12-2012

Electric Vehicles in China: Emissions, Health Impacts, and Equity

Shuguang Ji
sji1@utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Shuguang Ji entitled "Electric Vehicles in China: Emissions, Health Impacts, and Equity." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

Christopher Cherry, Major Professor

We have read this dissertation and recommend its acceptance:

Lee Han, Joshua Fu, Adam Petrie, Stephen Richards

Accepted for the Council:
Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Electric Vehicles in China:

Emissions, Health Impacts, and Equity

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Shuguang Ji

December 2012

DEDICATION

This dissertation is dedicated to all my family. Particularly to my loving and understanding parents -- my mother, Fengqin Zhang and my father, Ping Ji.

ACKNOWLEDGEMENTS

To finish this dissertation has been one of most significant landmarks to me. It would be an impossible mission to finish my dissertation without the guidance of my committee members, and support from my family and friends.

I would like to express my deepest appreciation to my advisor, Dr. Christopher Cherry. In the past four years, he has provided me with an excellent atmosphere to conduct research. Also, I have received his excellent guidance, caring, and patience. I would like to thank Dr. Lee Han, who corrects my research approach and helps me publish paper. I would like to thank Dr. Joshua Fu for guiding my research and helping me to develop my background in air pollution field. I would like to thank Dr. Adam Petrie for your guidance and support in my statistics degree. I would like to thank Dr. Stephen Richards, who is willing to participate in my defense committee and always prepares reference letter for me. I would like to thank Dr. Julian Marshall, who helps publish high quality papers and work with conscientiousness.

Special thanks go to Casey Langford, Ryan Overton, Stephanie Hargrove, Airton Kohls, Xiaoli Sun, Jun Xu, Ximiao Jiang, Hongtai Yang, David Jordan, Qiang Yang, Wei Lu, Taekwan Yoon, Amber Woodland, Andrew Campbell, Jianjiang Yang, Jun Liu, and Shanna Veilleux who as good friends are always willing to help me. It would have been a lonely lab without them.

I have to thank my parents and grandmother. They were always supporting me and encouraging me with their best wishes.

Finally, I would like to thank University of Tennessee Knoxville. I do have a sweet memory and make a lot of good friends here. I am so proud of being a VOL.

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-cars sales, too, are rapidly growing. Electric vehicles (EVs) in China are being considered as a strategy to improve air quality, energy efficiency, and reduce health impacts due to transport emissions. Because EVs have different pollution sources, namely electric generating units (EGUs), quantitative analysis for health impacts requires understanding the exposure efficiency of related pollution sources. In this dissertation, EVs will be analyzed in the context of the impacts on the environment, the differences in exposure efficiency of pollutants, the impacts on health, and the distribution of those impacts among different sectors of the population. This study compares 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 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 (EGU 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 for e-cars than for diesel cars (2.5× on average) and equal between e-cars and 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×). In addition, adoption of EVs could cause environmental equity problems in China at this time, since a vast majority (>83%) of pollutant emissions inhaled and subsequent health effects due to urban EV use could be distributed to communities whose incomes are lower than the cities where EVs are promoted. The findings highlight the importance of considering exposures, and especially the proximity of emissions to people, when evaluating environmental health impacts and equity concerns for EVs.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

China's rapid growth in income – annual gross domestic product (GDP) increases averaged 9-10% during 1978-2009 (NBS 2010) – has many impacts, including several with environmental health consequences. Outdoor air pollution is blamed for ~300,000 premature deaths in China each year (Millman, Tang et al. 2008). For several pollutants, including fine particles ($PM_{2.5}$), transportation is a significant and growing source of emissions (Cai and Xie 2007). Automobile ownership increased more than an order of magnitude in one decade, from 3 cars per 1,000 people in 1998 to at least 39 cars per 1,000 people in 2009 (Fridley, Aden et al. 2008; NBS 2010). Encouraging motorized transportation is a national strategy for economic and social development in China (Jie 2009; Zheng, Mehndiratta et al. 2012).

This research focuses on electric vehicles (EVs: electric cars [e-cars] and electric two-wheelers including electric bicycles and light electric scooters [e-bikes]) in China and 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 (Weinert, Ma et al. 2007; Jamerson and Benjamin 2009).

For EVs, combustion emissions occur where electricity is generated rather than where the vehicle is used (Sioshansi and Denholm 2009; Brinkman, Denholm et al. 2010; Huo, Zhang et al. 2010). 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 (Bennett, McKone et al. 2002; Evans, Wolff et al. 2002; Marshall, Teoh et al. 2005; Heath, Granvold et al. 2006). The net result for China is that it is unclear a priori whether EVs are an environmental health benefit or dis-benefit relative to CVs.

Prior research on environmental impacts of EVs in China (Cherry, Weinert et al. 2009; Huo, Zhang et al. 2010) and elsewhere (Funk and Rabl 1999; Lindly and Haskew 2002; Nansai, Tohno et al. 2002; Silva, Ross et al. 2009; Jansen, Brown et al. 2010) generally compares emission factors or greenhouse gas emissions (MacLean and Lave 2003; Samaras and Meisterling 2008; Stephan and Sullivan 2008; Wallington, Grahn et al. 2010), not exposures, intakes, or health effects. My research works to address this important knowledge gap. I 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. I also investigate the distribution of these impacts, focusing on equity changes when CVs are replaced by EVs.

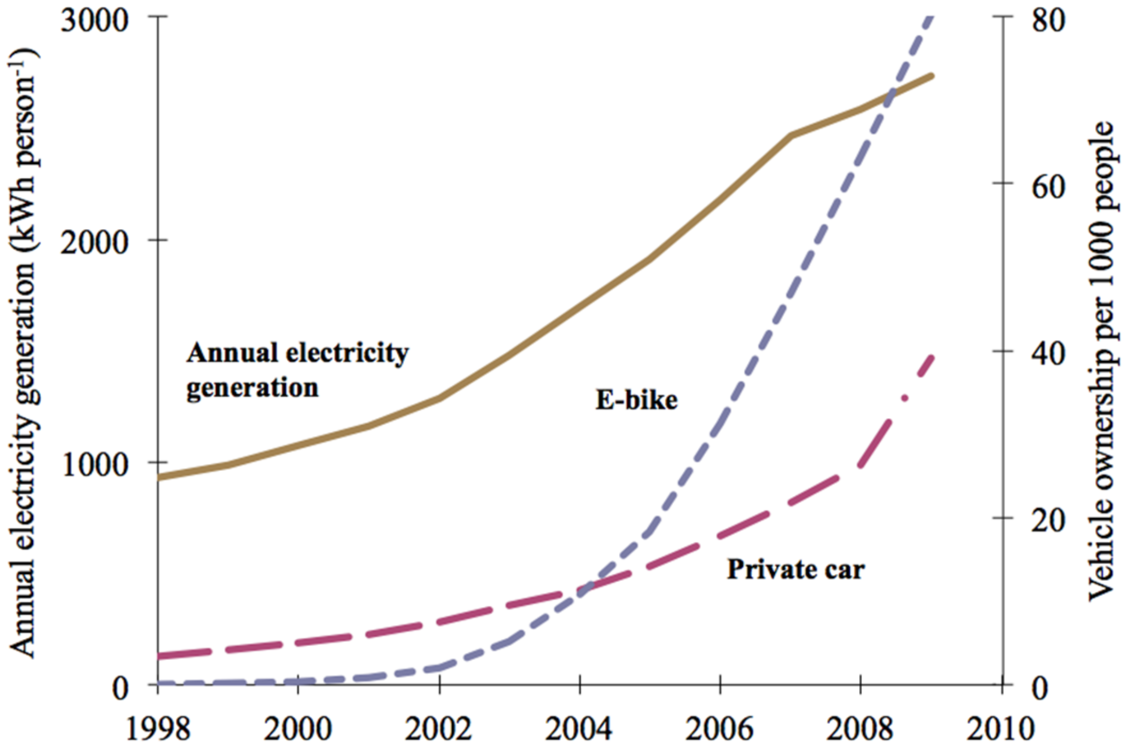


Figure 1.1. Motorization use and electricity generation in China normalized to population. During the past decade, e-bike ownership has grown from near-zero to ~2× greater than CVs.

1.1 Motivation

Sustainability is critical concerns for the development of each country worldwide, especially in China. China's economic development has been coupled with rapid environmental degradation. With the rapid increase of EVs, more attention should be paid to whether they should be supported or regulated. EVs are unique compared to CVs, because pollutants from EVs are not distributed among population sources in the same way as pollutants from tailpipes of CVs. As such, a vehicle with identical emission factors of a particular pollutant could have different health impacts and environmental justice implications, depending on the location of the pollution source (EGU or tailpipe).

1.2 Scope

This research is meant to primarily estimate environmental, health, and equity impacts of EVs, relative to alternative modes and fuels. Obviously, environmental, health, and equity impacts are a subset of important indicators when developing policy on different vehicle types. Other issues, such as safety, mobility, contribution to congestion, and economic development are also worth considering, together with environmental and health impacts. Interested readers can refer to published literature on some of these topics (Cherry 2007; Cherry and Cervero 2007; Weinert 2007; Lin, He et al. 2008; Ni 2008; Cherry, Weinert et al. 2009; Cherry, Weinert et al. 2009). The scope of this research is limited to the following topics, to begin to answer questions related to environmental impacts and ultimately health impacts related to EVs and CVs in China:

1. Refine estimation of emissions from EVs and CVs;
2. Estimate intake fraction of emissions from EVs and CVs;
3. Extend intake fraction to health impacts due to primary $PM_{2.5;}$
4. Analyze distributional equity impacts due to use of EVs.

1.3 Outline

This dissertation consists of five chapters. Chapter I is an introduction to the research. Motivation and scope of this research are described. In Chapter II, the previous related key findings are summarized. In Chapter III, the methods employed for this research are provided. Assumptions and data for this research are described. The findings of this research are presented and discussed in Chapter IV. Finally, in Chapter V, the conclusion and recommendation are made. Some detailed calculation results such as tables and figures are included in appendix.

CHAPTER II

LITERATURE REVIEW

In this chapter, the previous research work concerning policy and emissions on electric vehicles (EVs) in China and the theories and methods related to my research framework are reviewed. This section focuses on broad EV deployment strategies, and then covers EV emissions, exposure and health impacts, and distributional equity effects.

2.1 Overview of Electric Vehicle Development in China

Electric vehicles, including e-bikes and e-cars, are considered to balance mobility and air pollution control in China, especially as the number of e-bikes in China has skyrocketed from the 1990s. However, the views and opinions from local governments in China on e-bikes are mixed. Some think e-bikes present an alternative transportation mode for bus riders and bicyclists. With e-bikes, the travel time could be reduced and travel length could be extended relative to some modes. Proponents believe e-bikes can contribute to sustainable transportation. However, e-bikes are banned by some cities in China. The opinion of these governments is that e-bikes contribute to traffic conflicts, particularly in the big cities like Guangzhou and Shenzhen. This section reviews EV policy in China, focusing on concerns about EVs in China.

2.1.1 Electric bikes

Weinert et al. (2007) presented the first work that described the early history of e-bikes in China. The earliest appearance of e-bikes can be traced back to the foundation of Electric Vehicle Institute of China Electro-technical Society in 1987. Four years later, e-bikes were included into the 9th Five-Year plan of China as one of 10 main technology projects. Five-Year plans are a series of economy plans developed by central government in China and are expected to be completed in five years. In 1993, Shanghai became the center of e-bike development for all of China. In 1997, the first generation of commercial e-bikes was introduced into the market by Shanghai Cranes Electric Vehicle Company and in 1999, national e-bike standards were published in China and the first e-bike licenses were granted in Shanghai, Tianjin, Jiangsu, Zhejiang, Guangdong, Xichang, Yunnan, Anhui, and Hebei. In 2000, “Road Transportation Safety Law” was drafted to allow e-bikes to use bike lanes if the speed is lower than 20 kilometer per hour. This law was enacted in 2004.

Based on this study, the rapid growth of e-bikes starting in 1990s could be explained by several factors. For instance, throughout the late 1990s, the technology of e-bikes gradually improved. At the same time, the price of e-bikes gradually reduced while the income of urban households increased. The Chinese government was willing to support e-bikes as new transportation option. However, the investigation about the impacts on traffic, energy use, and environment due to adoption of e-bikes should be considered and analyzed in the future.

In 2007, another study was published about travel behavior, mode shift, and user safety of e-bikes in Shijiazhuang, China (Weinert, Ma et al. 2007). In this research, the reasons that people adopted e-bikes include reduction of trip time, increase of trip length, ability of carrying cargo and people, and easy operation. Most e-bike users switched to e-bikes from bus or bicycle in Shijiazhuang. Also e-bikes were considered an option for people who received insufficient public transportation service. Some of e-bike users could be considered potential consumers of private cars. Based on the survey, most e-bike users thought e-bikes were safer than bicycles when crossing intersections. They also believed bicycle riders and pedestrians present the major conflicts to automobile traffic. Coincidently, the bicycle riders, themselves, considered other bicycle riders as major traffic conflicts as well. However, higher speed e-bikes were not acceptable by most female users. Cherry and Cervero (2007) conducted a survey in Shanghai and Kunming of China. They found that most of e-bike users who were surveyed would switch to ride bus if e-bikes were banned in both cities. Also, some local governments, such as Dalian, were trying to improve the public transportation system in order to reduce the use of e-bikes or bicycles.

Weinert et al. (2008) conducted a force-field analysis on the development of e-bikes in China. They analyzed driving and resisting force for e-bikes adoption. For example, the driving force for national level support for the adoption of e-bikes was energy efficiency. Local bans on e-bikes because of safety considerations were resisting forces. They found that the driving forces outweighed resisting forces for e-bike adoption in China. This may accelerate the adoption of e-bikes in China.

Due to lack research on environmental impacts of e-bikes in China, Cherry et al. (2009) quantified the environmental impacts of e-bikes, beginning with the production processes through usage life, compared with bicycle, bus, motorcycle, and car. The research findings show that lifecycle emissions from e-bikes are lower than cars and motorcycles, comparable to buses, and higher than bicycles. E-bikes emitted more Sulfur dioxide (SO_2) compared with other modes, since electricity generation was mostly fossil-fuel based in China. Lead pollution due to the use and recycle of rechargeable batteries on board should also be considered.

Yang (2010) analyzed e-bike launching strategy of Chinese governments and potential impacts. The author pointed out that from the failed launching practice in Taiwan, subsidies from the governments may not be sufficient to foster the market of e-bikes. It should be noticed that the perspectives from the Chinese local governments are mixed. They are not certain whether e-bikes should be encouraged or regulated. From 2001 to 2009, there were eight cities with bans on e-bikes in China -- Wuhan, Fuzhou, Zhuhai, Guangzhou, Dongguan, Shenyang, Foshan, and Shenzhen. Changzhou and Changsha suspended issuing licenses for e-bikes. The author also concluded that bans on motorcycles are one of major contributors to rapid growth of e-bikes in China.

Rose (2012) reviewed e-bike policy and research globally. He primarily looked at impacts of e-bikes on mobility, safety, and environment. He suggested that future research should quantify these unresolved issues.

2.1.2 Electric cars

Huo et al. (2010) conducted research on environmental implication of e-cars in China under current (2008) and future (2030) pollution control strategies of power plants in China. This research attempts to highlight some environmental concerns due to e-car adoption. They found that e-cars may not reduce Carbon dioxide (CO_2) emissions significantly under the current energy structure of China. However, potential greater reduction in the future could happen since the power plants are becoming less polluting. Compared with gasoline cars, SO_2 emissions of e-cars could be three to ten times higher, and NO_X (Nitrogen oxide) emissions of e-cars could be doubled. In 2030, e-cars may have the similar emission rate of NO_X compared with gasoline vehicles due to the pollution control strategies of power plants in China; however, the emission rate of SO_2 may be still higher than gasoline cars.

Another recent study modeled CO_2 emissions from EVs in China (Doucette and McCulloch 2011). This research drew the same conclusion as other similar analysis such as Huo's (2010). In China, since the emissions of power plants have higher CO_2 intensity, EVs actually have similar or even higher CO_2 emission rates than CVs.

In addition, Doucette and McCulloch (2011) modeled CO_2 emissions for adoption of Plug-in Hybrid Electric Vehicles (PHEVs). They found that PHEVs could emit less CO_2 than EVs and CVs, if power generation had higher CO_2 intensity, such as in China.

Countries like China could not reach the goal of CO_2 reduction by adopting EVs and PHEVs without de-carbonization of power generation.

Yan and his colleagues (2010) analyzed rapid growth of energy demand and emissions from road transportation in China. They predicted that this rapid growth could continue in the next two to three decades and suggested that appropriate strategies should be planned to reduce the impacts on energy and environment due to this rapid growth. In the short and medium term, EVs may not necessarily reduce the fossil fuel use and greenhouse gas (GHG) emissions. However, in the long term, EVs might offer significant reduction in fossil fuel use and GHG emissions. They claimed that EVs are highly promising in contributing to oil security and urban air pollution reduction. EVs could facilitate in transition from fossil fuel to renewable energy smoothly and utilizing the power generated during the idle time.

