVs. Unique aspects of China include the large population and coal-heavy electricity system. Our findings show that replacing gasoline cars with e-cars will result in increased CO_2 from combustion emissions and all-cause mortality risk from primary $PM_{2.5}$ in most cities. Health risks attributable to other pollutants, including secondary $PM_{2.5}$, are uncertain. Lightweight EV's such as e-bikes can have environmental and health benefits because of their energy efficiency. Chinese policy makers should carefully proceed with deployment of plug-in vehicles and consider aggressive improvements in the power sector to realize anticipated gains in emissions and health.

Future research could explore whether results presented here hold for other countries and could model impacts of secondary $PM_{2.5}$. We highlight one distributional aspect of CV versus EV emissions (urban-rural exposure differences), leaving for future research a more significant exploration of environmental justice.

■ ASSOCIATED CONTENT

Ⓢ Supporting Information

Methods and data sources supporting the findings of this paper. This material is available free of charge via the Internet at http://pubs.acs.org.

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Supplemental Online Material (SOM)

Electric vehicles in China: emissions and health impacts

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There are two sections in this online Supporting Information document that parallel the main article:

Supporting Information – Methods

Supporting Information – Results

The results of the analyses are detailed for the 34 cities analyzed in this paper, including estimation of emission rates, intake fraction, excess mortality, and rural/urban distributional impacts. Table S1 provides regression coefficients for EGU iF estimation. Table S2 provides information about input variables and distributions for Monte Carlo simulation. Table S3 presents estimated average emission factors for EVs and CVs. Emission factors for non-$PM_{2.5}$ pollutants for EVs in 34 cities are in Table S4. Table S5 gives iF values for urban areas and EGUs. Table S6 illustrates excess mortality estimation based on assumed person-km traveled by vehicles and cities, based on the simulation. Table S7 illustrates the health analysis of $PM_{2.5}$ for Shanghai. Figure S1 presents a map of average emission factors of CO_2 and $PM_{2.5}$ for regional electricity grids. Figure S2 graphically illustrates different e-car CO_2 and $PM_{2.5}$ emission factors for electricity grids. The results of Monte Carlo simulation of $PM_{2.5}$ mortality risk per 10^{10} passenger-km for all 34 cities with the number of simulations per city proportional to population is shown in Figure S3. Figure S4 illustrates the Monte Carlo simulation of weighted average of 34 cities $PM_{2.5}$ mortality risk per 10^{10} passenger-km. Figure S5 is the scatter plot for $PM_{2.5}$ emission factors and proportion of risks to rural population from urban EV electricity use for each electricity grid.

Supporting Information - Methods

Emission Factors

To estimate EVs station-to-wheel emission factors, we identify two metrics. First, we use electricity generation and total emissions to estimate emission intensities of the power sector. These values are estimated by regional power sector, using the CARMA database[1] to track yearly electricity generation and CO_2 emissions. The NASA INTEX-B[2] dataset reports total emissions of conventional pollutants, including BC, CO, NO_X, $PM_{2.5}$, PM_{10}, SO_2, and VOC throughout China and is used in conjunction with the CARMA database to estimate emission intensity of electricity generation in grams per kilowatt hour (g kWh^{-1}). Second, the energy use of EVs (kWh km^{-1}), including transmission loss rates, is coupled with average emission intensity from the power sector (g kWh^{-1}). The product of electricity generation emission intensity and electricity use from vehicles results in station-to-wheel emission factors from EVs (g km^{-1}). In the process of estimating station-to-wheel emission factors, estimated energy requirements of EVs are obtained for several types of battery EVs such as existing Chinese e-bikes (average energy efficiency1.8 kWh $100km^{-1}$) and a compact e-car (average energy efficiency 18 kWh $100km^{-1}$).[3, 4] These energy requirements are reported as the energy required from station-to-wheel, namely the recharger or motor efficiency losses are included in the energy use rate. Moreover, we consider approximately 14% transmission and in-plant use loss in China.[5, 6] The average station-to-wheel emission factors of these pollutants are estimated for 16 relatively independent power grids in China.[7] For sake of this analysis, we assume that cities are served by power plants in the grid in which they are located. Data are unavailable for Tibet.

Intake Fraction (iF)

One-compartment model for urban iF. The one-compartment iF model estimates exposure of air pollution over a city that occupies a compartment bounded by the borders of the city and the atmospheric mixing height. This model is treated as an approximate method to estimate pollution exposure in urban areas. A one-compartment model may provide an acceptably accurate evaluation of spatially averaged concentrations in an urban area.[8, 9] The compartment model used here is static and is suitable for estimating iF for non-reacting or slowly reacting pollutants. The expression is as follows:

$$iF_{compartment} = \frac{BP}{uH\sqrt{A}}$$

Where, B is the population average breathing rate (m^3 person-s^{-1}) 14.5 based on metabolic activity studies;[10] P is the urban population for the designated city; H is the atmospheric mixing height (m); u is wind speed averaged over the mixing height (m s^{-1}); A is urban land area (m^2).