Ou and his colleagues (2010) analyzed life cycle GHG emissions of EVs in China. The life cycle included full fuel cycle, use-phase emissions, vehicle cycle, and battery manufacturing emissions. This research found that, without de-carbonization, the life cycle GHG emissions from EVs could be 3% to 36% lower than gasoline cars. If a de-carbonization strategy such as carbon dioxide capture and storage (CCS) technology was employed, the life cycle GHG emissions from EVs could be 60% to 70% lower than gasoline cars. The authors concluded that Chinese governments should consider the deployment of de-carbonization technology such as CCS to reach the goal of GHG reduction. However, the deployment of de-carbonization technology such as CCS at this time could be restricted by several technical uncertainties, such as potential CO_2 leakage, higher fossil energy consumption, and cost of commercialization.

Another study considered EVs as possible promising low-carbon vehicles in China in the future (Yao, Liu et al. 2011). However, in short term, advanced technologies in CVs could be a more realistic solution to energy saving and GHG reduction. The future of low-carbon vehicles such as EVs in China depends on three factors: improvements in technology, public awareness, and government guidance. They also presented detail analysis on CO_2 emissions of EVs in different regions of China. Since energy structure varies in different regions of China, emission rates of EVs were different as well. For example, in the north part of China, 98% of electricity was generated by coal-based power plants. EVs could increase CO_2 emissions by 7.3% compared with gasoline vehicles in this region. On the other hand, in the south part of China, approximately 35% electricity was from non-fossil-fuel power plants such as hydropower. CO_2 emissions from EVs in these regions could be around 30% lower than gasoline vehicles.

In 2009, Chinese government developed a GHG reduction goal by 2020 (State Council PRC 2009). In this strategic plan, the central government required that the percentage of GHG emissions normalized by GDP should be reduced by 40% to 45% of the 2005 level. However, Hao and his colleagues (2011) criticized whether the goal of GHG reduction could be reached in the road transportation sector. In that research, they quantified several scenarios for road transportation, and none of them could guarantee the reduction goal could be fulfilled by 2020. For instance, by considering adopting EVs in China, the

GHG emissions in road transportation sector could only be reduced by 0.5% in 2020, a slight change.

Zhang et al. (2011) analyzed public awareness and acceptance of EVs in China. They conducted a survey in Nanjing and received 299 respondents from driving school. The survey results show that government policies and fuel price have great impact on the users who want to purchase EVs. Recently, high fuel prices in China have already pushed some private car drivers to select public transportation again. In addition, they listed main factors that may influence consumers' purchases and acceptance of price of EVs including age, academic degree, annual income, number of vehicles, and the opinion of peers.

Zheng et al. (2012) conducted a survey concerning demonstration program of EVs in China launched in 2009. The purpose of their research is to better understand the current policy, problems, and uncertainties in the process of EVs deployment in China. They found that the impact of this demonstration program was still unclear since many EV deployment details are not published yet by the cities. The authors also provided some recommendations to this demonstration effort, such as incentive options, enhanced monitoring and evaluation strategy, and intercity collaboration.

Based on the review on previous research on the policy and research of EVs in China, I found that most of the existing research looks at GHG emission comparison, with a few studies focusing on conventional pollutants such as Particulate Matter (PM), SO_2, NO_X, and Hydrocarbon (HC). None of the existing literature analyzes health impacts from the PM emission of EVs. There is no previous research that considers equity problems due to adoption of EVs in China. My work attempts to quantify these issues.

2.2 Vehicle Emissions

2.2.1 Emissions of Conventional Vehicles

In this research, emissions of CVs are estimated based on previous research findings and emissions standards adopted in China. European Union motor vehicle emission standards are designed to limit tailpipe emissions of new vehicles sold in European Union. These standards (or equivalent) are also adopted by developing countries such as China (Fung, He et al. 2010). In 2000 and 2004, European Union I (Euro I) and II motor vehicle emission standards were adopted nationwide in China, respectively. In 2005 and 2008, Beijing municipal government introduced Euro III and Euro IV vehicle emission standards, respectively. In 2007, Euro III vehicle emission standards were implemented nationwide (Hao, Hu et al. 2006). Currently, the vehicle fleets with different emission standards co-exist in China. In this research, I look at the emissions from new vehicles with Euro III and IV emission standards. In my sensitivity analysis, the acceptable limits of $PM_{2.5}$ in the emission standards are treated as base case value. Oliver et al. (2009) estimated in-use vehicle emissions in Beijing, China. They tested emissions from 58 light-duty passenger cars in 2007 and found that new vehicles were getting cleaner due to the tightening emissions standards in China; however, the actual on-road emissions of vehicles were much higher than certified limits because of an aging fleet.

He et al. (2010) analyzed characteristics of vehicle emissions in China by using portable emission measurement system. They inspected 40 gasoline vehicles, 92 diesel vehicles, and 20 rural vehicles in Beijing, Xi'an, and Shenzhen. These vehicles had different emission control technologies, including Euro 0, Euro I, Euro II, Euro III, and Euro IV. The on-road emissions factors for these vehicles were estimated and compared. Based on the on-road tests, emissions from some tested vehicles are larger than the thresholds dictated by emission standards. They suggested that the emissions from rural vehicles should be paid more attention due to poor emission control technologies.

Additionally, in 2010, the International Council on Clean Transportation (ICCT) assessed the vehicle emission control program in China and impacts of various policy options in the short- and long-term (between 2010 and 2030) (Fung, He et al. 2010). In this assessment, the ICCT presented quantitative analysis of vehicle emissions based on the China Fleet Model (CFM). The health risks and costs due to exposure to these emissions were estimated as well. This is the most comprehensive study to investigate short- and long-term policy options for vehicle emissions control in China.

2.2.2 Emissions of Electric Vehicles

A few studies and datasets are available to estimate emission factors from power plants and ultimately EVs. A global comprehensive dataset, Carbon Monitoring for Action (CARMA) (CARMA 2010) tracks yearly electricity generation and CO_2 emissions. These data include all of China's fossil, hydropower, and nuclear EGUs and presents electricity generation (MWh) and total emissions (tons) and emission factors (tons MWh^{-1}) in 2007. The National Aeronautics and Space Administration (NASA) Intercontinental Chemical Transport Experiment-Phase B (INTEX-B) (Center for Global and Regional Environmental Research 2010) dataset reports total emissions of conventional pollutants, including black carbon (BC), Carbon monoxide (CO), NO_X, $PM_{2.5}$, PM_{10}, SO_2, organic carbon aerosol (OC), and nonmethane volatile organic compounds (NMVOC) 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}).

CARMA database was built to provide timely and accurate information about carbon emissions from the power sector, which contribute 26% of global CO_2 emissions. The CARMA database covers more than 50,000 power plants, 20,000 companies, and 200,000 regions worldwide. To estimate CO_2 emissions from power plants, regression methods were employed to create CARMA database. They found that power generated, fuel sources, and combustion technologies contributed significantly to the regression model. The CARMA database includes many aggregation tools, so the database can be used for local, regional, national and international comparisons (Wheeler and Ummel 2008).

In 2006, NASA launched INTEX-B program. The INTEX-B is an integrated observational mission involving multiple partners. One of the objectives of INTEX-B was to evaluate transport of pollution from Asia to North America and measure regional air quality. The data are presented as total emissions (tons) in each 0.5×0.5 degree grid (Zhang, Streets et al. 2009).

Zhu et al. (2005) reviewed the development of power industry and 16 power grids interconnections in China. They concluded that the power plants in China were primarily coal-based and the emissions from power sector, such as SO_2, CO_2, and NO_X were the largest contributor to these pollutants emissions in China. In addition, they estimated potential benefits of power grid interconnections in China. For instance, through regional power grid interconnection, the pollutants emissions could be separated from the locations where the power is used. This emissions spreading might reduce pollutants emissions and human exposure to these emissions. Moreover, the aggregation of power grid could help to avoid the construction of small EGUs, which are usually associated with higher pollutants emissions.

Cherry et al. (2009) analyzed environmental impacts of e-bikes in China. CARMA and INTEX-B databases were utilized to calculate the regional electricity generation emission factors. In this research, energy use rate of standard e-bikes in China was estimated (1.8 kWh $(100\text{-km})^{-1}$).

Cherry (2009) conducted market analysis and environmental impacts for electric two-wheelers in India and Vietnam. In his study, the energy use rates of e-bikes are estimated. The e-bikes are classified into three classes: lower power, intermediate, and advanced. The energy use rate of lower power e-bikes, which the maximum speed is less than 30 km h^{-1}, is 1.8 kWh $(100\text{-km})^{-1}$. The lower power e-bikes are primarily used in China. The energy use rate of intermediate e-bikes, which the maximum speed is less than 45 km h^{-1}, is 2.3 kWh $(100\text{-km})^{-1}$. The energy use rate of advanced e-bikes, which the maximum speed is less than 55 km h^{-1}, is 3.1 kWh $(100\text{-km})^{-1}$. It is worthy of note that intermediate and advanced e-bikes are not widely manufactured in China, since the manufactures are inclined to develop slower and lighter e-bikes under the pressure of regulation.

The energy use rates of e-cars are usually an order larger than e-bikes. For example, the energy use rate of a BYD e6 (a Chinese brand EV) is at least 18 kWh $(100\text{-km})^{-1}$ (Green Car Congress 2009). The energy use rate of Nissan Leaf is approximately 21 kWh $(100\text{-km})^{-1}$ (Green Car Congress 2010). The energy use rates of EVs in France are about 25 kWh $(100\text{-km})^{-1}$ (Wang 2011).

2.2.3 Well-to-station Emissions

Well-to-station emissions include fossil energy extraction, refining, storage, and transportation processes. Previous energy life cycle research findings for CVs and EVs in China are utilized to estimate average well-to-station emissions. Wei and his colleagues

(2006) conducted comparative study on life cycle assessment for alternative vehicle fuels in China. In this research, the authors estimated life cycle emissions of conventional pollutants, including CO_2, CO, NO_X, SO_X, VOC, and PM, from gasoline vehicles and fuel cell vehicles. Di et al. (2007) estimated life cycle inventories for electricity generation in China. In this research, they linked one kWh of usable electricity in China in 2002 to the life cycle emissions of CO_2, CO, NO_X, SO_2, NMVOC, CH_4, PM and heavy metals from thermal power plants. Hu et al. (2008) conducted life cycle energy, environment, and economic assessment for biodiesel and conventional diesel fuels in China. In this research, the authors estimated proportions of pollutants (HC, CO, PM, CO_2, NO_X, SO_X) at various stages during the life cycle of conventional diesel fuel. These stages include crude oil extraction and transportation, crude oil refining, conventional diesel fuel transportation, and conventional diesel fuel use.

2.3 Intake Fraction

Bennett et al. (2002) first formally defined intake fraction (iF). It is simply the proportion of a pollutant emitted that is inhaled by people (Bennett, McKone et al. 2002; Marshall, Riley et al. 2003; Marshall and Nazaroff 2004; Marshall, Teoh et al. 2005; Zhou, Levy et al. 2006). Actually, this concept appeared in research literature over 16 years before Bennett's definition (Evans, Wolff et al. 2002; Greco, Wilson et al. 2007), and has been referred to by several other names. For instance, in 1986, Harrison et al. (1986) used exposure efficiency. The definition of exposure efficiency from Harrison is "the fraction of total production which is likely to reach people, or the ratio of human intake to the amount emitted". Smith (1988) referred to it as exposure factor and defined it as the fraction of total population exposure to total emissions. In another study, Smith (1993) referred to iF as exposure effectiveness. Jolliet and Crettaz (1997) used fate factor. Lai (2000) used inhalation transfer factor. Hertwich (2001) used potential intake. In general, iF and exposure efficiency are two major terms to define this concept (Evans, Wolff et al. 2002; Greco, Wilson et al. 2007). Michael et al. (2002) reviewed the uses of exposure evaluation for science and policy. They proposed several factors to guide the approaches for exposure assessment.

Stevens et al. (2007) calculated iF for the Mexico City Metropolitan Area using several different methods: a steady box model, a dynamic box model, a regression model, a particle composition model, and an atmospheric dispersion and chemistry model. They conclude that iFs calculated by multiple rapid-assessment models are meaningful, even with limited data.

2.3.1 One-compartment Model

The compartment model is one of the methods to estimate iF. A single compartment or a set of linked compartments could be used for compartment model (Evans, Wolff et al. 2002). In my research, a single compartment is employed for this modeling approach, since prior research for urban areas in the US (Marshall, Teoh et al. 2005) and Mexico

(Stevens, de Foy et al. 2007) suggests that the one-compartment model yields similar results as more detailed models.

The one-compartment model estimates concentrations based on a mass-balance, assuming that the air is well mixed over the city as a box. The square base of this box is city area *A* and the height of this box is *H*. The wind blows perpendicular to one side of the box at a constant velocity *u* and this wind moves clean air into the box and flushes pollution out. The volume of this box is $u \times H \times \sqrt{A}$ per unit of time as wind moves through the box. In this box, the emission rate of the pollutant is assumed as *E*. Under these conditions, the concentration of pollutant *C* in this box is:

$$C = \frac{E}{uH\sqrt{A}} \quad (2.1)$$

Assuming *B* is breathing rate and *P* is population is this area, the intake of the pollutant *I* is:

$$I = C \times B \times P \quad (2.2)$$

Intake fraction is defined as the proportion of a pollutant emitted that is inhaled by people. Thus the iF can be estimated by using equation 2.3:

$$iF_{one-compartment} = \frac{Total\_Intake}{Total\_Emission} = \frac{I}{E} = \frac{C \times B \times P}{E} = \frac{E \times B \times P}{E \times u \times H \times \sqrt{A}} = \frac{BP}{uH\sqrt{A}} \quad (2.3)$$

It is worth mentioning that one-compartment model is not exactly identical to box model. The box model assumes that the air pollutants are uniformly distributed in the box without considering advection and diffusion (Carella and Mudu 2009).

Luo et al. (2010) estimated the iF of non-reactive emissions from mobile sources in Hong Kong by using box model. They found that when the ambient concentration of a pollutant was used to calculate urban iF, the influence of upwind transport of pollutants cannot be ignored. In this study, one-compartment model is used to estimate iFs for emissions from urban mobile source. Apte et al. (2012) estimated iF for distributed ground-level emissions in 3646 global cities, in which they defined an urban area with a population over 100,000 as a “city”. In this study, they provided the iF estimate for Beijing, China, as 73 ppm (parts per million). This estimation is similar to the result in this research.

2.3.2 Regression Model

Zhou et al. (2003) conducted a case study about estimating iF of power plant emissions in Beijing, China using a simplified regression approach. The CALPUFF model was utilized for this research. CALPUFF is an advanced modeling system for the simulation of air pollution dispersion. This study presented the approach to calculating iF of power plant emissions by using the CALPUFF model in China. The iF estimates from this study were an order of magnitude larger than the US estimates. The iF of primary fine particles was on the order of 10^{-5}. The iFs of SO_2, SO_4, and NO_3 are on the order of 10^{-6}.

Li and Hao (2003) developed a regression model for iF of primary and secondary PM from power plants in Hunan province, China. In total, 17 power plants and 24 stacks were analyzed. The CALPUFF model was used to simulate ambient concentration of pollutants. The population database was at the county level. They found that stack height of power plants and aggregate population contributed significantly to intake in the regression model.

Zhou et al. (2006) evaluated the impacts of emission source location on iF at 29 power plants in China. Annual average iFs at each site were estimated. The CALPUFF model was used to simulate the emission concentration of pollutants. In the regression analysis, iFs are the dependent variables; meteorological data and population within different radii (100km, 500km, 1,000km, and over 1,000km) of the power plants are independent variables. They found that population variable can predict iF from criteria pollutants emitted from power plants. The R^2 values were from 0.86 to 0.95 across pollutants. They concluded that the iF of power plant emissions in China can be estimated by simple regression model. This regression model is used in this study to estimate iFs of power plants.

2.4 Health Impacts

Air pollution has harmful impacts on public health. Outdoor air pollution is blamed for approximately 300,000 premature deaths in China each year (Millman, Tang et al. 2008). Among air pollutants, particulate matter, especially particulate matter with aerodynamic diameter smaller than 2.5 μm ($PM_{2.5}$), have the most damaging to public health (Zhang, Song et al. 2007). $PM_{2.5}$, also called fine particle, is considered to be associated with higher risk of mortality, since fine particles can be breathed more deeply into the lungs and are more toxic than larger particles (Dockery, Pope et al. 1993). A series of studies concerning air pollution impacts on public health were conducted beginning in the 1990s in China (Bingheng, Haidong et al. 2011). The findings from these studies showed the harmful impacts on human health from air pollution, such as excess mortality risk. While there are many different types of pollution emitted from CVs, buses and EVs, this research 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 (Health Effects Institute 2004). In this research, I only look at the mortality risk under long-term exposure of $PM_{2.5}$. Since when we conduct analysis on annual mortality, the main impacts of air pollution, including acute effects, are associated with long-term exposure (Boldo, Medina et al. 2006).

Pope et al. (2002) assessed the relationship between long-term exposure to $PM_{2.5}$ and all-cause, lung cancer, and cardiopulmonary mortality. In this study, the vital status and cause of death data were collected by the ACS. This dataset was part of the Cancer Prevention II study conducted by ACS, which included approximately 1.2 million adults in 1982. The findings of this research were that each 10 μg m^{-3} increases in the concentration of $PM_{2.5}$ could be associated with 4%, 6%, and 8% increase in all-cause mortality, cardiopulmonary mortality, and lung cancer mortality respectively.

Levy et al. (2009) evaluated efficiency-equality tradeoffs for controlling emissions from urban mobile sources. In this study, they concluded research findings about impacts of $PM_{2.5}$ on public health. They found that each 10 μg m^{-3} increase in the concentration of $PM_{2.5}$ could be related to 10% increases in all-cause mortality. They also concluded the lower-bound and upper-bound of this increasing rate as 3% and 20% per 10 μg m^{-3} increase in the concentration of $PM_{2.5}$.

Xie and his colleagues (2011) conducted analysis about the human health impact of exposure to airborne particulate matter in Pearl River Delta, China. They estimated that, for long-term exposure (over 30 years), each 10 μg m^{-3} increase in the concentration of $PM_{2.5}$ resulted in an increase in all-cause annual mortality rate of 7.6%. Yang et al. conducted a study of $PM_{2.5}$ related mortality in Guangzhou, China (Yang, Peng et al. 2012). They found that each 10 μg m^{-3} increase in the concentration of $PM_{2.5}$ could be related to 0.9%, 1.22%, and 0.97% increases in all-cause mortality, cardiovascular mortality, and respiratory mortality respectively.

2.5 Equity

Currently, sustainable development is one of crucial consideration on the international political agenda. The scholars suggest that it is the time for the governments at different levels to learn the principles and practical approaches used to evaluate sustainability, environmental justice, and equity (Agyeman, Bullard et al. 2002). Based on the report of Our Common Future, also known as the Brundtland Report, published by United Nations World Commission on Environment and Development (WCED) in 1987, sustainable development can be defined as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED 1987). Sustainable development consists of three components: economic development, social equity, and environmental protection. Sustainable development is the development that guarantees intergenerational equity through simultaneously addressing these three components (WHO 2005).

In this research, I mainly look at equity problems due to pollution exposure by adopting EVs in China since there are few studies on this topic. Equity is an ethical concept that qualifies fairness (Braveman and Gruskin 2003; Povlsen, Borup et al. 2011). As defined by Whitehead, equity is a "moral and ethical dimension and refer to differences which are unnecessary and avoidable, and are also considered unfair and unjust" (Whitehead 1992; Povlsen, Borup et al. 2011). Therefore, equity analysis should include three major determinants: whether the differences are unnecessary, avoidable, and remediable (Levy, Chemerynski et al. 2006).

In order to evaluate the policies in terms of equity, we have to measure equity. Currently, there are several metrics used to measure equity. For example, inequality metrics, social gradient, social welfare functions, cost-benefit analysis, and incidence analysis are primary methods. The concepts of these measure approaches are introduced in the following sections.

(1) Inequality metrics

Equality is generally described as "uniformity in rights or experiences despite differences in resources, capabilities and backgrounds" (Levy, Chemerynski et al. 2006). Inequality can be measure by several indicators, such as Gini index, Atkinson index, Theil index, and coefficient of variation (Levy, Wilson et al. 2007). Inequality metrics are primarily used to measure the degree of income inequality in a population. They are also employed in measuring the degree of health inequality (Levy, Chemerynski et al. 2006).

(2) Social gradient

The social gradient metric was first employed to evaluate the relationship between occupation and chronic disease in the 1974 (Reid, Hamilton et al. 1974). It has been widely used to measure whether a pollution source has disproportionate impacts on low socioeconomic position individuals. Pearce et al. (2006) examined whether there is a social gradient related to exposure to air pollution in Christchurch, New Zealand (Jamie, Simon et al. 2006). They demonstrated that different social groups were exposed to different level of air pollution and lower socioeconomic communities were exposed to higher level of air pollution. They also found that the groups who produced a large portion of air pollution were different from the groups who suffer from high level of air pollution.

(3) Social welfare function

Social welfare function is defined as “a method for obtaining group preferences, given the preferences of the individual members of the group” (Goodman and Markowitz 1952). Social welfare function is a framework to rank policies as function of individual utilities (Pattanaik 1968).

(4) Cost-benefit analysis

Cost-benefit analysis is used to compare costs and benefits of a project or policy. In general, cost-benefit analysis can be conducted by three steps. Firstly, we have to define the cost and benefit elements for the project or policy. Then, we have to convert the costs and benefits in monetary term. Finally, we have to compare the benefits with the costs to make adoption recommendation of the proposed project or policy (Bootman, Rowland et al. 1979). There are ways to apply this approach to subgroups, though cost-benefit analysis is criticized for lost resolution of impacts.

(5) Incidence analysis

Incidence analysis is traditionally used to study tax burden of a policy change as individual income increases (Graetz 1975). It has also been employed to examine environmental policies recently.

By using the metrics introduced above, many studies were conducted to measure equity problems concerning pollution exposure and health risk. For example, Levy et al. (2002) estimated the distribution of health benefits owing to emission control strategies at five power plants in the Washington, DC, area. They compared primary and secondary PM related mortality for the pre-control and post-control scenarios and found that half of the health benefits accrued among the 25% of the population with lower education level (below high school). Touche et al. (2005) also examined inequity involving the locations and emissions of power plants in Texas. They suggested that the power plants using more hazardous fossil fuel were likely to be constructed in the lower socioeconomic communities.

Levy and his colleagues (2007) evaluated the efficiency and equity implications of power plant air pollution control strategies in the United States. They associated $PM_{2.5}$ concentration with mortality risk for each pollution control scenario. The spatial inequality of health risk was estimated by Atkinson index and other metrics. This research demonstrated an approach for quantifying equity implications of air pollution control strategies. Levy et al. (2009) evaluated efficiency-equality tradeoffs for mobile source control strategies in Boston, Massachusetts. They highlighted the impacts of $PM_{2.5}$ from urban mobile source and linked $PM_{2.5}$ concentration to mortality risk. The Atkinson index was primarily used to quantify changes in the distribution of mortality risk. Atkinson index uses inequality aversion parameter to evaluate inequality concerns. It is useful to find which results of allocations contributed most to the inequality. Levy's study provided policy makers an approach to select the optimal air pollution strategies by considering efficiency-equality tradeoffs.

Brajer et al. (2010) explored environmental equity in China. They associated China's air pollution with urban income inequality problems. The urban income inequality was measured by indicators like Gini coefficient and Theil's L and T indices from 1995 to 2004. Then pollution-adjusted incomes were used to recalculate income inequality. They suggested that, in a developing country, improving welfare distribution can coexist with environmental protection.

Schoolman and Ma (2012) quantified environmental inequality due to exposure to pollution in Jiangsu Province, China. Regression approaches were employed for this analysis. By analyzing the locations and emissions of pollution related facilities in Jiangsu, they found that the townships with higher proportion of rural migrants, who have no *Hukou* in Jiangsu, were likely to be exposed to high level of air and water pollution. They also examined other low socioeconomic status population such as the employers in "dirty and hard" industry in Jiangsu and found similar conclusions.

CHAPTER III

METHODS

My investigation follows a conventional risk assessment framework, but based on pollutant intake (mass inhaled) rather than concentration. Methods are summarized next, and key steps are in Figure 3.1. First, emissions and iFs are estimated to identify population intake. Then, by linking population intake to toxicity of the pollutants, potential health risk could be obtained. This research presents emissions for several pollutants, but focuses 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 (Muller and Mendelsohn 2007), because primary $PM_{2.5}$ is relatively non-reactive, thereby simplifying the requirements for fate and transport modeling, and because peer-reviewed literature provides the information needed for analyses here.

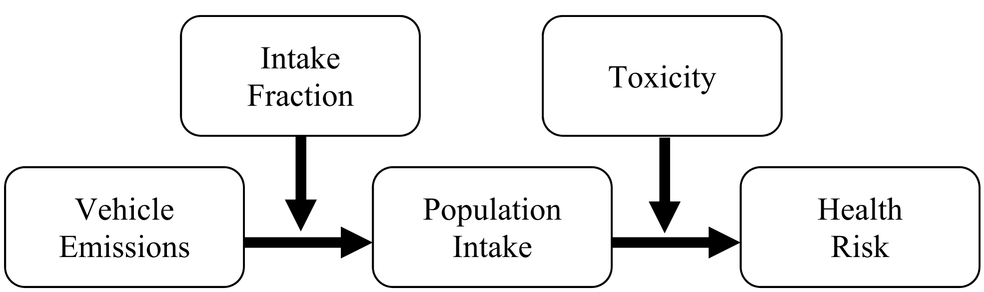


Figure 3.1. Summary of intake-based health risk assessment employed here.

Secondary $PM_{2.5}$, also with important health effects, is explored briefly in the Chapter V Discussion, but is not a focus of this research. My health risk assessment will only include combustion emissions, though the relative magnitude of fuel life cycle emissions is discussed in Chapter IV. My investigation considers five vehicle technologies and 34 vehicle-use locations covering all of China's urbanized provinces. This research estimates exposure from emissions generated at ~1,000 fossil EGU's. My primary results employ point estimates for input parameters. Then Monte Carlo (MC) simulation is conducted to identify the sensitivity of the results to variability and uncertainty. In Chapter IV, I illustrate an example of the policy significance of the research by considering a deployment scenario for one city (Shanghai). I examined socioeconomic status differences in exposures and health impacts attributable to urban use of EVs.

3.1 Emission

In this study, I focus on station-to-wheel emissions and their health impacts. I also present fuel well-to-station emissions for reference. Well-to-station emissions are released in the processes of coal mining and processing for EVs and oil extraction and refining for CVs. Here, a station is a fueling station (CV) or an electric charging station (EV). Health impacts from well-to-station emissions are not estimated since location and population information are unavailable for those activities.

For CVs, combustion emission factors are taken from literature and emission standards (Xie, Song et al. 2006; Meszler 2007; Cherry, Weinert et al. 2009; Oliver, Gallagher et al. 2009; Hao, Yu et al. 2010; He, Yao et al. 2010). For EVs, EGU emission factors are estimated based on electricity generation rates (CARMA 2010) and modeled total EGU emissions (Center for Global and Regional Environmental Research 2010). Power-sector EGU emission factors vary among regional electricity grids in China (Zhu, Zheng et al. 2005), owing to differences in fuels (fossil versus renewable), fuel quality, combustion conditions, and emission controls. My EV emission factors include loss from in-plant use and transmission. Average well-to-station emissions are taken from literature for CVs and EVs (Wei, Shen et al. 2006; Di, Nie et al. 2007; Hu, Tan et al. 2008).

3.1.1 Electricity Vehicle Emission Factor (Station-to-Wheel)

To estimate EV emission factors, two metrics are identified. First, electricity generation and total emissions are used to estimate emission intensities of the power sector. These values are estimated by regional power sector, using the CARMA database (CARMA 2010) to track yearly electricity generation and CO2 emissions. The NASA INTEX-B (Center for Global and Regional Environmental Research 2010) 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 and in-plant using loss rate, 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 emission factors from EVs (g km^{-1}). In the process of estimating EV 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 $(100\text{-km})^{-1}$) and a compact e-car (average energy efficiency 18 kWh $(100\text{-km})^{-1}$) (Cherry, Weinert et al. 2009; Green Car Congress 2009). 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, approximately 14% transmission and in-plant use loss in China is taken into account (Lawrence Berkeley National Laboratory 2004). The calculation steps are shown in Figure 3.2 (flow chart). The average emission factors of these pollutants are estimated for 15 relatively independent power grids in China as show in Figure 3.3 (Zhu, Zheng et al. 2005). For sake of this analysis, I assume that cities are served by EGUs in the grid in which they are located. Data are unavailable for Tibet power grid.

To illustrate the case of Shanghai belonging to East China power grid; in 2007, the total amount of $PM_{2.5}$ emitted and total electricity generated by EGUs in the East China power grid are 219,261 metric tons and 591,515,249 MWh, respectively. An emission rate of $PM_{2.5}$ in the East China power grid can be obtained by dividing total amount of $PM_{2.5}$ emitted by total electricity generated in this grid. After unit conversion, the emission rate of $PM_{2.5}$ in East China power gird is 0.37 g kWh^{-1}. If 1.8 kWh $(100\text{-km})^{-1}$ was used as the energy use rate of e-bike and by considering 14% in-plant and transmission loss rate in China, the total energy use rate of e-bike is 2.1 kWh $(100\text{-km})^{-1}$. Multiplying this total energy use rate of e-bike by the emission rate of $PM_{2.5}$ in East China power grid, the $PM_{2.5}$ emission factor of e-bike in Shanghai is 0.78 g $(100\text{-km})^{-1}$.

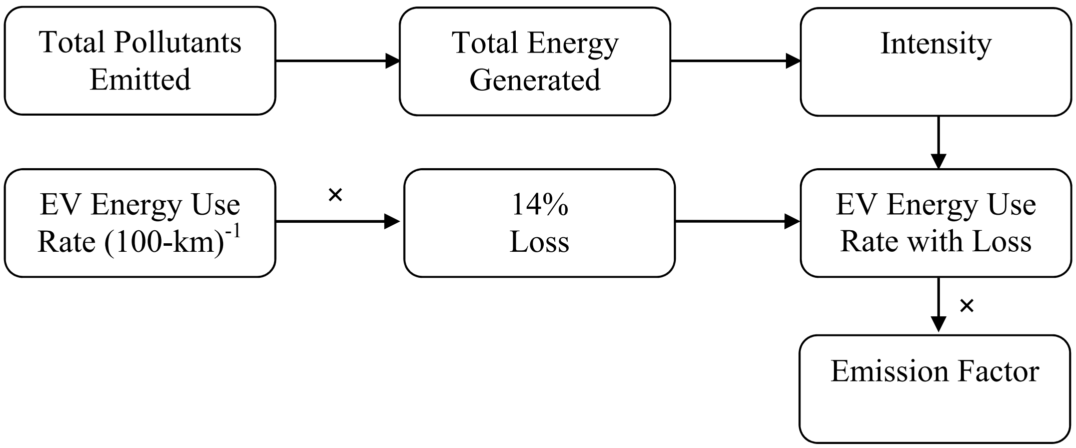


Figure 3.2. Calculating emission factors of electric vehicle. "Loss" represents the transmission and in-plant use loss of electricity generated in China.

Figure 3.3. Power grid networks in China (Zhu, Zheng et al. 2005).

3.2 Intake Fraction

Intake fraction is defined as the proportion of a pollutant emitted that is inhaled by people (Bennett, McKone et al. 2002). By definition, iF can be estimated based on the formula below:

$$iF = \frac{Total\_Intake}{Total\_Emissions} \quad (3.1)$$

The expectation is that a pollution source in a densely populated urban area has a higher proportion of the emitted pollutants inhaled by the population. On the contrary, pollution emitted from a remote source in a rural area will have a smaller portion of the pollution inhaled. A few previous investigations have addressed this subject. Marshall et al. (2005) used three methods to estimate iF for vehicle tailpipe emissions in US urban areas. The results presented in their work can be used to estimate intake of emissions of non-reactive or slowly reacting pollutants, particularly in urban air sheds. Zhou et al. (2006) presented an analysis on evaluating the influence of EGU location on population exposure in China. Their findings demonstrate that iF for EGUs in China can be calculated via applying regression models, with most iF explained by population surrounding EGUs. Cherry (2007) applied the relevant methods into two large cities in China – Kunming and Shanghai to compare iFs between urban source emissions (tailpipes) and remote emissions (EGUs).

3.2.1 One-compartment Model for Urban iF

The one-compartment model can be carried out by two primary approaches: a steady-state model and a dynamic model. For the steady-state model, it assumes that emissions keep constant over a given day in the compartment. The emissions entering and leaving the compartment are always equal in steady-state model. The steady-state model may cause upwards bias because of the assumptions that emissions equally enter and leave the compartment evenly during a 24-hour period, when there could be residual emission concentration from a previous time period. On the contrary, the temporal changes of air system are considered by the dynamic model. However, the dynamic model may cause downwards bias, because it assumes that emissions at upper layer of compartment will never re-enter the compartment as the mixing height of air system decreases (Stevens, de Foy et al. 2007).