Regression Model for EGUs iF. Intake fraction of EGU emissions can be calculated based on previous multivariate regression analyses of many EGUs in China.[11] The following relationships between iF and population in Table S1 is used to predict iF of EGUs emission in China. The population living in the radii of 100km, 500km, 1000km and farther than 1000km from more than 1000 fossil EGUs in China are estimated using GIS, based on the EGUs location presented in the CARMA database and county-level Chinese population data from the 2000 Census.[12] The coefficients in Table S1 and related population are applied to estimate iF from EGU emissions using the following relationships:

$$iF_j^k = \sum_{i=1}^{n} \alpha_i^k P_i$$

Here, iF_j^k is the iF of pollutant k from EGU j. P_i is the population in each i radius from the EGU; α_i^k is the parameter estimate for pollutant k on the pollution in each i radius of the EGU. The α_i^k parameters are given in Table S1. Intake fraction of pollutants from each EGUs is estimated and the capacity-weighted average iF of all EGUs in a grid is applied to develop an average iF parameter for each electricity grid. Zhou et al.[11] only predicted the coefficient for iF of PM_1 and PM_3 based on their atmospheric dispersion modeling results. We interpolate the iF calculated from PM_1 and PM_3 relationships to estimate $PM_{2.5}$ iF.

Table S1. Regression Coefficient for EGU iF Estimation[11]

	R^2	Pop. <=100 km	100km<Pop.<500km	500km<Pop.<1000km	Pop.>=1000 km
SO_2	0.95	9.5E-8** (3.9E-8)	1.2E-8** (4.6E-9)	2.5E-9 (2.3E-9)	1.4E-9** (7.0E-10)
PM_1	0.95	1.3E-7* (8.2E-8)	2.0E-8** (9.8E-9)	9.8E-9** (4.8E-9)	2.9E-9** (1.5E-9)
PM_3	0.89	1.2E-7* (7.9E-8)	1.3E-8** (9.4E-9)	4.5E-9 (4.6E-9)	1.5E-9** (1.4E-9)
PM_7	0.88	9.1E-8** (4.7E-8)	7.1E-9* (5.7E-9)	2.1E-9 (2.8E-9)	7.8E-10* (8.5E-10)
PM_{13}	0.87	6.4E-8** (2.6E-8)	3.6E-9 (3.1E-9)	5.6E-10 (1.5E-9)	4.5E-10 (4.7E-10)
SO_4	0.93	1.5E-8 (4.2E-8)	6.0E-9* (5.1E-9)	5.9E-9** (2.5E-9)	1.8E-9** (7.6E-10)
NO_3	0.86	2.9E-8 (5.0E-8)	9.6E-9** (6.0E-9)	2.0E-9 (2.9E-9)	1.3E-9** (9.1E-10)

1. ** Parameter estimate significant at 0.05 level.
2. * Parameter estimate significant at 0.10 level.
3. Numbers in parenthesis are the standard error of parameter estimates.
4. PMx= particulate matter with diameter precisely equal to x μm.
5. Population variable in millions of people.
6. No intercept term is used in the above regression models and R-square is not corrected for the mean.

Public Health Impacts

While there are many different types of pollution emitted from CVs and buses and EVs, this paper focuses on primary $PM_{2.5}$ because of its well-documented health effects. It is important to note however that omission of other pollutants does not minimize their impact.[13] The mortality risks due to $PM_{2.5}$ and chronic cancer risk owing to diesel particulate matter (DPM) present the largest concern associated with diesel vehicle emissions. Because most PM emissions from diesel engines are smaller than 1 μm in diameter, it is acceptable to consider all DPM as $PM_{2.5}$.[14] The value of the *unit dose*, or the total amount of $PM_{2.5}$ inhaled for each case of premature mortality, is estimated from the American Cancer Society (ACS) cohort.[15] Their research concludes that, with each 10 $\mu g\ m^{-3}$ increase in average $PM_{2.5}$ ambient concentrations, the risk of all-cause mortality will increase approximately 4%. Chinese death rate is approximately 7 deaths (1000 people)$^{-1}$ year^{-1} in 2009.[16] Therefore, in China, a 4% increase in the death rate is 0.28 deaths (1000 people)$^{-1}$ year^{-1}. Assuming a breathing rate is 14.5 m^3 person^{-1} day^{-1} - namely 5292.5 m^3 person^{-1} year^{-1}, exposure to 10 $\mu g\ m^{-3}$ $PM_{2.5}$ concentration elevation would lead to an inhalation intake rate of 52925 μg person^{-1} year^{-1}, or equivalently 5.3 deaths kg^{-1}, or 188 g death^{-1}. The mortality risk is calculated based on a 1-year exposure periods. We consider primary $PM_{2.5}$ station-to-wheel emission factors from gasoline cars, diesel cars, and diesel buses using on-road empirical estimates.

Sensitive Analysis

Monte Carlo simulation is employed to conduct sensitivity analysis. The distribution type and boundaries for each input variable depend on observations from peer-reviewed literature and authors' professional judgment. The details are shown in Table S2.

Table S2. Input Variables and Distributions for Monte Carlo Simulation

Variable	Mode	Base-case value	Distribution used in Monte Carlo simulations	Units
Energy Efficiency[1]	E-bike	1.8	Triangular (1.2, 2.1)	kWh $100km^{-1}$
	E-car	18	Triangular (11, 25)	
Station-to-wheel $PM_{2.5}$ Emission Factor[2]	Gasoline Car	5	Triangular (1, 10)	mg km^{-1}
	Diesel Car	50	Normal (50, 5.5)	
	Diesel Bus	600	Triangular (200, 1000)	
Intake Fraction	E-bike	iF*[3]	Normal (iF*, 2.3)[5]	ppm
	E-car	iF*	Normal (iF*, 2.3)	
	Gasoline Car	iF**[4]	Triangular (0.5iF**, 1.5iF**)	
	Diesel Car	iF**	Triangular (0.5iF**, 1.5iF**)	
	Diesel Bus	iF**	Triangular (0.5iF**, 1.5iF**)	
Load Factor[7]	E-bike	1	(Constant)	person $vehicle^{-1}$
	E-car	1.5	Uniform (1.3, 1.7)	
	Gasoline Car	1.5	Uniform (1.3, 1.7)	
	Diesel Car	1.5	Uniform (1.3, 1.7)	
	Diesel Bus	50	Uniform (25, 75)	
Dose Response[8]	Mortality	4%	Triangular (1%, 20%)	