In this research, the dynamic one-compartment model to estimate iF of emissions in urban areas is employed. This model is expressed in equation 3.2.

$$iF_{compartment} = \frac{BP}{uH\sqrt{A}} \quad (3.2)$$

Where, B is the population average breathing rate (m^3 person-s^{-1}) 14.5 based on metabolic activity studies (Layton 1993); 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). A merit of the dynamic one-compartment model is fine-scale temporal resolution; a weakness is lack of information about within-urban spatial variability. 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 (NBS 2010). 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 dataset provides hourly estimates at 0.5°-0.667° spatial resolution; this one-compartment model simulates three years of air dispersion, using 0.1-minute time steps. To avoid discontinuities in modeled meteorological data, I linearly interpolated the hourly raw data to 0.1-minute increments. For example, the urban population in Shanghai is 11,969,400 and the urban area is 2,649 km^2. The harmonic mean product of mix height and wind speed is 772.12 m^2s^{-1}. I use 14.5 $m^3person^{-1}s^{-1}$ as average population breathing rate in Shanghai. Plug these numbers back to the formula (3.2) and obtain urban iF in Shanghai: 50.6 ppm (intake per million). Harmonic mean is used because it is less biased and closer to the true average of the population by discounting the large outliers.

Emissions from outside of the urban area are not considered in one-compartment model (Stevens, de Foy et al. 2007). Therefore, the results calculated by one-compartment model in this research are intraurban iFs. Previous studies suggest that intraurban iFs estimated by one-compartment model are accurate within a factor of ~2 or better for primary pollutants (Marshall, Riley et al. 2003; Marshall, Teoh et al. 2005; Stevens, de Foy et al. 2007; Apte, Bombrun et al. 2012). 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, my findings should be considered suggestive rather than definitive.

3.2.2 Regression Model for EGUs iF

I estimate iF of EGU emissions based on previous multivariate regression analyses of many EGUs in China (Zhou, Levy et al. 2006). Under most circumstances, the closer the population lives to the EGU, the more exposure they have to emissions from that EGU, estimated by a simple regression model. The coefficients of regression model are listed in Table 3.1.

The coefficients of regression model and population variables are applied to estimate iF from EGU emissions using the following relationships:

$$iF_j^k = \sum_{i=1}^{n} \alpha_i^k P_i \quad (3.3)$$

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 3.1.

The population living in the radii of 100km, 500km, 1,000km, and farther than 1,000km from ~1,000 fossil EGUs in China are estimated using ArcGIS, based on the EGUs location from the CARMA database and county-level Chinese population data from 2000 census dataset (All China Marketing Research Co. Ltd. 2003). 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. (2006) only predicted the coefficient for iF of PM_1 and PM_3 based on their atmospheric dispersion modeling results. I interpolate the iF calculated from PM_1 and PM_3 relationships to estimate $PM_{2.5}$ iF. To illustrate, take Shanghai Gaoqiao power plant as an example, the populations within three buffer zones of this EGU are collected. The calculations of iF for $PM_{2.5}$ are presented in Table 3.2. First, iF in each radius is estimated for PM_1 and PM_3. By summing up iFs in different radii, total iF is obtained for Gaoqiao power plant in Shanghai. Intake fraction of $PM_{2.5}$ is acquired by interpolation. For primary $PM_{2.5}$ emitted from Gaoqiao power plant, ~80% and ~40% emissions are inhaled by the population within 1,000 km and 500 km respectively. After obtaining iFs for each EGU, I aggregate the EGUs for each power grid and the iF for each power grid are weighted by the energy generated by each EGU in specific power grid.

Table 3.1. Regression Coefficient for Electricity Generating Unit iF Estimation (Zhou, Levy et al. 2006).

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

Table 3.2. Calculation of $PM_{2.5}$ Intake Fraction for Shanghai Gaoqiao Power Plant.

Item	Variable	<=100km	100km to 500 km	500km to 1000km	>1000km	Total
1	Population (in million)	6.7	124.4	448.1	721.0	
2	Coefficient (PM_1)	1.3E-7	2.0E-8	9.8E-9	2.9E-9	
3	Coefficient (PM_3)	1.2E-7	1.3E-8	4.5E-9	1.5E-9	
1×2	Intake Fraction (PM_1)	8.7E-7	2.5E-6	4.4E-6	2.1E-6	9.9E-6
1×3	Intake Fraction (PM_3)	8.0E-7	1.6E-6	2.0E-6	1.1E-6	5.5E-6
Interpolate	Intake Fraction ($PM_{2.5}$)	8.2E-7	1.8E-6	2.6E-6	1.4E-6	6.6E-6
Proportion of total intake in East China grid ($PM_{2.5}$)		2.5E-9	5.4E-9	7.8E-9	4.2E-9	2.0E-8

3.3 Health Impacts Analysis

While iF is an important indicator of health impacts, assuming each vehicle has similar emission rates, a full health analysis is required to extend iF results to robust policy development. There are two main factors that influence health impacts. First, emission rates are important as a baseline of comparison. Second, exposure to those emissions is important. For most environmental comparisons between transportation modes, comparing emission rates is acceptable, because the location of the pollution source is the same and thus the iF is also the same. However, EVs are unique because they have different emission source and iFs compared to CVs.

While there are many different types of pollution emitted from CVs, buses, and EVs, this research 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 (Health Effects Institute 2004). 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 $PM_{2.5}$ (Marshall and Nazaroff 2002). In addition, in this research, I mainly look at the death risk under long-term exposure of $PM_{2.5}$, since when we analyze annual mortality, the main impacts of air pollution, including acute effects, are associated with long-term exposure (Boldo, Medina et al. 2006). The value of the *unit dose*, or the total amount of $PM_{2.5}$

inhaled for each case of all-cause mortality, is estimated from this ACS cohort (Pope, Burnett et al. 2002). Their research concludes that, with each 10 μg 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 (1,000 people)$^{-1}$ year^{-1} in 2009 (CIA 2009). Therefore, in China, a 4% increase in the death rate is 0.28 deaths (1,000 people)$^{-1}$ year^{-1}. Assuming that breathing rate is 14.5 m^3 person^{-1} day^{-1} - namely 5292.5 m^3 person^{-1} year^{-1}, exposure to 10 μg 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 one-year exposure period.

3.4 Sensitivity Analysis

The sensitivity analysis attempts to quantify the uncertainty in the outputs of the intake-based health risk assessment by considering the uncertainty in the inputs in this assessment framework. The purpose of the sensitivity analysis is to test the robustness of the results and make conclusions more credible. MC simulation is employed to conduct this sensitivity analysis. The concept of MC simulation is to randomly generate sets of input variables, where the input variables are assigned specific probability distributions. Then the solution is estimated by running a large number simulations (Rüdisüli, Schildhauer et al. 2012). In this research, a transport mode shift scenario is designed. I assume a large shift from CVs to EVs (perhaps through a major policy intervention). Specifically, I assume 10^{10} vehicle kilometers traveled by CVs are substituted by EVs (e.g., 10^6 vehicles, each traveling 10^4 km y^{-1}). The MC simulation is conducted to simulate $PM_{2.5}$ intake-based health risk assessment for all 34 cities. A large number of runs of MC simulation are carried out by two approaches. In one approach, 10,000 MC simulations are carried out with the number of simulations per city proportional to its population. The purpose of this approach is to allocate more simulations to the cities with large population than the cities with small population. The other approach is 1,000 simulations are run for each city and the average excess deaths are weighted by population in each city. My MC simulation consists of four steps:

(1) ***Define the input variables***

In this step, the input variables are determined based on the flow chart shown in Figure 3.2. The input variables include energy efficiency of EVs, $PM_{2.5}$ emission factors, iFs, load factors, and dose-response.

(2) ***Generate input variables randomly from a probability distribution***

The distribution type and boundaries for each input variable depend on observations from peer reviewed literature and my professional judgment. The details are shown in Table 3.3. In MC simulation, the input variables, such as energy efficiency of EVs, $PM_{2.5}$ emission factors of gasoline car and diesel bus, iFs of CVs, and dose response, are given triangular distributions. The triangular distribution is often used as a subjective judgment of uncertainty for a variable, which there is limited sample data. It is based on lower bound, upper bound, and modal value for this variable (Frey and Cullen 1995). The input factors, such as $PM_{2.5}$ emission factors of diesel car and iFs of EVs are assigned normal distributions based on previous research findings. The load factors of e-car and CVs are assigned uniform distributions. The uniform distribution is used as a subjective description of a variable for which we can only estimate the lower bound and upper bound for this variable (Frey and Cullen 1995).

(3) *Perform a deterministic computation on the inputs*

The intake-based health risk assessment could be described mathematically as shown in equation 3.4. For EVs, emission factors are generated by dividing power grid emission intensities listed in Table 3.3 by energy efficiencies of e-cars and e-bikes. By randomly generating sets of inputs, health risks (excess death) for each city can be calculated.

$$\textit{Excess Death} = (\textit{Emission Factor} \times \textit{iF} \times \textit{Dose Response}) / \textit{Load Factor} \quad (3.4)$$

(4) *Aggregate the results*

In this step, the results from MC simulation are aggregated to obtain the approximation of excess deaths after switching from CVs to EVs for each city. Standard deviations are also provided to look at how much variation exists from the mean value of excess deaths.

Table 3.3. 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 $(100\text{-km})^{-1}$
	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 (Ni 2011) and upper bound (Cherry, Weinert et al. 2009); E-car energy efficiency source: lower bound (Liu, Wu et al. 2011) and upper bound (Wang 2011).
2. Gasoline car $PM_{2.5}$ emission factor: lower bound (Fung, He et al. 2010) and upper bound (Oliver, Gallagher et al. 2009); diesel car $PM_{2.5}$ emission factor (He, Yao et al. 2010); diesel bus $PM_{2.5}$ emission factor: lower bound (Yan and Crookes 2010) and upper bound (Wang, Westerdahl et al. 2011).
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 (Zhou, Levy et al. 2006).
6. The distribution of intake fraction of CVs is based on: (Zhou, Fu et al. 2010).
7. Passenger car load factor source: lower bound (Heidelberg 2008) and upper bound (Lin, Mao et al. 2006). Bus load factor source: (Yang, Yu et al. 2007).
8. Dose response source (Pope, Burnett et al. 2002; Heidelberg 2008; Levy, Greco et al. 2009; Zhou, Fu et al. 2010; Xie, Liu et al. 2011). Percentage increase in mortality rate per 10 μg m^{-3} increase in $PM_{2.5}$.

3.5 Equity Analysis

To explore the equality and equity concerns caused by EVs adoption, three quantitative analyses are conducted. I start by calculating the location of EGU's relative to urban areas where EVs are located. For each power grid, I consider the per capita gross regional product (CGRP) as an indicator of average individual income in the county to evaluate if EGU's are located in counties that have much lower CGRP than the cities that rely on the electricity produced.

EGU location is important, but the incidence of emission impacts on health is more important. Assuming most EV's will be adopted in urban areas first, it is important to understand the urban/rural equality of impacts. To extend this further, I consider the average income disparity between urban/rural counties as an indicator of fairness of impacts. To do this, I first calculate what the proportion of air pollution from EGUs that will be inhaled by rural versus urban population. In this step, I attempt to find out the population who will intake the primary $PM_{2.5}$ emissions from EGUs in urban and rural areas. The intake calculations in section 3.2.2 are repeated, but distinguishing urban versus rural intakes using the population in China's 660 classified cities (NBS 2010). The portion of emissions from EGUs inhaled by urban and rural population is estimated for each power grid in China.

Urban and rural intake is a proxy for opportunities and income. Using county-level CGRP, one can directly evaluate the relationship between exposure and income. In the third approach, exposure is compared to the exposure and income of the city where the EV is operated. A county could have “low/high exposure” meaning that the exposure (defined as total intake in the county) is lower/higher for that county than the city where the EV is operated. Similarly, the county could have “low/high income” meaning that the income (defined by CGRP) is lower/higher for that county than the city income. From this categorization, population exposure to primary $PM_{2.5}$ emissions is classified into four groups to aid in equity analysis: low income and low exposure, low income and high exposure, high income and low exposure, and high income and high exposure. To do estimate low/high exposure/income, EGU iFs within different radii (100 km, 100-500 km, 500-1,000 km, and >1,000 km) are estimated for each EGU by regression method introduced in session 3.2.2. The counties within these radii are identified for each EGU. I then assign EGU iFs in different radii of EGUs to those counties located in corresponding radius. From this approach, I can apply a total exposure value to each county in China (from EGU’s in a specific grid) that would result from the operation of an EV in a particular city. So, operating an EV and producing emissions from one city would result in emissions from several power plants in a grid that emit pollution across China and are ultimately inhaled by all counties. The exposure of emissions produced from the EV’s in that city can be allocated to each county based on their estimated iFs. Subsequently, case studies are conducted individually for each of 34 cities. In the case studies, I assume that 10^{10} vehicle kilometers traveled by CVs are substituted by e-cars in each city. Then primary $PM_{2.5}$ emissions from the corresponding power grid can be calculated. Multiplying primary $PM_{2.5}$ emissions by EGU iFs of counties, exposure to primary $PM_{2.5}$ emissions of counties can be estimated for this shift. This approach is useful to evaluate inequality concerns that if CVs are replaced in urban area, what will happen to the distribution of pollutant exposure across China due to this shift. The basis of this analysis hinges on the reasonable assumption of the one-compartment iF model that almost all urban source emissions are inhaled in the air shed of the urban area (so all exposure is experienced by residents with the same CGRP as the city). The ultimate goal of this approach is to analyze the degree of exposure inequality taking into account the income and pollutant exposure factors. In this approach, 2000 CGRP data at county level (All China Marketing Research Co. Ltd. 2003)are used as to estimate average income. Though these data are old, they are the most recent publically available disaggregate census data. The 2010 census data are not released in this format yet.

Several inequality/inequity metrics were introduced in section 2.5 and are common methods for evaluating distributional equity between alternatives. In this analysis, I focus on evaluating equity implications of EVs, but stop short of comparing them with the equity implications of CV emissions. This aggregate iF-based equity approach does not consider intra-urban distributional equity or the effects of exposure in microenvironments, where roadside emissions generally have higher impacts on the poor than the generally wealthier car-driving population (Han and Naeher 2006).

CHAPTER IV

RESULTS

4.1 Emission Factor

Emission factors vary by vehicle, fuel, and region. This research focuses on station-to-wheel emission factors, but also reports average well-to-station emissions in this section. In Table 4.1, the midpoint emission factors of EVs and CVs are provided. Figure 4.1 compares emissions between vehicle types for four pollutants. Considering station-to-wheel emission factors in Table 4.1, e-cars emit more NO_X, SO_2, PM, and CO_2 comparing with gasoline car, diesel car, motorcycle, and bus. The CO emissions of e-cars are lower than gasoline cars, diesel cars, motorcycles, and buses. The HC emissions of e-cars are similar to gasoline cars, diesel cars, and buses. E-bike has smallest emissions in terms of CO, NO_X, HC, and CO_2. However, SO_2 emissions of e-bike are larger than CVs. E-bike may emit more PM than gasoline cars, depending on the power grid the e-bike is recharged in. In addition, the HC emissions from motorcycle are significantly higher than all other vehicles.

Table 4.1. 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 (Meszler 2007).
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} (Xie, Song et al. 2006; Cherry, Weinert et al. 2009; Hao, Yu et al. 2010) 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, I employ 0.404 as energy conversion factor, meaning generation of 1 kWh electricity will require 0.404 kg standard coal (Xiaohua and Zhenming 1997).

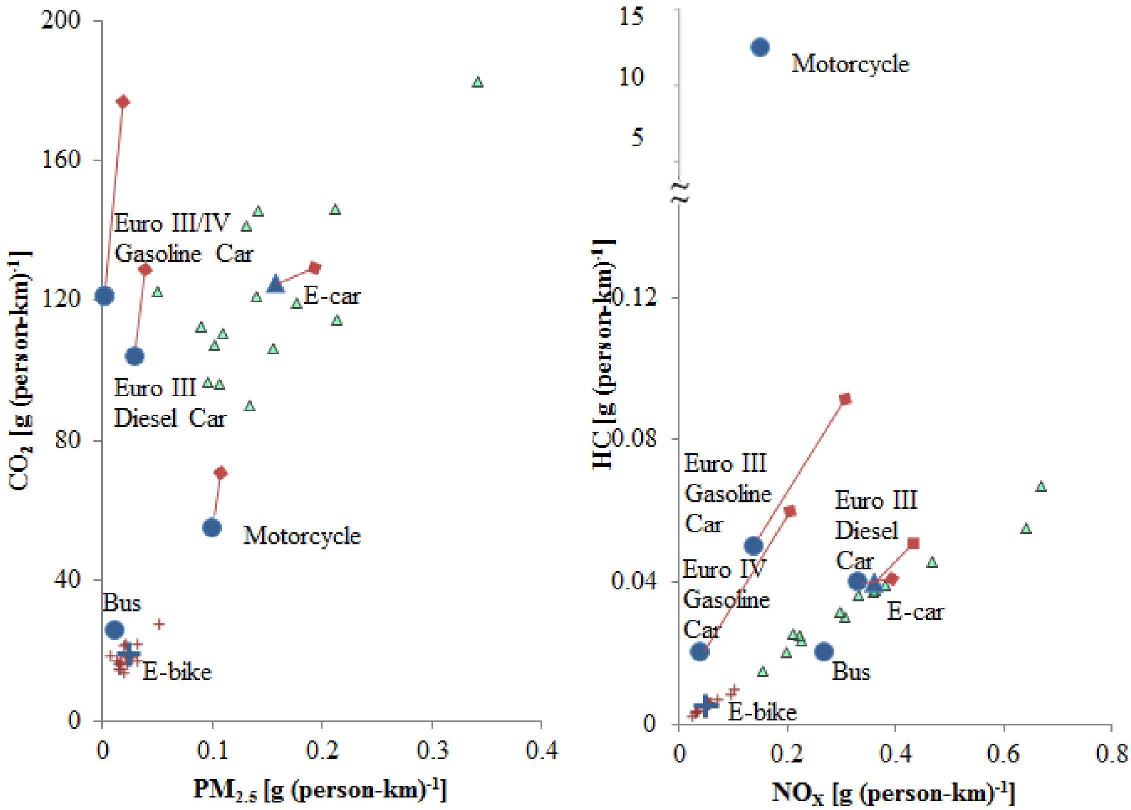


Figure 4.1. Emission factors of EVs and CVs (g person-km^{-1}) for four pollutants where each axis represents a unique pollutant. Large circle icons indicate CVs. Small non-circle icons indicate EVs (e-car: triangle-icon; e-bike: plus-icon), with emission factors that vary among the 15 electricity grids. Large non-circle icons indicate the arithmetic mean of the 15 values per EV. Lines from icons indicate well-to-station emissions where diamond endpoints 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.