Notes:
1. E-bike energy efficiency source: lower bound[17] and upper bound[3]; E-car energy efficiency source: lower bound[18] and upper bound[19].
2. Gasoline car $PM_{2.5}$ emission factor source: lower bound[20] and upper bound[21]; diesel car $PM_{2.5}$ emission factor source.[22]
3. iF* is the point estimate for the EGU iF for EVs in a specific city.
4. iF** is the point estimate for the tailpipe iF for a CV in a specific city.
5. Normal (iF*, 2.3) indicates a normal (Gaussian) distribution, with mean = iF* and standard deviation = 2.3 ppm. The value for the standard deviation (2.3 ppm) is the model residual standard deviation for EGU iF source.[11]
6. The distribution of intake fraction of CVs is based on: Zhou et al.[23].
7. Passenger car load factor source: lower bound[24] and upper bound [25].
8. Dose response source.[15, 23, 24, 26, 27] The value indicates the percentage increase in mortality rate per 10 μg m^{-3} increase in $PM_{2.5}$.

Supporting Information – Results

Well-to-station emissions include fossil energy extraction, refining, storage, and transportation processes. We use previous energy life cycle analyses for CVs and EVs in China to estimate average well-to-station emissions (Table S3). Well-to-station emissions are lower for motorcycle, e-bike and diesel bus than for cars. Compared to a new (Euro IV) gasoline car, average e-car emissions are about 4× lower for CO, 2× lower for NOx, 4× lower for HC, 3× lower for SO_2, 15× lower for CO_2 and 2× greater for $PM_{2.5}$ and PM_{10}. This finding reflects, in part, that oil production and refining can generate greater HC, CO_2, NOx and SO_2 per kilometer driven (but lower PM) than electricity generation. In general, well-to-station fuel emissions constitute a small portion (<20%) of total well-to-wheel emissions for EVs and diesel cars. However, well-to-station emissions can constitute a large portion of total well-to-wheel emissions for several gasoline car pollutants.

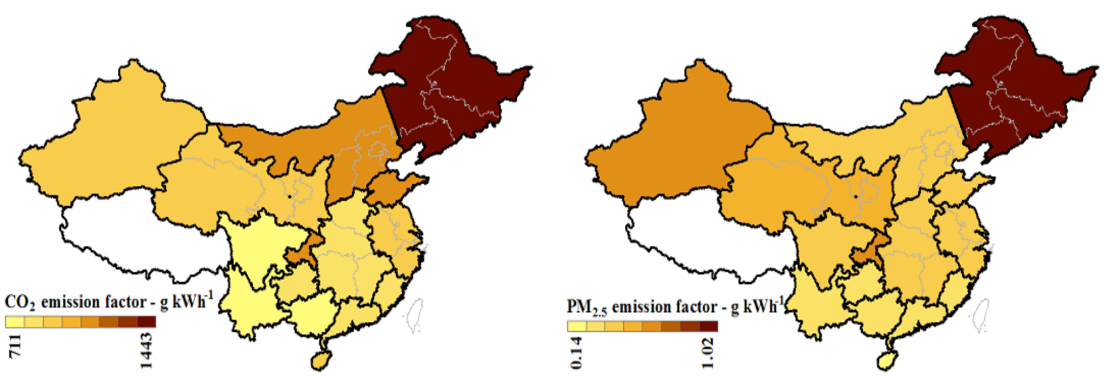

Figure S1. Average station-to-wheel emission factors for CO_2 (left plot) and $PM_{2.5}$ (right plot) for China's 15 electricity grids.