4.1.1 EGU station-to-wheel emission rates

There are 16 relatively independent power grids in China. In this research, 15 power grids (excluding Tibet) are considered, and it is assumed that cities in the same grid will share power from all EGUs proportional to the plant's capacity. This is a necessary simplifying assumption due to the aggregate nature of the data. However, it is worth noting that this simplification may neglect the impacts of marginal emissions.

The CARMA database (CARMA 2010) includes location information for most EGUs in China, including all known power generating sources. Several EGUs with unknown locations were added manually based on the nearest town. ArcGIS was used to distribute EGUs throughout China. The power generation and CO_2 emissions in 2007, by power grid, are reported in Table 4.2. Regional conventional pollution emission are obtained by the similar method; using the NASA INTEX-B database (Center for Global and Regional Environmental Research 2010) to identify total emissions from the power sector in each power grid, divided by the total power generation. Table 4.3 shows the emission intensities of conventional pollutants in each power grid. From the results, it can be concluded that the power grids in north part of China, such as Northeast China power grid, North China power grid, and Shandong power grid, have higher emissions than the grids in south. This is because most of EGUs located in north part of China are coal based. In contrast, hydropower sources are common in southern China, such as Sichuan power grid, Guangxi power grid, and Yunnan power grid. For example, 99% electricity is generated by fossil fuel in Beijing; however, only 32% electricity is generated by fossil fuel in Sichuan (NBS 2010).

Table 4.2. Energy Generation and CO_2 Emissions by Power Grid.

Grid	Energy (MWh)	CO_2 (metric ton)	CO_2 Intensity (g kWh^{-1})
Northeast China	260,690,799	341,145,218	1,443
North China	536,918,724	559,455,125	1,149
Central China	512,959,690	389,966,507	838
East China	591,515,249	512,954,657	956
Northwest China	219,154,490	187,160,835	941
Chongqing	33,692,300	35,199,506	1,152
Fujian	97,726,863	77,526,067	874
Guangdong	214,789,577	164,915,606	846
Guangxi	83,336,750	57,596,237	762
Guizhou	123,259,963	99,248,666	888
Hainan	10,062,775	8,835,896	968
Shandong	240,036,295	243,011,157	1,116
Sichuan	140,090,421	90,332,875	711
Xinjiang	21,294,688	17,472,092	904
Yunnan	77,243,571	53,231,831	760

1. Tibet grid is not considered.

Table 4.3. Emission Intensities of Conventional Pollutants by Power Grid (g kWh^{-1}).

Grid	BC	CO	NO_x	PM_{10}	$PM_{2.5}$	SO_2	VOC
Northeast China	1.4E-02	1.3	5.3	1.7	1.0	6.4	0.5
North China	1.1E-02	0.7	2.8	0.7	0.4	6.0	0.3
Central China	1.6E-02	0.8	3.0	0.8	0.5	6.0	0.3
East China	8.3E-03	0.8	2.8	0.7	0.4	4.7	0.3
Northwest China	6.5E-03	0.7	2.6	0.9	0.5	6.1	0.3
Chongqing	2.6E-02	0.9	3.7	1.0	0.6	11.8	0.4
Fujian	4.0E-03	0.5	1.7	0.5	0.3	2.2	0.2
Guangdong	3.3E-03	0.5	1.8	0.5	0.3	3.0	0.2
Guangxi	2.6E-03	0.3	1.2	0.5	0.3	4.2	0.1
Guizhou	6.5E-03	0.5	1.8	0.4	0.3	8.7	0.2
Hainan	3.0E-04	0.4	1.6	0.3	0.1	3.4	0.2
Shandong	1.6E-02	0.7	2.9	0.7	0.4	7.5	0.3
Sichuan	1.6E-02	0.6	2.4	0.7	0.4	8.7	0.2
Xinjiang	1.7E-02	1.1	5.1	1.1	0.6	6.0	0.4
Yunnan	8.2E-03	0.6	2.3	0.5	0.3	5.7	0.2

1. Tibet grid is not considered.

4.1.2 Emission Factors of Electric Vehicles

Emission intensity for EGUs is the rate of total pollutants emitted divided by total energy generated in the same region. Intensity provides us with how many pollutants (grams) are emitted per unit of electricity generated (kWh). Intensity is the base to estimate emission factors for different EVs. With electricity consumption per 100 km for different EVs (as shown in Table 4.4 and EGU emission intensity, emission factors for EVs can be estimated. The emission factors of EVs in 34 cities are shown in Appendix Table A.1. One can see quickly that emission factors vary considerably by regional grid. For example, Beijing has much higher emission factors than Chengdu on almost all metrics. This is because Chengdu relies heavily on hydropower sources -- 67% electricity in the Sichuan power grid is generated by hydropower (NBS 2010). While Beijing relies almost exclusively on coal power sources and 99% electricity is generated by fossil fuel based EGUs (NBS 2010). Similarly, conventional pollutant emission rates vary by city, depending power source. Emission factors of EVs can be compared cautiously with emission factors of CVs (diesel or gasoline), but since health impacts are the final metric of interest, emission factors alone do not explain all of the costs or benefits of EVs relative to CVs. It should be noted that, as EV and CV technology matures, energy efficiency is expected to improve for both technologies. This would subsequently reduce the emission rates to some extent though it is unclear which technology would benefits more from possible technology improvements.

Table 4.4. EV Energy Use Rate (kWh $(100\text{-km})^{-1}$).

	Outlet Electricity (kWh $(100\text{-km})^{-1}$)	Include 14% Transmission and In-Plant Loss in China (kWh $(100\text{-km})^{-1}$)
E-bike	1.8	2.1
E-car	18.0	20.9

1. Data Sources (Cherry, Weinert et al. 2009; Green Car Congress 2009; Yo-Bykes 2009).

4.1.3 Well-to-station Emissions

Well-to-station emissions include fossil energy extraction, refining, storage, and transportation processes. I use previous energy life cycle analyses for CVs and EVs in China to estimate average well-to-station emissions (Table 4.1). 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.

4.1.4 Discussion

The order-of-magnitude variability in EGU emission factors by region (Figure 4.2 and Appendix Figure A.1) 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 city they are in (Appendix Table A.1); I estimate that an e-car (180 Wh km^{-1}) (Green Car Congress 2009) 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.

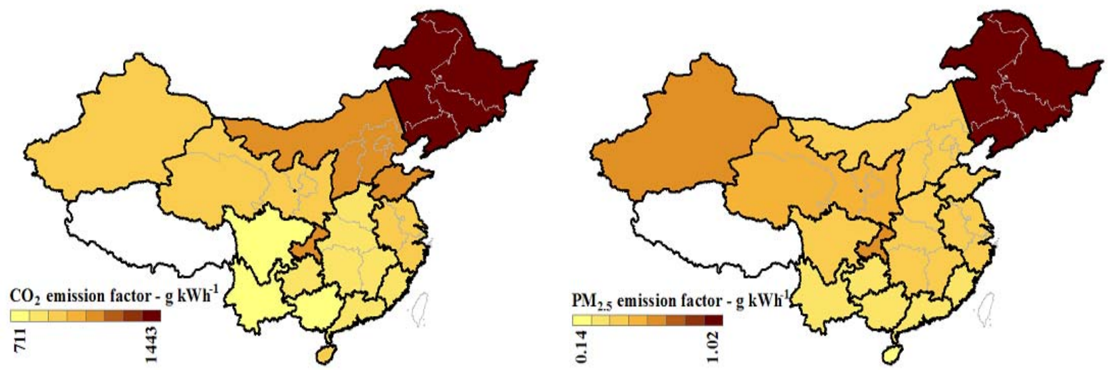


Figure 4.2. Average station-to-wheel emission factors for CO_2 (left plot) and $PM_{2.5}$ (right plot) for China's 15 electricity grids.

4.2 Intake Fraction

4.2.1 One-compartment Model for Urban Intake Fraction

One-compartment iF model was based on previous research showing that air pollution over a city 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 ambient concentrations in urban areas.

For the 34 Chinese cities studied meteorological (mixing height and wind speed), urban population data and urban land area were collected. Applying the one-compartment equation (equation 3.2), iFs are shown in Appendix Table A.2. In general, iFs are determined by two major factors: population density and meteorological condition. For those cities with large population density, such as Beijing, Shanghai, and Shijiazhuang, iFs can be much higher. For those coastal cities, such as Dalian, Qingdao, Suzhou, and Wuxi, the meteorological condition (stronger wind speed) could quickly disperse pollutants.

4.2.2 Regression Model for EGU Intake Fraction

Intake fractions of EGU emissions can be calculated based on regression method proposed by Zhou and Levy et al. (2006). The purpose of regression method is to estimate iF for EGUs in different locations using the coefficients that represent the influence of meteorological and population. The electricity generation units are classified into different regional power grid networks and the iF for each network is averaged. The intake fractions for each power grid are shown in Table 4.5. I interpolate the iF calculated from PM_1 and PM_3 relationships presented by Zhou and Levy et al. (2006) to estimate $PM_{2.5}$ iF.

4.2.3 Discussion

Estimated iFs for $PM_{2.5}$ (Figure 4.3 and Appendix Table A.3) 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 (Smith 1993; Ott, Steinemann et al. 2006), 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).

Table 4.5. Weighted Average iF by Regional Grid and Pollutant Intake Per Million

Grid	SO_2	PM_1	$PM_{2.5}$	PM_3	PM_7	PM_{13}	SO_4	NO_3
Northeast China Grid	2.89	6.05	4.06	3.40	1.87	1.02	3.13	2.32
North China Grid	4.00	8.68	5.89	4.96	2.72	1.38	4.16	3.07
Central China Grid	5.49	11.89	8.22	7.00	3.92	1.98	5.29	3.95
East China Grid	5.53	11.68	8.17	7.00	3.98	2.07	5.10	3.92
Northwest China Grid	3.21	7.21	4.80	4.00	2.17	1.11	3.71	2.52
Chongqing Grid	5.18	10.41	7.45	6.46	3.82	2.13	4.43	3.49
Fujian Grid	5.85	11.78	8.32	7.17	4.09	2.16	4.93	4.21
Guangdong Grid	5.07	10.50	7.42	6.39	3.72	2.02	4.59	3.48
Guangxi Grid	4.03	8.59	5.85	4.94	2.72	1.40	4.07	3.11
Guizhou Grid	4.25	9.06	6.19	5.23	2.87	1.46	4.24	3.26
Hainan Grid	3.35	6.81	4.68	3.97	2.24	1.23	3.31	2.57
Shandong Grid	5.36	10.88	7.64	6.56	3.71	1.95	4.67	3.92
Sichuan Grid	4.42	8.83	6.24	5.38	3.13	1.74	3.91	3.14
Xinjiang Grid	2.37	4.89	3.24	2.69	1.46	0.82	2.71	2.01
Yunnan Grid	3.14	6.77	4.54	3.79	2.07	1.08	3.46	2.50

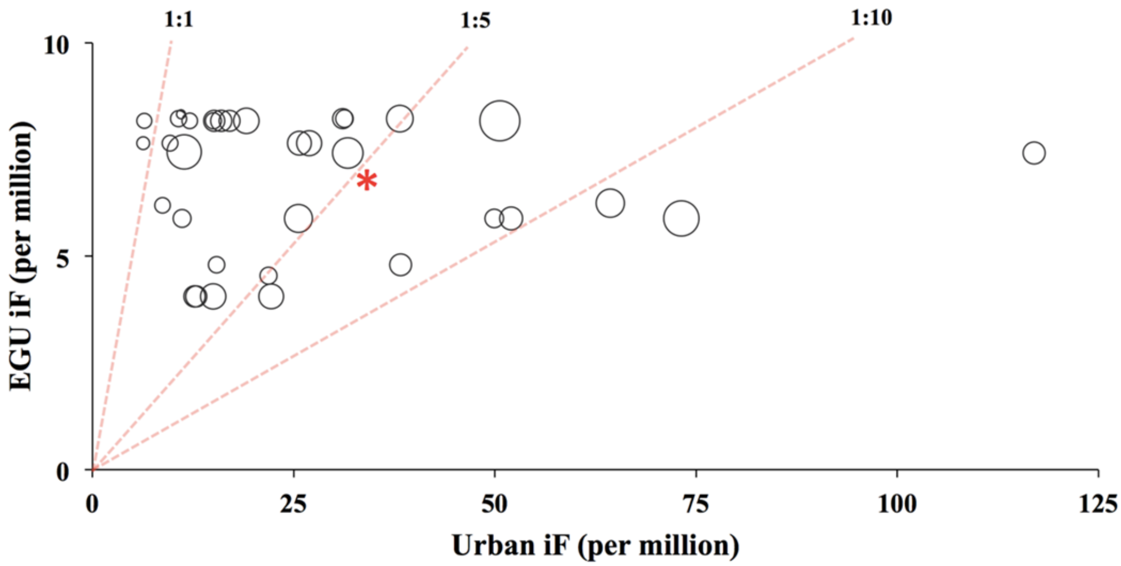


Figure 4.3. Intake fraction for primary $PM_{2.5}$ in the 34 urban areas considered here. The area of each icon is proportional to population. The population-weighted average value is indicated with an asterisk. For reference, dashed lines show constant urban/EGU iF ratios.

4.3 Health Impact

A mortality dose-response function based on the ACS cohort (Pope, Burnett et al. 2002) is employed for health impacts analysis. The published concentration-based toxicity (average 4% increase in mortality per 10 μg m^{-3}) is converted into an intake-based toxicity (5.3 deaths per kilogram inhaled), by assuming a population-average breathing rate (Layton 1993) of 14.5 m^3 d^{-1} $person^{-1}$ and Chinese baseline annual mortality of 7 deaths per 1,000 persons (CIA 2009). My approach applies the ACS finding that $PM_{2.5}$ exhibits, at the population level, a linear no-threshold dose response.

Table 4.6 and Appendix Table A.4 provide 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 lower $PM_{2.5}$ environmental health impact for gasoline cars than e-cars. Here and below, comparisons employ a basis of 10^{10} km y^{-1} and employ units of ppm for iF. Furthermore, in this research, my assumption is that 10^{10} kilometers are traveled by each type of vehicles alone, though these vehicles do co-exist in real fleets. However, it is easy to estimate the mortality risks for mixing fleets via weighting the results in Table 4.6. For example, in Shanghai, Cherry et al (2007) observed that approximately 10%, 40%, 50% of 10^{10} kilometers are traveled by e-cars, gasoline cars, and diesel buses respectively.

Under this scenario, $PM_{2.5}$ mortality risks should be 22 excess deaths (10% × 26 + 40% × 9 + 50% × 32).

Table 4.6. Example Calculation: Health Effects of $PM_{2.5}$ in Shanghai 10^{10} Vehicle km Traveled by Vehicle Type.

	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

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.

Results for all cities are in Figure 4.4. The bus/e-bike plot (Figure 4.4f) 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 4.4a, Figure 4.4b) may provide a useful counterfactual for car owners; for most but not all cities, impacts from e-cars are lower than for diesel cars but higher than for gasoline cars.

In general, based on Figure 4.4, 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 a many e-bike users would switch to bus (50-65%) or car-based modes (20-25%) if the e-bike became unavailable (Cherry and Cervero 2007).

A useful aspect of Figure 4.4 is investigation of the variability among cities, and therefore of the robustness of the comparisons to spatial differences. In some cases (Figure 4.4e and Figure 4.4f), comparisons yield the same results for all cities. In other cases, variability among cities is large: in Figure 4.4c and Figure 4.4d, the cities are split roughly evenly (60/40) as to which vehicle-type has lower public health impacts. Importantly, Figure 4.4 compares total health impacts but without consideration for *who* is exposed.