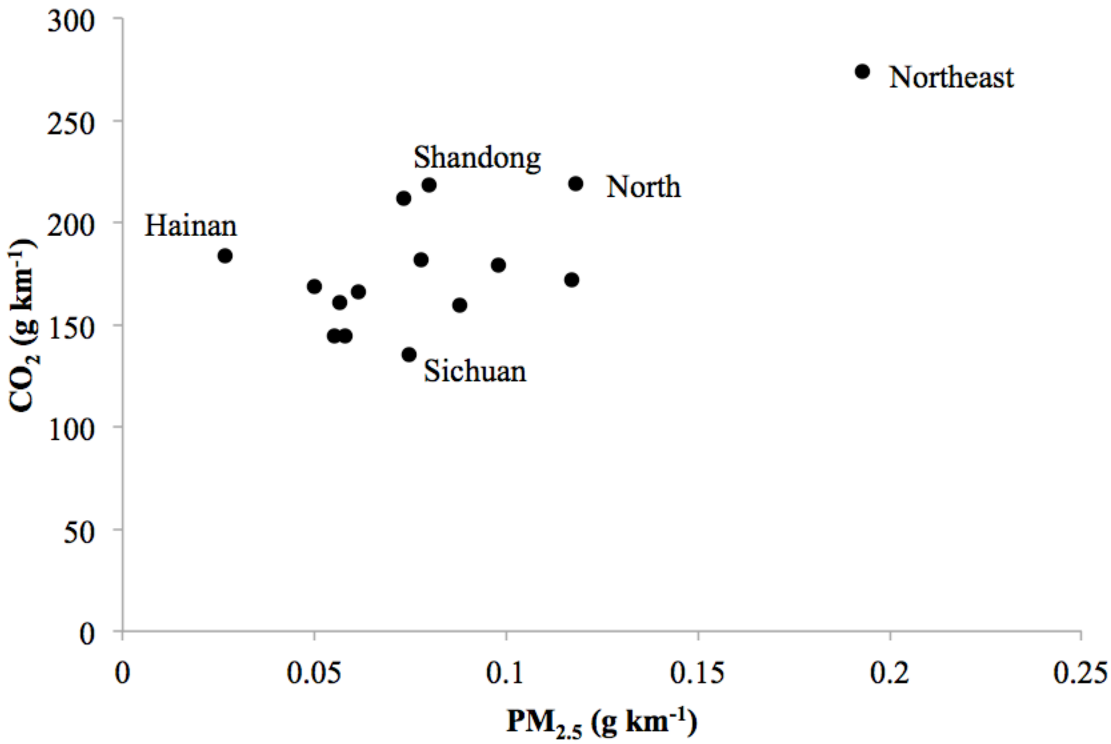

Figure S2. Average e-car station-to-wheel emission factors for CO_2 and $PM_{2.5}$ for China's 15 electricity grids. In general, points in the lower left represent grids in the southwest and points on the upper right represent grids in the northeast.

Table S3. Midpoint Emission Factors of EVs and CVs (g person-km^{-1})

	CO	NO_X	HC	SO_2	$PM_{2.5}$	PM_{10}[6]	CO_2
Euro III Diesel Car	0.43	0.33	0.04	-	0.03	-	104
(17 km l^{-1})	(0.19)	(0.05)	(0.001)	(N/A)		(0.004)	(22.6)
Euro III Gasoline Car	1.23	0.14	0.05	-	0.003	-	121
(12.8 km l^{-1})	(0.04)	(0.14)	(0.04)	(0.09)		(0.008)	(54.1)
Euro IV Gasoline Car	0.27	0.04	0.02	-	0.003	-	121
(12.8 km l^{-1})	(0.04)	(0.14)	(0.04)	(0.09)		(0.008)	(54.1)
Electric Car (E-car)	0.09	0.36	0.04	0.74	0.058	0.10	125
(18 kWh (100 km)$^{-1}$)	(0.01)	(0.06)	(0.01)	(0.03)		(0.015)	(3.7)
Motorcycle	1.25	0.15	12.55	-	0.1	-	55
(40 km l^{-1})	(0.12)	(0.03)	(0.001)	(N/A)		(0.003)	(14.4)
Electric Bike (E-Bike)	0.014	0.05	0.005	0.11	0.009	0.015	18.8
(1.8 kWh (100 km)$^{-1}$)	(0.001)	(0.01)	(0.001)	(0.01)		(0.002)	(0.6)
Bus	0.16	0.27	0.02	0.002	0.012	-	25.5
(2.2 km l^{-1})	(0.04)	(0.01)	(0.0002)	(0.001)		(0.001)	(5.2)

1. Values without parenthesis are station-to-wheel emission factors. Values in parenthesis are average well-to-station emission factors.
2. Midpoint Car (diesel, gasoline, e-cars) load factors assume 1.5 persons, bus load factor assumes 50 people and motorcycle and e-bike load factors assume 1 person. The vehicle emission factor is averaged over all passengers to estimate emissions per person kilometer.
3. Average station-to-wheel emission factors of various pollutants for EVs are weighted by electricity generation in each electricity network.
4. Motorcycle emission factors reported in Meszler[28]
5. Several studies measure bus emission factors with comparable fuel quality, engine technology and exhaust treatments as those in China. Emission factors of $PM_{2.5}$ range from 0.2-1.0 g km^{-1}with a mean of 0.6 g km^{-1} [3, 29, 30] or 0.012 g person-km^{-1}.
6. The well-to-station emission factors of PM_{10} include emissions of $PM_{2.5}$ and PM_{10}.
7. In the process of estimating well-to-station emissions for coal-based electricity generation, we employ 0.404 as energy conversion factor, meaning generation of 1 kWh electricity will require 0.404 kg standard coal.[31]

Table S4. Station-to-wheel Emission Factors of EVs with Representative Energy Efficiency (g $100km^{-1}$)

City	Vehicle	$PM_{2.5}$	PM_{10}	SO_2	NO_X	VOC	BC	CO	CO_2
Beijing	E-bike	0.80	1.34	11.46	5.38	0.56	0.02	1.38	2183
	E-car	7.97	13.36	114.57	53.84	5.58	0.21	13.80	21828
Changchun	E-bike	1.93	3.19	12.16	10.02	1.00	0.03	2.47	2741
	E-car	19.29	31.90	121.62	100.21	10.01	0.26	24.73	27414
Changsha	E-bike	0.88	1.46	11.40	5.68	0.59	0.03	1.45	1593
	E-car	8.79	14.60	114.00	56.80	5.86	0.31	14.50	15926
Changzhou	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167
Chengdu	E-bike	0.75	1.27	16.60	4.59	0.45	0.03	1.11	1351
	E-car	7.48	12.70	166.00	45.90	4.50	0.31	11.10	13508
Chongqing	E-bike	1.18	1.99	22.30	7.03	0.68	0.05	1.69	2189
	E-car	11.80	19.90	223.00	70.30	6.82	0.49	16.90	21886
Dalian	E-bike	1.93	3.19	12.16	10.02	1.00	0.03	2.47	2741
	E-car	19.29	31.90	121.62	100.21	10.01	0.26	24.73	27414
Foshan	E-bike	0.57	0.95	5.62	3.34	0.38	0.01	0.93	1608
	E-car	5.67	9.54	56.20	33.40	3.76	0.06	9.28	16085
Guangzhou	E-bike	0.57	0.95	5.62	3.34	0.38	0.01	0.93	1608
	E-car	5.67	9.54	56.20	33.40	3.76	0.06	9.28	16085
Guiyang	E-bike	0.50	0.85	16.50	3.37	0.36	0.01	0.88	1687
	E-car	5.01	8.47	165.00	33.70	3.56	0.12	8.80	16868
Hangzhou	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167
Harbin	E-bike	1.93	3.19	12.16	10.02	1.00	0.03	2.47	2741
	E-car	19.29	31.90	121.62	100.21	10.01	0.26	24.73	27414
Huai'an	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167
Jinan	E-bike	0.73	1.24	14.20	5.44	0.56	0.03	1.39	2121
	E-car	7.34	12.40	142.00	54.40	5.62	0.31	13.90	21209
Kunming	E-bike	0.58	1.03	10.80	4.45	0.47	0.02	1.17	1444
	E-car	5.80	10.30	108.00	44.50	4.74	0.16	11.70	14437
Lanzhou	E-bike	0.98	1.69	11.60	4.97	0.55	0.01	1.35	1789
	E-car	9.80	16.90	116.00	49.70	5.46	0.12	13.50	17891
Nanjing	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167