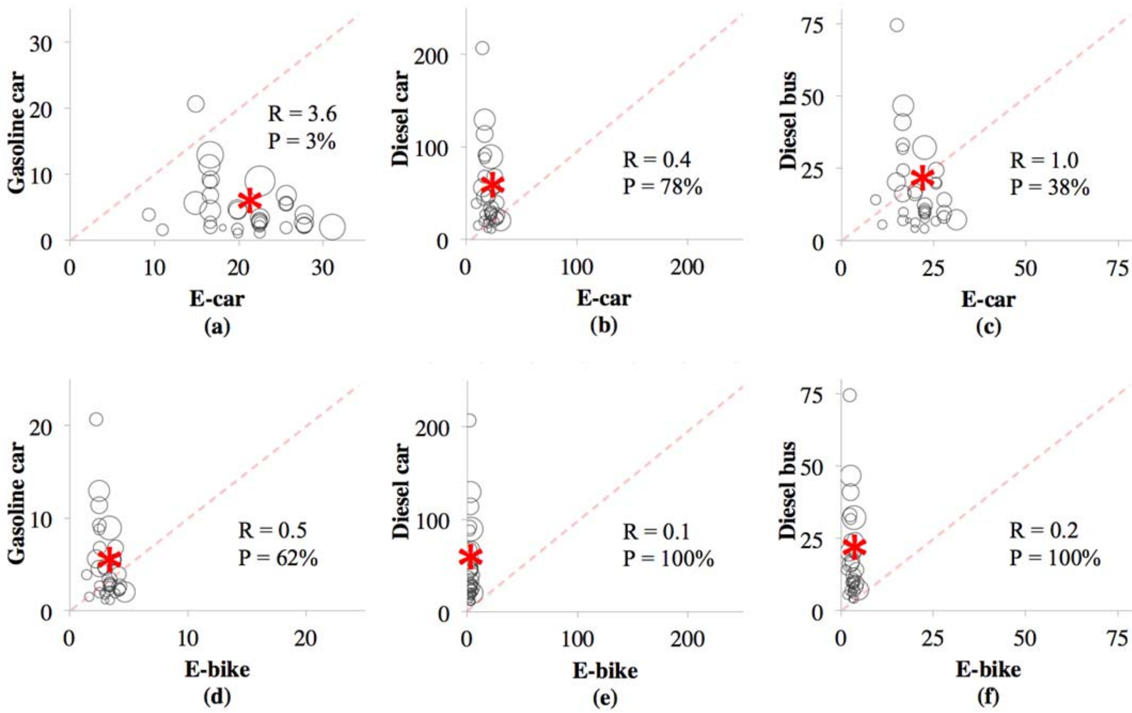


Figure 4.4. $PM_{2.5}$ excess deaths per 10^{10} passenger-km, for the 34 cities considered. Icon size is proportional to city population. In each plot, "R" is the population-weighted average ratio between x- and y- axes, "P" is the proportion of the population (among the 34 cities) for which the mortality 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 note of Table 4.6.

4.4 Sensitivity Analysis

In the previous sections, analyses employed point estimates for input variables. Here I develop a MC simulation to explore variability and uncertainty in input variables (Table 3.3) and their propagation through my analyses to a range of outcomes (Figure 4.5). As described in equation 3.4 a random number for each input variable is generated by a random number generator that have distributions drawn from Table 3.3.

The results shown in Figure 4.5 are obtained by carrying out a total of 10,000 Monte Carlo simulations, with the number of simulations per city proportional to population. The shapes of the regions in Figure 4.5 are similar to Figure 4.4, 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 4.5) than in Figure 4.4. From the results, it can be concluded that health impacts for e-bikes are always lower than for diesel cars and buses, and similar to the health impacts for gasoline cars. However, the health impacts for e-cars are likely to be much higher than for gasoline cars, lower than for diesel cars, and slight higher than for buses.

A similar analysis (Figure 4.6) simulating the population-weighted average mortality risks. Firstly, 1,000 MC simulations are carried out for all 34 cities individually. Then, population-weighted average mortality risks for each run of the MC simulation are calculated by formula 4.2. In 4.2, $Death_j$ is the mortality risks of the j^{th} run. p_i is the population in each i city; d_i is the mortality risks estimate for i city in j^{th} run.

$$Death_j = \frac{\sum_{i=1}^{34} p_i d_i}{\sum_{i=1}^{34} p_i} \quad (4.2)$$

The simulation results (Figure 4.6) reveals similar results comparing to the asterisk in Figure 4.5 but with less variance because of averaging. In this analysis, health impacts for e-bikes are significantly lower than for gasoline cars, diesel cars, and buses. Health impacts for e-cars are always higher than for gasoline cars, lower than for diesel cars, and slightly higher than for buses. Appendix Table A.5 presents detail results of excess mortality per 10^{10} Person-km traveled by vehicle and city based on MC simulation. Numbers in parenthesis are the standard deviation of results.

Based on simulation outcomes, in the short terms, gasoline cars are more competitive than e-cars as to the mitigation of mortality risks due to $PM_{2.5}$. However, e-cars perform better than diesel cars and may have the similar impacts compared with diesel bus as far the mitigation of mortality risks due to $PM_{2.5}$. E-bikes perform significantly better than all other vehicles in terms of mitigation of mortality risks due to $PM_{2.5}$. In the long term, because of the improvements in technology and government guidance, e-cars may be considered as a realistic solution to mitigate the mortality risks due to $PM_{2.5}$.

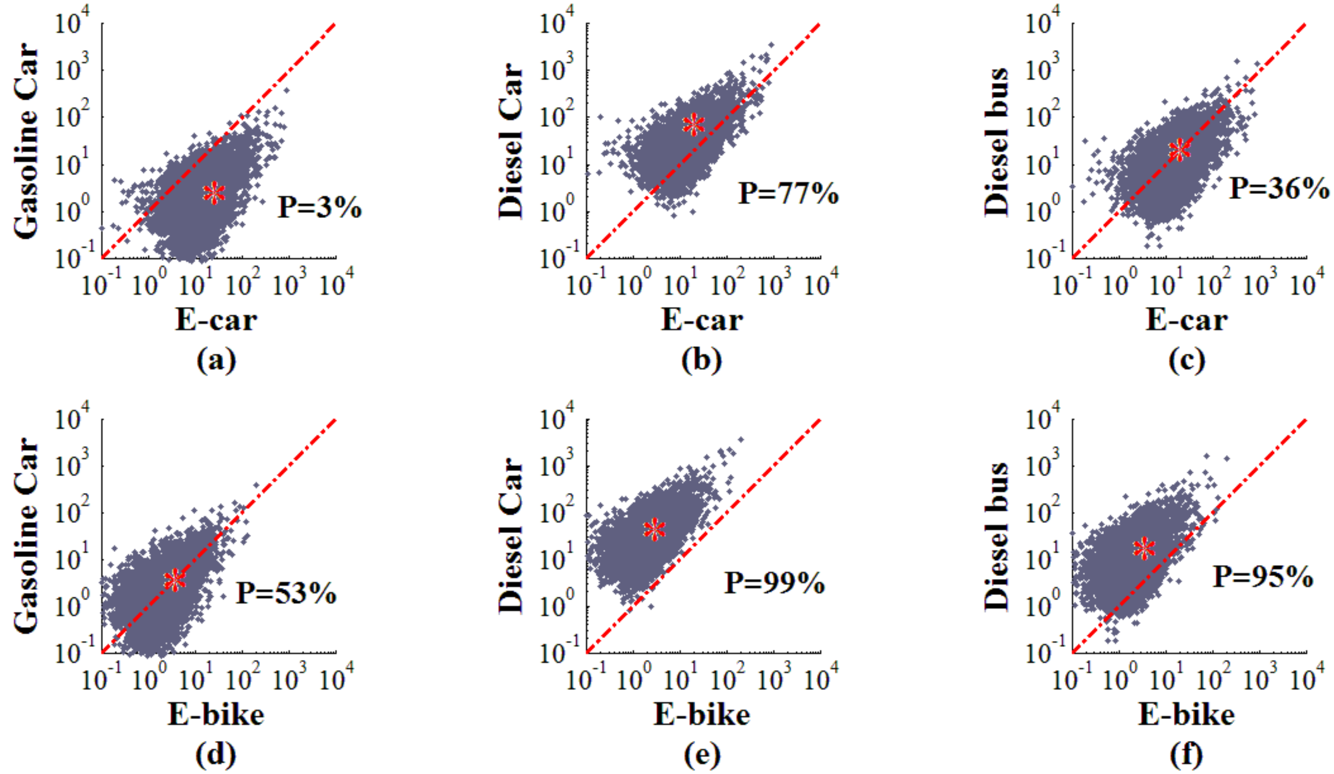


Figure 4.5. Monte Carlo simulation of $PM_{2.5}$ excess deaths per 10^{10} passenger-km for all 34 cities considered. Logarithmic-scale axes are applied in this plot. In each plot, "P" is the proportion of the simulation outcomes for which the mortality risk is lower for EVs that for CVs. The dashed lines on each plot are 1:1 lines. The population-weighted average value is indicated with an asterisk.

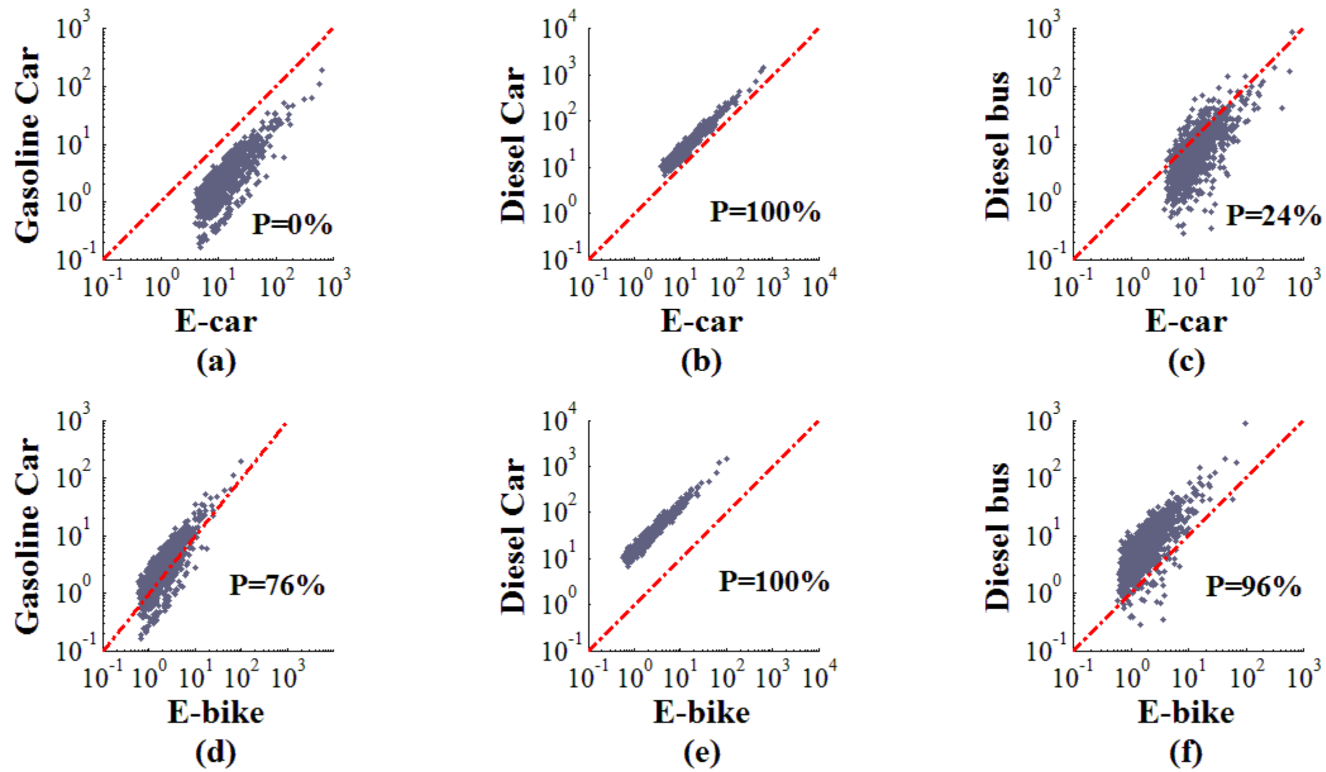


Figure 4.6. Monte Carlo simulation of weighted average of 34 city $PM_{2.5}$ excess deaths per 10^{10} passenger-km. Logarithmic-scale axes are applied in this plot. In each plot, "P" is the proportion of the simulation outcomes for which the mortality risk is lower for EVs that for CVs. The dashed lines on each plot are 1:1 lines.

4.5 Equity Analysis

Electric Vehicles are a possible contributor to sustainable transportation development. One of the primary concerns for sustainability is social equity, focusing on the fairness of outcomes across populations, presently and in the future. Unfortunately, EVs may cause social equity concerns. I approach the equity question using three methods:

(1) Power Plant Location

(2) Urban/Rural Intake

(3) Income/Exposure Disparity

4.5.1 Power Plant Location

One approach to evaluate equality of EGU location is to focus on the EGU location relative to where EV's are likely used. The median CGRP at the county level is 4,401 RMB [US$660] in 2000. I classify all counties below this median as "low income" and all counties above this as "high income". This approach parallels other approaches to evaluate equity of power plant location in China (Schoolman and Ma 2012). In China, ~30% of power plants are located in the low income counties (as shown in Figure 4.7). The residents in these regions will likely face added air quality health burdens if EV use increases in urban areas. Therefore, it is necessary to develop some metrics to characterize this problem. While this approach suggests inequity of impacts, it does not focus on the true impact of power plants -- emissions, exposure, and intake. The next two methods focus how emissions and ultimately health effects are allocated to urban/rural and high/low income areas of China.

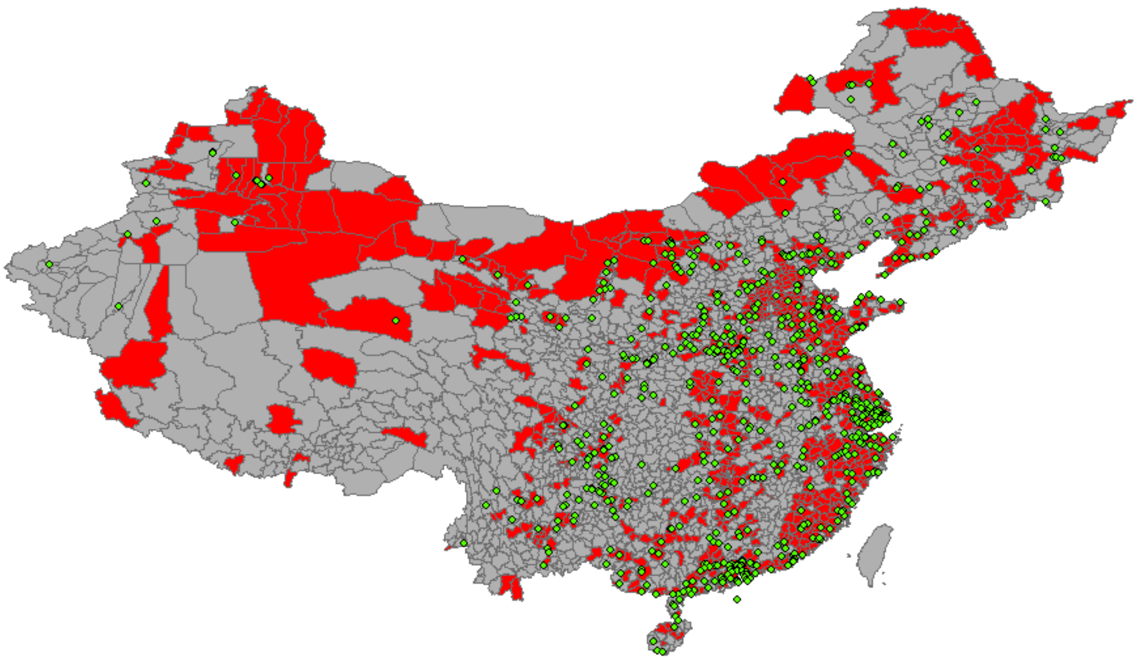


Figure 4.7. Map of year 2000 county-level CGRP and distribution of electricity generating units (power plants) in China. The regions in red are high income regions, where CGRP is more than national median (4,401 RMB [US$660]). The regions with grey are low income regions, where CGRP is less than the national median. The green dots represent electricity generation units.

4.5.2 Urban versus Rural Intake Approach

Since EVs are likely to be deployed primarily in urban areas first (Zheng, Mehndiratta et al. 2012), I investigate urban/rural intake, focusing on the percentage of total intake that is borne by rural populations. In order to identify the portion of primary $PM_{2.5}$ emissions from EGUs inhaled by urban population, I repeat calculations for iFs for urban population only in China's designated 660 cities. For example, in East China power grid where Shanghai is located, 47% of urban EV emissions are inhaled by non-urban populations. It is important to note that I consider all urban areas equally and EGUs in a power grid and emissions and intake are assigned to all cities in China relative to the proportion of intake they consume. I find that, on average, ~ half (52%) of urban EV emissions from urban use of EVs are inhaled by non-urban populations. In 2000, 65% of China's population was living in non-urban areas. Figure 4.8 shows this parameter by electricity 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 (2,253 RMB [US$338] rural versus 6,280 RMB [US$941] urban) to 3.1× in 2011 (6,977 RMB [US$1,046] rural versus 21,810 RMB [US$3,270] urban) (NBS 2012). Almost all inhaled emissions from CVs are inhaled in the city where the CV is operated. In general, urban use of EVs rather than CVs typically moves the emissions, exposures, and health impacts to more rural locations.

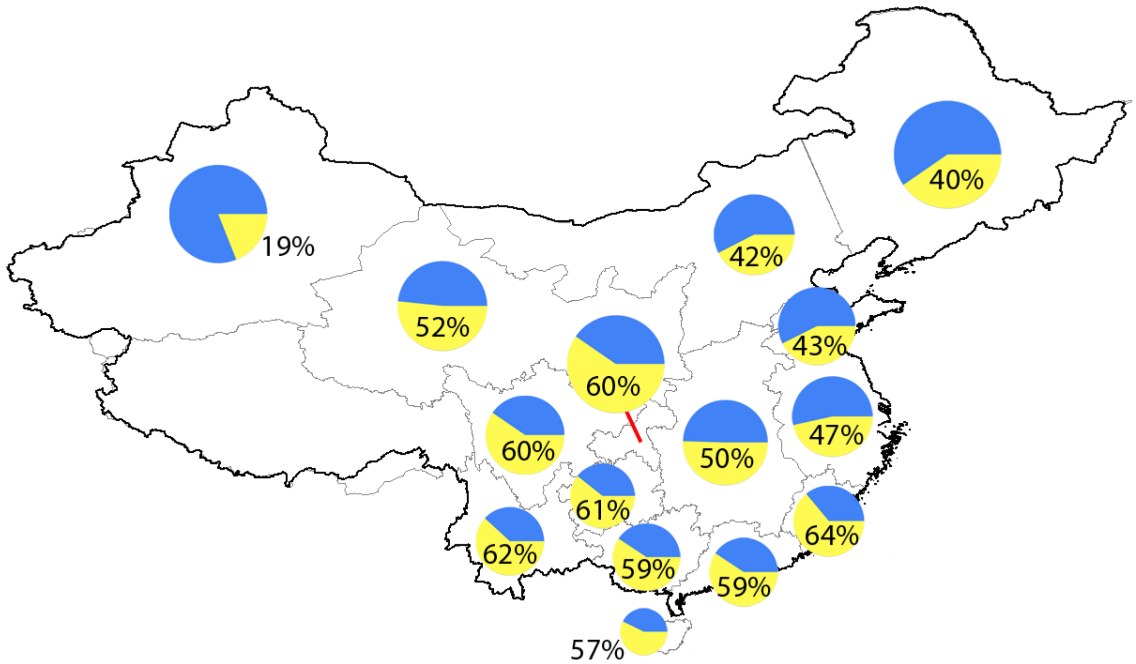


Figure 4.8. Portion of primary $PM_{2.5}$ health impacts from electricity generating units experienced by rural versus urban populations. Icon area is proportional to $PM_{2.5}$ emission factor (g km^{-1}) for an EV in that power grid. Numbers identify non-urban mortality impact proportions, i.e., of the total mortality impacts attributable to primary $PM_{2.5}$ from electricity generation – here, owing to urban use of EVs.

4.5.3 Income/Exposure Disparity Analysis

Urban/rural status is a proxy for income. In general, urban areas have higher incomes than rural areas. There are cases where low-income urban counties could have lower incomes than high-income rural counties. To address this, I take a direct income/exposure disparity approach, focusing on specific cities where e-cars are likely to operate and evaluating EV emissions, exposures, and health impacts on specific counties. I add one dimension by tabulating these exposures with incomes (approximated by CGRP). This direct comparison approach contrasts exposures and incomes directly with the exposures and incomes of the city where the EV is operated. Figure 4.9 presents exposure versus income distribution for over 2,300 counties in China after EVs are used in 12 representative cities. Appendix Figure A.3 shows the same chart for all 34 cities in this analysis. In these figures, each county is represented by a dot and the city where the EV is operated is represented by the intersection of the red lines. Here we can see where the majority of exposure and health effects occur compared to the base exposure/income relationship of the city where the EVs are operated. From this figure, the cities with high income level, such as Beijing, Dalian, Shanghai, and Guangzhou, a large portion of primary $PM_{2.5}$ emissions are inhaled by populations who have lower income compared to them. In contrast, lower-income cities have a substantially higher exposure in higher income counties.

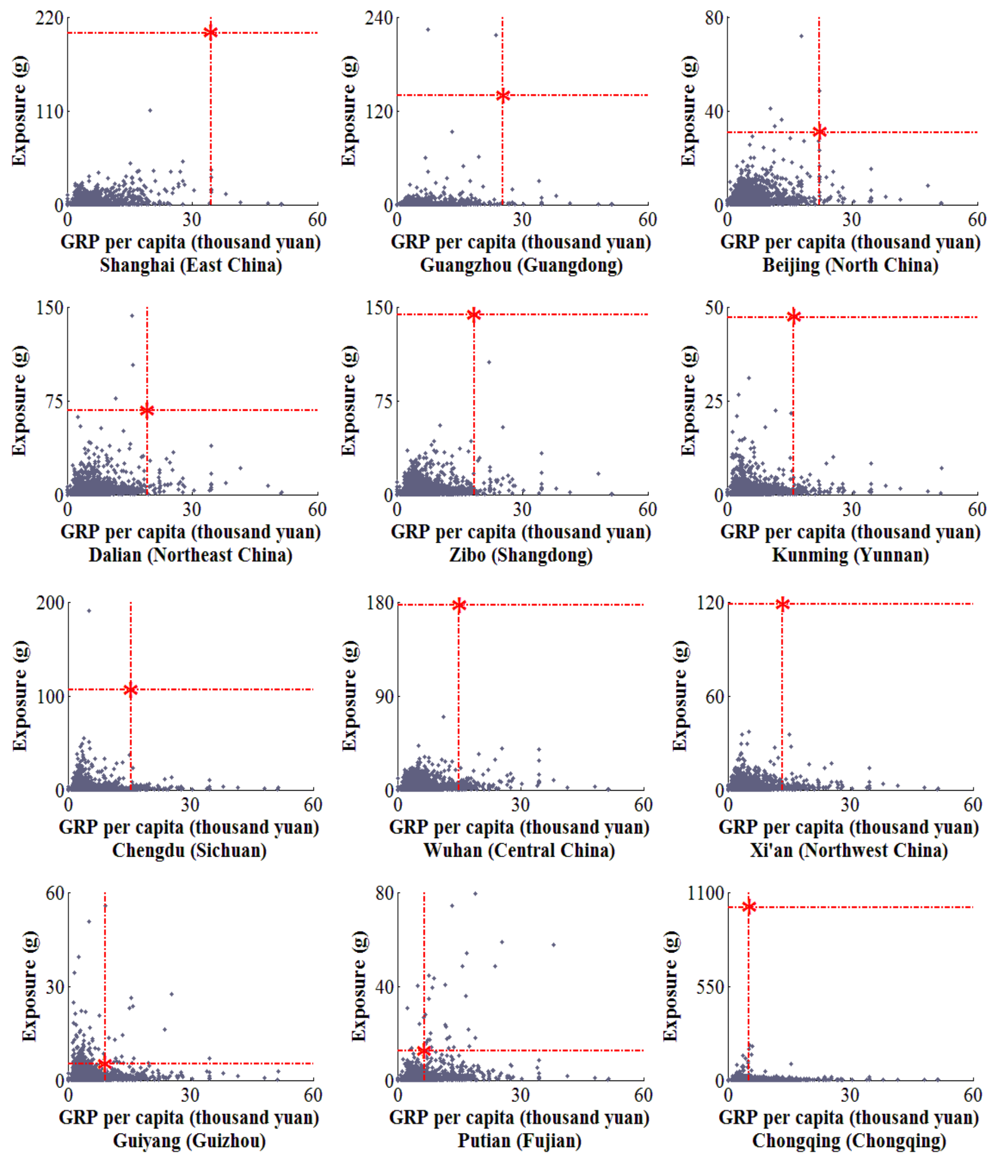


Figure 4.9. Exposure to primary $PM_{2.5}$ emissions due to EV shift. The red dash lines divide counties into four groups -- low income with low exposure (bottom left), low income with high exposure (top left), high income with low exposure (bottom right), and high income with high exposure (top right). The cross point (marked as asterisk) of dash lines represents city using e-cars.

Table 4.7 reports the detail proportion of exposures to primary $PM_{2.5}$ emissions from EV use in four groups: low income with low exposure (bottom left of Figure 4.9 quadrant), low income with high exposure (top left), high income with low exposure (bottom right), and high income with high exposure (top right) compared with the income and exposure level of the city adopting EVs. For example, in Shanghai, if 10^{10} vehicle traveled kilometers travel by e-cars, residents in Shanghai will have 200 g of cumulative exposure (~1 death) to primary $PM_{2.5}$ emissions from this switch. Moreover, over 94.3% (6,436 g or ~34 deaths) of primary $PM_{2.5}$ emissions from this switch will be inhaled by populations who have lower income than residents in Shanghai; and ~3.3% of those emissions are inhaled by the poorest 10^{th} of the China's population (i.e. in counties whose CGRP is in the bottom 10^{th} percentile in China (<1,969 RMB [US$300])). Another example, under the same scenario (10^{10} vehicle traveled kilometers travel by e-cars in Chongqing), the residents in Chongqing will have 1008 g of cumulative exposure to primary $PM_{2.5}$ emissions (~5 deaths) from this switch, which it accounts for 11% of total exposure (9167 g or ~49 deaths). The reason why the cumulative exposure to primary $PM_{2.5}$ emissions of residents in Chongqing is larger than other cities might be that the residents in Chongqing are proximate to all EGUs in Chongqing power grid that these EGUs have second highest $PM_{2.5}$ emission factor comparing with other power grids (except Northeast China power grid). In contrast, for instance, Shanghai is located in East China power grid, which there are over 200 EGUs in this power grid, but these EGUs are distributed in 4 provinces. Therefore, Shanghai should have relatively low $PM_{2.5}$ concentration compared to Chongqing. In addition, because Chongqing is the city with the largest population in China (NBS 2012), the exposure to emissions for residents in

Chongqing should be relatively higher than other cities.

In these four groups, the counties with low income but high exposure to the emissions should be highlighted, since it is unfair to them if the benefits of EV use are realized in the cities while the environmental cost are borne by the poorer county residents who do not benefit from EV use. By averaging the results of 34 cities, if EVs are used in urban areas, emissions from EGUs will be dispersed to 79% (range: 37-94%) of counties in China with lower income and lower exposure level to primary $PM_{2.5}$ than cities where EVs are used. 5% (range 0-28%) of counties in China suffering from the emissions due to this adoption are those have lower income but high exposure level compared with cities. The remaining 16% are higher income counties and most have lower pollution exposure compared with urban communities using EVs. It is also worth mentioning that, on average, 5% (range 3-12%) of emissions from EGUs are inhaled by the poorest 10th of the China's population. These analyses contrast the case of CVs where almost all tailpipe emissions are inhaled in the city where the CV is used. The results confirm that adoption of EVs could result increase environmental equity challenges in China. It should also be noted that these analyses are not unique to EVs, but are common among all electricity demand from urban areas.

It is important to note one key limitation of this equity analysis -- relying on 12-year old census data, which is the most recent data available in the needed format. For instance, in the past decade, the GDP capita in China rose from 7,858 RMB [US$1,180] in 2000 to 35,083 RMB [US$5,300] in 2011, and the average annual income growth rates are 12%

and 11% in urban and rural area respectively (NBS 2012). Moreover, the urban-rural disparity in average income per capita increased from 2.8× in 2000 (2,253 RMB [US$338] rural versus 6,280 RMB [US$941] urban) to 3.1× in 2011 (6,977 RMB [US$1,046] rural versus 21,810 RMB [US$3,270] urban). These changes should cause the dots in Figure 4.9 shift towards the right side of the figure, and dots representing urban counties shift faster than those representing rural counties. At the same time, urbanization in China increased from 36% urban population to 50% urban population (NBS 2012). This urbanization may cause emission exposure increases in urban areas, but reduce the low income exposure rates. This change should cause the dots representing urban counties shift upward and the dots representing rural counties shift downward in Figure 4.9. Furthermore, unregistered migrants who work in urban area with rural *hukou* (thus counted as rural population) might cause disparity in equity analysis as well. On the one hand, the potential increases in population for adding migrants in could cause higher urban exposure rates. This change should cause the dots representing urban counties shift upward in Figure 4.9. On the other hand, the unregistered migrants may cause reduction in estimated CGRP, because unregistered migrants who contribute to urban GRP, but this GRP was divided by smaller urban populations (not including unregistered migrants). This change should cause the dots representing urban counties move towards left side in Figure 4.9.

Table 4.7. Proportion of Exposures in Four Groups due to Urban EV Use.

	H_iL_e	H_iH_e	L_iL_e	L_iH_e	Exposure in Low Income	Exposure in Bottom 10^{th} %tile
Shanghai	5.7%	0.0%	94.3%	0.0%	94.3%	3.3%
Ningbo	2.2%	4.5%	82.4%	10.9%	93.3%	3.3%
Hangzhou	4.5%	2.9%	90.9%	1.6%	92.5%	3.3%
Wuxi	3.7%	4.3%	88.5%	3.5%	92.0%	3.3%
Suzhou	1.8%	6.9%	76.2%	15.1%	91.3%	3.3%
Guangzhou	6.0%	0.0%	82.7%	11.3%	94.0%	3.5%
Qingdao	3.1%	0.0%	92.9%	4.0%	96.9%	2.9%
Beijing	4.3%	0.0%	91.8%	3.1%	94.9%	4.7%
Jinan	6.4%	0.0%	91.8%	1.9%	93.6%	2.9%
Foshan	3.1%	9.9%	70.3%	16.7%	87.0%	3.5%
Nanjing	10.8%	2.9%	86.3%	0.0%	86.3%	3.3%
Dalian	6.1%	0.0%	90.4%	3.5%	93.9%	5.0%
Zibo	9.4%	0.0%	90.6%	0.0%	90.6%	2.9%
Tianjin	9.4%	0.0%	90.6%	0.0%	90.6%	4.7%
Changzhou	7.5%	8.6%	78.8%	5.2%	84.0%	3.3%
Kunming	7.2%	0.0%	92.8%	0.0%	92.8%	10.0%
Harbin	11.0%	0.0%	87.5%	1.6%	89.0%	5.0%
Shenyang	12.7%	0.0%	87.3%	0.0%	87.3%	5.0%
Chengdu	6.5%	0.0%	90.0%	3.5%	93.5%	7.5%
Wuhan	10.8%	0.0%	89.2%	0.0%	89.2%	4.5%
Xi’an	9.9%	0.0%	90.1%	0.0%	90.1%	9.5%
Tangshan	13.5%	2.1%	83.7%	0.7%	84.4%	4.7%
Changsha	10.7%	4.3%	81.9%	3.0%	85.0%	4.5%
Changchun	18.2%	2.7%	79.1%	0.0%	79.1%	5.0%
Taiyuan	16.2%	2.7%	80.4%	0.7%	81.1%	4.7%
Zhengzhou	14.9%	2.1%	83.1%	0.0%	83.1%	4.5%
Shijiazhuang	20.2%	2.1%	77.8%	0.0%	77.8%	4.7%
Lanzhou	11.2%	4.0%	79.6%	5.2%	84.8%	9.5%
Guiyang	9.8%	6.3%	54.2%	28.2%	82.4%	12.1%
Zaozhuang	33.3%	9.1%	57.1%	0.5%	57.6%	2.9%
Xiangfan	19.2%	13.4%	49.4%	18.0%	67.4%	4.5%
Putian	27.2%	28.4%	39.6%	4.7%	44.4%	3.3%
Huai’an	28.4%	27.8%	37.2%	6.6%	43.8%	3.3%
Chongqing	44.7%	0.0%	55.3%	0.0%	55.3%	7.1%
Average	**12.0%**	**4.3%**	**79.2%**	**4.4%**	**83.6%**	**4.9%**

1. L_iL_e: low income with low exposure; H_iL_e: high income with low exposure; L_iH_e: low income with high exposure; H_iH_e: high income with high exposure.

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

Electric vehicles are often proposed as a “sustainable” approach for increasing urban mobility and economic development. An implicit assumption is that air quality and health impacts are lower for EVs than for CVs. This research aims to test that assumption for primary $PM_{2.5}$.

In several cases, my findings (Figure 4.4) exhibit strong spatial variability among locations. I 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-mile, 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.

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 I 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} (Cherry and Cervero 2007). Calculations similar to those in Table 4.6 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 (2007; Cherry, Weinert et al. 2009). For this simple illustration, I 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), and I 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 re-distributed 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.