Ningbo	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167
Putian	E-bike	0.62	1.03	4.24	3.15	0.38	0.01	0.94	1662
	E-car	6.15	10.30	42.40	31.50	3.79	0.08	9.36	16619
Qingdao	E-bike	0.73	1.24	14.20	5.44	0.56	0.03	1.39	2121
	E-car	7.34	12.40	142.00	54.40	5.62	0.31	13.90	21209
Shanghai	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167
Shenyang	E-bike	1.93	3.19	12.16	10.02	1.00	0.03	2.47	2741
	E-car	19.29	31.90	121.62	100.21	10.01	0.26	24.73	27414
Shijiazhuang	E-bike	0.80	1.34	11.46	5.38	0.56	0.02	1.38	2183
	E-car	7.97	13.36	114.57	53.84	5.58	0.21	13.80	21828
Suzhou	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167
Taiyuan	E-bike	0.80	1.34	11.46	5.38	0.56	0.02	1.38	2183
	E-car	7.97	13.36	114.57	53.84	5.58	0.21	13.80	21828
Tangshan	E-bike	0.80	1.34	11.46	5.38	0.56	0.02	1.38	2183
	E-car	7.97	13.36	114.57	53.84	5.58	0.21	13.80	21828
Tianjin	E-bike	0.80	1.34	11.46	5.38	0.56	0.02	1.38	2183
	E-car	7.97	13.36	114.57	53.84	5.58	0.21	13.80	21828
Wuhan	E-bike	0.88	1.46	11.40	5.68	0.59	0.03	1.45	1593
	E-car	8.79	14.60	114.00	56.80	5.86	0.31	14.50	15926
Wuxi	E-bike	0.78	1.32	8.89	5.36	0.58	0.02	1.44	1817
	E-car	7.77	13.20	88.90	53.60	5.84	0.16	14.40	18167
Xi'an	E-bike	0.98	1.69	11.60	4.97	0.55	0.01	1.35	1789
	E-car	9.80	16.90	116.00	49.70	5.46	0.12	13.50	17891
Xiangfan	E-bike	0.88	1.46	11.40	5.68	0.59	0.03	1.45	1593
	E-car	8.79	14.60	114.00	56.80	5.86	0.31	14.50	15926
Zaozhuang	E-bike	0.73	1.24	14.20	5.44	0.56	0.03	1.39	2121
	E-car	7.34	12.40	142.00	54.40	5.62	0.31	13.90	21209
Zhengzhou	E-bike	0.88	1.46	11.40	5.68	0.59	0.03	1.45	1593
	E-car	8.79	14.60	114.00	56.80	5.86	0.31	14.50	15926
Zibo	E-bike	0.73	1.24	14.20	5.44	0.56	0.03	1.39	2121
	E-car	7.34	12.40	142.00	54.40	5.62	0.31	13.90	21209

Table S5. Average iF Comparison – Urban vs. EGUs

City	iF-Urban (ppm) Non-reactive Station-to-wheel Emissions from CVs (including $PM_{2.5}$)	iF - EGUs (ppm) Station-to-wheel Emissions from EVs							
		$PM_{2.5}$ (Interpolated)	SO_2	PM_1	PM_3	PM_7	PM_{13}	SO_4	NO_3
Beijing	73.2	5.9	4.0	8.7	5.0	2.7	1.4	4.2	3.1
Changchun	12.9	4.1	2.9	6.1	3.4	1.9	1.0	3.1	2.3
Changsha	31.3	8.2	5.5	11.9	7.0	3.9	2.0	5.3	4.0
Changzhou	12.1	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Chengdu	64.3	6.2	4.4	8.8	5.4	3.1	1.7	3.9	3.1
Chongqing	11.4	7.4	5.2	10.4	6.5	3.8	2.1	4.4	3.5
Dalian	12.7	4.1	2.9	6.1	3.4	1.9	1.0	3.1	2.3
Foshan	116.8	7.4	5.1	10.5	6.4	3.7	2.0	4.6	3.5
Guangzhou	31.7	7.4	5.1	10.5	6.4	3.7	2.0	4.6	3.5
Guiyang	8.7	6.2	4.3	9.1	5.2	2.9	1.5	4.2	3.3
Hangzhou	17.0	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Harbin	15.0	4.1	2.9	6.1	3.4	1.9	1.0	3.1	2.3
Huai'an	6.5	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Jinan	25.7	7.6	5.4	10.9	6.6	3.7	2.0	4.7	3.9
Kunming	21.9	4.5	3.1	6.8	3.8	2.1	1.1	3.5	2.5
Lanzhou	15.4	4.8	3.2	7.2	4.0	2.2	1.1	3.7	2.5
Nanjing	19.1	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Ningbo	15.0	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Putian	11.0	8.3	5.9	11.8	7.2	4.1	2.2	4.9	4.2
Qingdao	26.9	7.6	5.4	10.9	6.6	3.7	2.0	4.7	3.9
Shanghai	50.6	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Shenyang	22.2	4.1	2.9	6.1	3.4	1.9	1.0	3.1	2.3
Shijiazhuang	52.0	5.9	4.0	8.7	5.0	2.7	1.4	4.2	3.1
Suzhou	15.1	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Taiyuan	49.9	5.9	4.0	8.7	5.0	2.7	1.4	4.2	3.1
Tangshan	11.1	5.9	4.0	8.7	5.0	2.7	1.4	4.2	3.1
Tianjin	25.6	5.9	4.0	8.7	5.0	2.7	1.4	4.2	3.1
Wuhan	38.2	8.2	5.5	11.9	7.0	3.9	2.0	5.3	4.0

Wuxi	16.0	8.2	5.5	11.7	7.0	4.0	2.1	5.1	3.9
Xi'an	38.3	4.8	3.2	7.2	4.0	2.2	1.1	3.7	2.5
Xiangfan	10.7	8.2	5.5	11.9	7.0	3.9	2.0	5.3	4.0
Zaozhuang	6.3	7.6	5.4	10.9	6.6	3.7	2.0	4.7	3.9
Zhengzhou	31.1	8.2	5.5	11.9	7.0	3.9	2.0	5.3	4.0
Zibo	9.6	7.6	5.4	10.9	6.6	3.7	2.0	4.7	3.9
Average	**27.2**	**6.8**	**4.7**	**9.8**	**5.8**	**3.3**	**1.7**	**4.5**	**3.4**

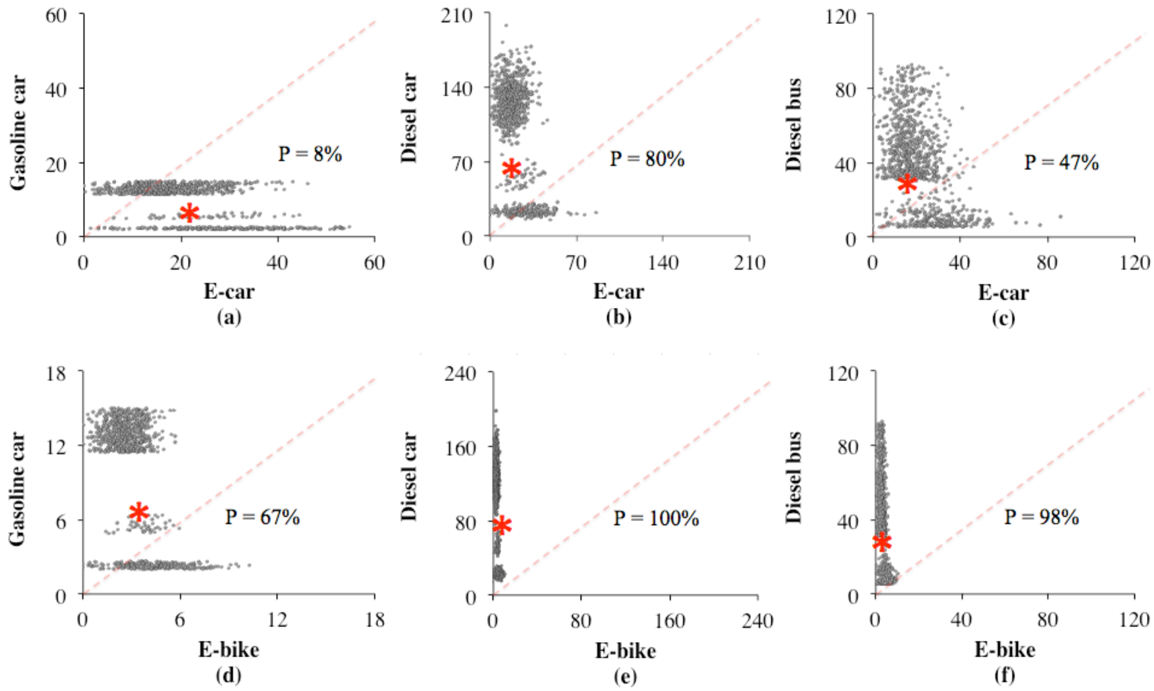

Figure S3. Monte Carlo simulation of $PM_{2.5}$ mortality risk per 10^{10} passenger-km for all 34 cities considered. A total of n=10,000 Monte Carlo simulations was carried out, with the number of simulations per city proportional to population. In each plot, "P" is the proportion of the simulation outcomes for which the mortality risk is lower for EVs that for CVs. The dashed lines on each plot are 1:1 lines. The population-weighted average value is indicated with an asterisk.

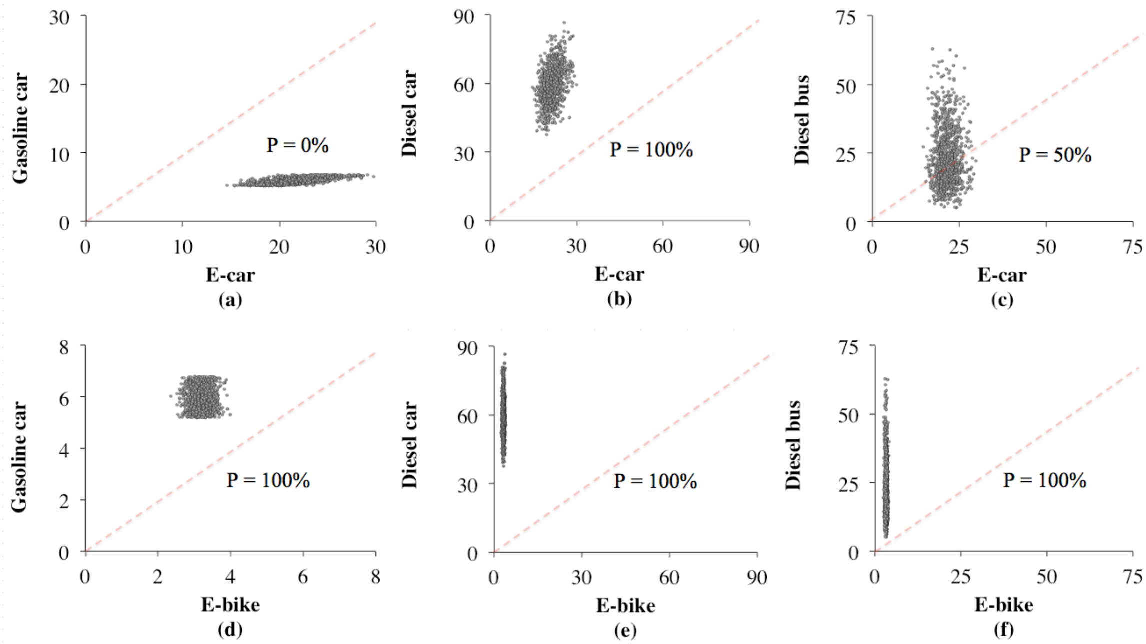

Figure S4. Monte Carlo simulation of weighted average of 34 city $PM_{2.5}$ mortality risk per 10^{10} passenger-km. Population-weighted average mortality risk is calculated from simulation of 34 cities (asterisk in Figure 6). Simulation totaled 1,000 runs per city. This graph illustrates a random sample of calculated points. In each plot, "P" is the proportion of the simulation outcomes for which the mortality risk is lower for EVs that for CVs. The dashed lines on each plot are 1:1 lines.

Table S6. Excess Mortality per 10^{10} Person-km Traveled by Vehicle and City based on Monte Carlo Simulation

City	E-bike	E-Car	Diesel Car (Euro III)	Gasoline Car (Euro III)	Bus
Beijing	2.5 (1.0)	16.9 (7.3)	130.7 (17.5)	13.1 (1.0)	51.5 (23.3)
Changchun	4.1 (2.4)	27.1 (17.1)	23.0 (3.1)	2.3 (0.2)	9.1 (4.1)
Changsha	3.9 (1.1)	26.3 (8.8)	55.9 (7.5)	5.6 (0.4)	22.0 (10.0)
Changzhou	3.4 (1.0)	22.7 (7.7)	21.6 (2.9)	2.2 (0.2)	8.5 (3.8)
Chengdu	2.5 (0.9)	16.5 (6.8)	114.8 (15.4)	11.5 (0.9)	45.3 (20.5)
Chongqing	4.7 (1.4)	31.8 (11.2)	20.4 (2.7)	2.0 (0.2)	8.0 (3.6)
Dalian	4.1 (2.5)	27.6 (17.6)	22.7 (3.0)	2.3 (0.2)	8.9 (4.0)
Foshan	2.2 (0.7)	14.6 (5.7)	208.9 (28.0)	20.9 (1.6)	82.3 (37.2)
Guangzhou	2.2 (0.7)	15.0 (5.5)	56.6 (7.6)	5.7 (0.4)	22.3 (10.1)
Guiyang	1.6 (0.6)	11.1 (4.6)	15.5 (2.1)	1.5 (0.1)	6.1 (2.8)
Hangzhou	3.4 (0.9)	22.6 (7.5)	30.4 (4.1)	3.0 (0.2)	12.0 (5.4)
Harbin	4.2 (2.4)	28.8 (17.5)	26.8 (3.6)	2.7 (0.2)	10.6 (4.8)
Huai'an	3.4 (0.9)	22.5 (7.7)	11.5 (1.5)	1.2 (0.1)	4.5 (2.1)
Jinan	2.9 (0.9)	19.6 (6.9)	45.9 (6.1)	4.6 (0.4)	18.1 (8.2)
Kunming	1.4 (0.7)	9.2 (5.3)	39.1 (5.2)	3.9 (0.3)	15.4 (7.0)
Lanzhou	2.5 (1.2)	16.7 (8.9)	27.5 (3.7)	2.7 (0.2)	10.8 (4.9)
Nanjing	3.4 (0.9)	23.1 (7.6)	34.1 (4.6)	3.4 (0.3)	13.4 (6.1)
Ningbo	3.4 (0.9)	22.7 (7.8)	26.8 (3.6)	2.7 (0.2)	10.6 (4.8)
Putian	2.7 (0.7)	18.3 (5.9)	19.6 (2.6)	2.0 (0.2)	7.7 (3.5)
Qingdao	3.0 (0.9)	20.5 (7.2)	48.0 (6.4)	4.8 (0.4)	18.9 (8.6)
Shanghai	3.4 (1.0)	22.8 (7.9)	90.4 (12.1)	9.0 (0.7)	35.6 (16.1)
Shenyang	4.1 (2.4)	28.0 (17.5)	39.6 (5.3)	4.0 (0.3)	15.6 (7.1)

Shijiazhuang	2.5 (1.0)	16.7 (7.3)	92.9 (12.4)	9.3 (0.7)	36.6 (16.5)
Suzhou	3.4 (1.0)	22.7 (7.9)	27.0 (3.6)	2.7 (0.2)	10.6 (4.8)
Taiyuan	2.5 (1.0)	16.9 (7.3)	89.1 (11.9)	8.9 (0.7)	35.1 (15.9)
Tangshan	2.5 (1.0)	16.4 (7.4)	19.8 (2.7)	2.0 (0.2)	7.8 (3.5)
Tianjin	2.5 (1.0)	17.0 (7.5)	45.7 (6.1)	4.6 (0.3)	18.0 (8.1)
Wuhan	3.8 (1.1)	25.6 (8.7)	68.2 (9.1)	6.8 (0.5)	26.9 (12.2)
Wuxi	3.4 (0.9)	22.7 (7.5)	28.6 (3.8)	2.9 (0.2)	11.3 (5.1)
Xi'an	2.5 (1.2)	17.1 (8.8)	68.4 (9.2)	6.8 (0.5)	27.0 (12.2)
Xiangfan	3.8 (1.1)	25.4 (8.7)	19.1 (2.6)	1.9 (0.1)	7.5 (3.4)
Zaozhuang	3.0 (0.9)	19.9 (7.4)	11.2 (1.5)	1.1 (0.1)	4.4 (2.0)
Zhengzhou	3.8 (1.1)	25.6 (8.8)	55.5 (7.4)	5.6 (0.4)	21.9 (9.9)
Zibo	3.1 (0.9)	20.6 (7.1)	17.2 (2.3)	1.7 (0.1)	6.8 (3.1)

1. Numbers in parenthesis are the standard deviation of results

Table S7. Public Health Analysis of $PM_{2.5}$ in Shanghai

	Station-to-wheel Emission Factor (g person-km^{-1})	Station-to-wheel Emission Factor Ratio (CV/EV)	iF (ppm)	iF Ratio	Mortality Risk (per 10^{10} person-km)	Mortality Ratio
Diesel Bus (50 Person)	0.012	1.5	50.6	6.2	32.2	9.6
E-bike	0.008		8.2		3.4	
Diesel Car	0.033	0.6	50.6	6.2	89.5	4.0
Gasoline Car (Euro IV)	0.003	0.06	50.6	6.2	9.0	0.4
E-Car	0.058		8.2		22.5	

1. Car (diesel, gasoline, e-cars) load factors assume 1.5 persons, bus load factor assumes 50 people and motorcycle and e-bike load factors assume 1 person. The vehicle emission factor is averaged over all passengers to estimate emissions per person kilometer.

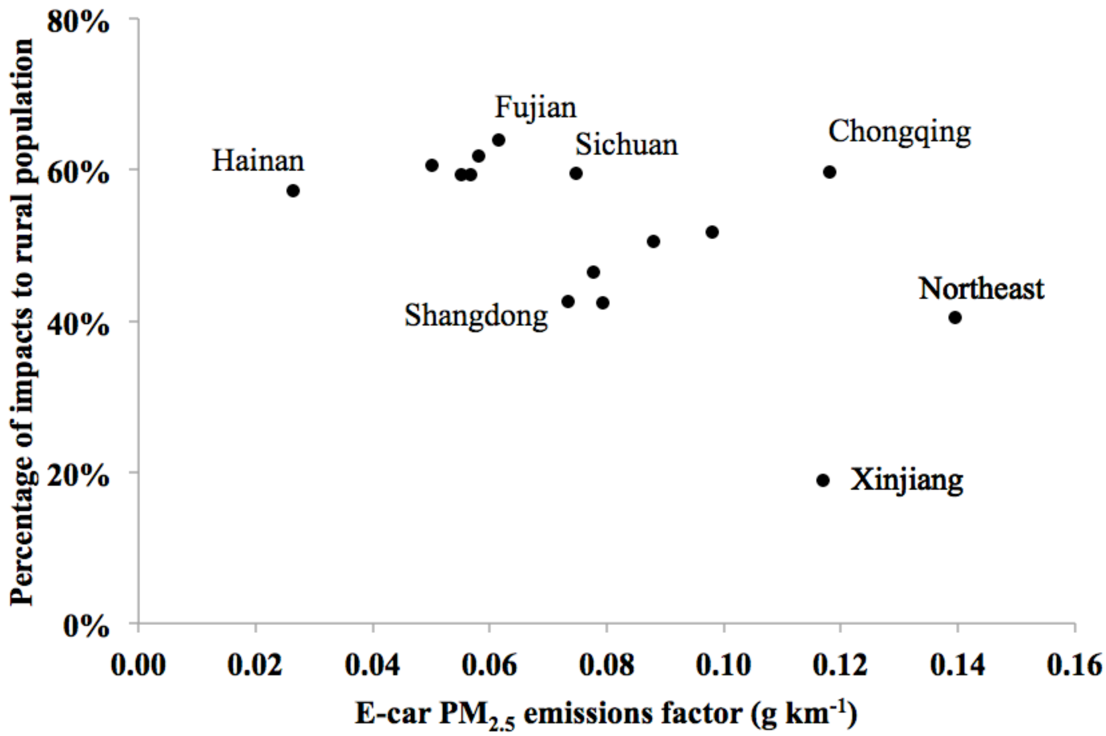

Figure S5. E-car $PM_{2.5}$ station-to-wheel emission factors and proportion of impacts of urban EV use to non-urban populations. In general, urban use of EVs rather than CVs moves emissions and health impacts to rural locations. The data exhibit a weak negative relationship between emission factors and proportion of health impacts born by rural populations, implying that grids with higher emission factors are more urbanized.

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