Moreover, we cannot ignore environmental inequity caused from replacing CVs by EVs in China. If this shift takes place, most emissions and health impacts can be distributed to the communities outside the city where EVs are used. A vast portion (over 83% on average) of primary $PM_{2.5}$ emissions from EGUs will be inhaled by communities that have lower income comparing with the city where EVs are used. The poorest communities, where the incomes are in the bottom 10^{th} percentile in China will suffer from 5% of total primary $PM_{2.5}$ emissions from EV shift. These poorest communities may not afford or benefit from EVs in cities. Future policy should aim to remedy this inequity.

This research has several important limitations. As such, results should be considered suggestive rather than conclusive. A simple one-compartment model is used 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. My iF estimates reflect ambient concentrations only, and do not consider microenvironments (Han and Naeher 2006). Average EGU emission factors were employed here for EV charging; however, EV emissions can be sensitive to temporal (time-of-day; seasonal) charging patterns (Jansen, Brown et al. 2010; McCarthy and Yang 2010; Sioshansi, Fagiani et al. 2010). Apendix Figure A.4 presents three typical recharging profiles of e-bike batttery. Appendix Figure A.4a shows 6-hour recharging profile of e-bike battery after complete discharge. Appendix Figure A.4b is 14-hour recharging profile of e-bike battery after ~30% discharge. It can be seen that there is somewahat significant parasitic load, about 70~80 Wh, over 12 hours of excess recharging. It is quite low thought, but actual recharging energy will be doubled. Appendix Figure A.4c describes one hour recharging profile of e-bike battery after very light discharge. From this panel of figures, it can be concluded that the enery required for recharging varies in recharging process. It could result in emission factors of EVs varies temporally. My approach implicitly assumes that $PM_{2.5}$ emissions from electricity generation and from CVs tailpipe exhaust are equally toxic. I focus on one pollutant (primary $PM_{2.5}$) and one outcome (mortality), and therefore estimate a fraction of total health impacts. Prior analyses considering multiple pollutants and health outcomes indicate that results of the pairing I employed ($PM_{2.5}$; mortality) generally dominates comparative analyses (Muller and Mendelsohn 2007; Health Effects Institute 2010).

For the electricity sector in China, future changes in emissions are uncertain. Zhao et al. (2008) 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), and 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 (Jansen, Brown et al. 2010; McCarthy and Yang 2010; Sioshansi, Fagiani et al. 2010)). 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 instance PM emissions from a 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.

Traditionally, compartment model is only used to estimate iFs for non-reactive pollutants, such as primary $PM_{2.5}$. Primary $PM_{2.5}$ is emitted directly from the source like EGUs and internal combustion vehicles. The pollutants such as SO_2, NO_X, and organics are regarded as reactive pollutants, since secondary PM could be formed from them through photochemical processes. Therefore, it was generally considered not accurate to estimate iFs for reactive pollutants without considering secondary PM formation. A new study suggests that iFs for non-reactive pollutants may be reasonably applied to some reactive pollutants such as SO_2, NO_x, and organics, since the half-life for these reactive pollutants is longer than 10 hours (Apte, Bombrun et al. 2012). However, those iFs still cannot be applied to pollutants formed from secondary processes. Based on this assumption, I conducted a preliminary analysis for the mortality risks of SO_2 and NO_X. Since SO_2 emissions are approximate to zero for gasoline cars and diesel cars (as shown in Table 4.1), I only compare the mortality risks between EVs and diesel bus. In addition, I only consider Beijing as case study and the EGU iF of NO_X (7.4 ppm) for Beijing is obtained from (Ho and Nielsen 2007). 1.4% and 1.5% are used as base values of dose response for SO_2 and NO_X emissions respectively (Chen, Hong et al. 2004). The results are shown in Appendix Figure A.5 and Figure A.6. From the results of SO_2 analysis, diesel bus has better performance than EVs for all 34 cities. Since SO_2 emissions from gasoline cars and diesel cars are pretty small, in the short term, CVs are more realistic solutions to mitigate the mortality risks due to SO_2 emissions comparing with EVs. In the long term, as adoption and improvements of desulfurization technology, SO_2 emissions from EGUs in China could be expected to reduce considerably and EVs might be comparable to CVs in terms of SO_2 emissions. In the case study of Beijing, e-bikes have better performance than CVs considering NO_X mortality risks. E-cars have lower mortality risks than diesel cars and diesel bus; but have similar mortality risks as gasoline cars.

Results above investigate primary pollutants. As a sensitivity analysis, I 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 $PM_{2.5}$, I employ two approaches. First, I apply the Zhou et al. (2006) 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, I use recently published global-average iF values for archetypal urban, rural, and remote environments (Humbert, Marshall et al. 2011); a main limitation is the use of global-average, rather than China-specific, values. Results, 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. I conclude that, while this dissertation focuses on primary PM, robust exploration of secondary PM is warranted.

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 generating system. My 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 are uncertain.

Lightweight EV's such as e-bikes have clear 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.

LIST OF REFERENCES

Agyeman, J., R. D. Bullard, et al. (2002). "Exploring the Nexus: Bringing Together Sustainability, Environmental Justice and Equity." Space and Polity **6**(1): 77-90.

All China Marketing Research Co. Ltd. (2003). "2000 China County Population and Socioeconomic Indicators with County Map."

Apte, J. S., E. Bombrun, et al. (2012). "Global Intraurban Intake Fractions for Primary Air Pollutants from Vehicles and Other Distributed Sources." Environmental Science & Technology **46**(6): 3415-3423.

Bennett, D. H., T. E. McKone, et al. (2002). "Peer Reviewed: Defining Intake Fraction." Environmental Science & Technology **36**(9): 206A-211A.

Bingheng, C., K. Haidong, et al. (2011). "Air Pollution and Health Studies in China--Policy Implications." Journal of the Air & Waste Management Association **61**(11): 1292-1299.

Boldo, E., S. Medina, et al. (2006). "Apheis: Health Impact Assessment of Long-term Exposure to PM_{2.5} in 23 European Cities." European Journal of Epidemiology **21**(6): 449-458.

Bootman, J. L., C. Rowland, et al. (1979). "Cost-Benefit Analysis." Evaluation & the Health Professions **2**(2): 129-154.

Brajer, V., R. W. Mead, et al. (2010). "Adjusting Chinese income inequality for environmental equity." Environment and Development Economics **15**(03): 341-362.

Brauer, M., J. S. Evans, et al. (2002). "Policy uses of particulate exposure estimates." Chemosphere **49**(9): 947-959.

Braveman, P. and S. Gruskin (2003). "Defining equity in health." Journal of Epidemiology and Community Health **57**(4): 254-258.

Brinkman, G. L., P. Denholm, et al. (2010). "Effects of Plug-In Hybrid Electric Vehicles on Ozone Concentrations in Colorado." Environmental Science & Technology **44**(16): 6256-6262.

Cai, H. and S. Xie (2007). "Estimation of vehicular emission inventories in China from 1980 to 2005." Atmospheric Environment **41**(39): 8963-8979.

Carella, B. and P. Mudu (2009). "Exposure to Air Pollution: An Intake Fraction Application in Turin Province." Archives of Environmental & Occupational Health **64**(3): 156-163.

CARMA. (2010). "Carbon Monitoring for Action " Retrieved May 1, 2010, from http://carma.org.

Center for Global and Regional Environmental Research (2010). Emission Data.

Chen, B., C. Hong, et al. (2004). "Exposures and health outcomes from outdoor air pollutants in China." Toxicology **198**(1–3): 291-300.

Cherry, C. (2007). Electric Two-Wheelers in China: Analysis of Environmental, Safety, and Mobility Impacts. PhD Dissertation, University of California-Berkeley.

Cherry, C. (2009). Electric Two-Wheelers in India and Viet Nam**:** 54.

Cherry, C. and R. Cervero (2007). "Use Characteristics and Mode Choice Behavior of Electric Bike Users in China." Transport Policy **14**(3): 247-257.

Cherry, C., J. X. Weinert, et al. (2009). Electric Bikes in the People's Republic of China (PRC)-Impact on the Environment and Prospects for Future Growth Asian Development Bank.

Cherry, C. R., J. X. Weinert, et al. (2009). "Comparative environmental impacts of electric bikes in China." Transportation Research Part D: Transport and Environment **14**(5): 281-290.

CIA (2009). People: China, https://www.cia.gov/library/publications/the-world-factbook/geos/ch.html.

Di, X., Z. Nie, et al. (2007). "Life cycle inventory for electricity generation in China." The International Journal of Life Cycle Assessment **12**(4): 217-224.

Dockery, D. W., C. A. Pope, et al. (1993). "An Association between Air Pollution and Mortality in Six U.S. Cities." New England Journal of Medicine **329**(24): 1753-1759.

Doucette, R. T. and M. D. McCulloch (2011). "Modeling the CO2 emissions from battery electric vehicles given the power generation mixes of different countries." Energy Policy **39**(2): 803-811.

Doucette, R. T. and M. D. McCulloch (2011). "Modeling the prospects of plug-in hybrid electric vehicles to reduce CO2 emissions." Applied Energy **88**(7): 2315-2323.

Evans, J. S., S. K. Wolff, et al. (2002). "Exposure efficiency: an idea whose time has come?" Chemosphere **49**(9): 1075-1091.

Frey, C. and A. Cullen (1995). Distribution Development for Probabilistic Exposure Assessment. the 88th Annual Meeting of Air and Waste Management Association, Pittsburgh, Pennsylvania.

Fridley, D., N. Aden, et al. (2008). China Energy Databook.

Fung, F., H. He, et al. (2010). Overview of China's vehicle emission control program past successes and future prospects, International Council on Clean Transportation**:** 190.

Funk, K. and A. Rabl (1999). "Electric versus conventional vehicles: social costs and benefits in France." Transportation Research Part D: Transport and Environment **4**(6): 397-411.

Goodman, L. A. and H. Markowitz (1952). "Social Welfare Functions Based on Individual Rankings." American Journal of Sociology **58**(3): 257-262.

Graetz, M. J. (1975). "ASSESSING DISTRIBUTIONAL EFFECTS OF INCOME-TAX REVISION - SOME LESSONS FROM INCIDENCE ANALYSIS." Journal of Legal Studies **4**(2): 351-368.

Greco, S. L., A. M. Wilson, et al. (2007). "Spatial patterns of mobile source particulate matter emissions-to-exposure relationships across the United States." Atmospheric Environment **41**(5): 1011-1025.

Green Car Congress. (2009). "BYD Plans Limited Introduction of e6 EV in US Next Year." from http://www.greencarcongress.com/2009/08/byde6-20090822.html.

Green Car Congress. (2010). "US EPA rates Nissan LEAF fuel economy as 99 mpg-equivalent (combined)." from http://www.greencarcongress.com/2010/11/leaf-20101122.html#more.

Han, X. and L. P. Naeher (2006). "A review of traffic-related air pollution exposure assessment studies in the developing world." Environment International **32**(1): 106-120.

Hao, H., H. Wang, et al. (2011). "Fuel conservation and GHG (Greenhouse gas) emissions mitigation scenarios for China's passenger vehicle fleet." Energy **36**(11): 6520-6528.

Hao, J., J. Hu, et al. (2006). "Controlling vehicular emissions in Beijing during the last decade." Transportation Research Part A: Policy and Practice **40**(8): 639-651.

Hao, Y., L. Yu, et al. (2010). "Analysis of Driving Behavior and Emission Characteristics of Diesel Transit Buses Using PEMS' Measurements." the 89th Transportation Research Board Annual Meeting.

Harrison, K., D. Hattis, et al. (1986). Implications of chemical use for exposure assessment: development of an exposure-estimation methodology for application in a useclustered priority setting system. US EPA, MIT Center for Technology Policy and Industrial Development.

He, K., Z. Yao, et al. (2010). Characteristics of vehicle emissions in China based on portable emission measurement system. 19th Annual International Emission Inventory Conference San Antonio, Texas.

Health Effects Institute (2004). Health Effects of Outdoor Air Pollution in Developing Countries of Asia: A Literature Review.

Health Effects Institute (2010). Outdoor Air Pollution and Health in the Developing Countries of Asia: A Comprehensive Review.

Heath, G. A., P. W. Granvold, et al. (2006). "Intake fraction assessment of the air pollutant exposure implications of a shift toward distributed electricity generation." Atmospheric Environment **40**(37): 7164-7177.

Heidelberg, I. f. E. a. E. R. (2008). Transport in China: energy consumption and emissions of different transport modes, Institute for Energy and Environmental Research Heidelberg**:** 80.

Hertwich, E. G., S. F. Mateles, et al. (2001). "Human toxicity potentials for life-cycle assessment and toxics release inventory risk screening." Environmental Toxicology and Chemistry **20**(4): 928-939.

Ho, M. S. and C. Nielsen (2007). Clearing the Air: The Health and Economic Damages of Air Pollution in China, The MIT Press.

Hu, Z., P. Tan, et al. (2008). "Life cycle energy, environment and economic assessment of soybean-based biodiesel as an alternative automotive fuel in China." Energy **33**(11): 1654-1658.

Humbert, S., J. D. Marshall, et al. (2011). "Intake Fraction for Particulate Matter: Recommendations for Life Cycle Impact Assessment." Environmental Science & Technology **45**(11): 4808-4816.

Huo, H., Q. Zhang, et al. (2010). "Environmental Implication of Electric Vehicles in China." Environmental Science & Technology **44**(13): 4856-4861.

Jamerson, F. E. and E. Benjamin (2009). Electric Bikes Worldwide Reports -100,000,000 Light Electric Vehicles in 2009.

Jamie, P., K. Simon, et al. (2006). "Every breath you take? Environmental justice and air pollution in Christchurch, New Zealand." Environment and Planning A **38**: 20.

Jansen, K. H., T. M. Brown, et al. (2010). "Emissions impacts of plug-in hybrid electric vehicle deployment on the U.S. western grid." Journal of Power Sources **195**(16): 5409-5416.

Jie, Y. (2009). Impact Analysis of Transportation Industry on China's Economy. Management and Service Science, 2009. MASS '09. International Conference on.

Jolliet, O. and P. Crettaz (1997). "Fate coefficients for the toxicity assessment of air pollutants." The International Journal of Life Cycle Assessment **2**(2): 104-110.

Lai, A. C. K., T. L. Thatcher, et al. (2000). "Inhalation Transfer Factors for Air Pollution Health Risk Assessment." Journal of the Air & Waste Management Association **50**(9): 1688-1699.

Lawrence Berkeley National Laboratory (2004) "China Energy Databook 6.0."

Layton, D. W. (1993). "Metabolically Consistent Breathing Rates for Use in Dose Assessments." Health Physics **64**(1): 22-36.

Levy, J., S. Chemerynski, et al. (2006). "Incorporating concepts of inequality and inequity into health benefits analysis." International Journal for Equity in Health **5**(1): 2.

Levy, J. I., S. L. Greco, et al. (2009). "Evaluating Efficiency-Equality Tradeoffs for Mobile Source Control Strategies in an Urban Area." Risk Analysis **29**(1): 34-47.

Levy, J. I., A. M. Wilson, et al. (2007). "Quantifying the Efficiency and Equity Implications of Power Plant Air Pollution Control Strategies in the United States." Environ Health Perspect **115**(5).

Levy, J. L., S. L. Greco, et al. (2002). "The importance of population susceptibility for air pollution risk assessment: A case study of power plants near Washington, DC." Environmental Health Perspectives **110**(12): 1253-1260.

Li, J. and J. Hao (2003). "Application of Intake Fraction to Population Exposure Estimates in Hunan Province of China." Journal of Environmental Science and Health, Part A **38**(6): 1041-1054.

Lin, L., B. Mao, et al. (2006). "A preliminary analysis on rational development of urban taxi traffic." Urban Transport of China **4**: 4.

Lin, S., M. He, et al. (2008). "Comparison Study on Operating Speeds of Electric-Bicycle and Bicycle: Experience from Field Investigation in Kunming." Transportation Research Record, Journal of the Transportation Research Board **2048**: 52-59.

Lindly, J. K. and T. A. Haskew (2002). "Impact of electric vehicles on electric power generation and global environmental change." Advances in Environmental Research **6**(3): 291-302.

Liu, Z., Q. Wu, et al. (2011). "Study on the energy consumption economy of electric vehicle based on test bench simulation." ACTA Scientiarum Naturalium Universitatis SUNYATSENI **50**(1): 5.

Luo, Z. W., Y. G. Li, et al. (2010). "Intake fraction of nonreactive motor vehicle exhaust in Hong Kong." Atmospheric Environment **44**(15): 1913-1918.

MacLean, H. L. and L. B. Lave (2003). "Life Cycle Assessment of Automobile/Fuel Options." Environmental Science & Technology **37**: 5445-5452.

Marshall, J. D. and W. W. Nazaroff (2002). Risk Assessment of Diesel-Fired Back-up Electric Generators Operating in California. Oakland, CA, Environmental Defense.

Marshall, J. D. and W. W. Nazaroff (2004). Using Intake Fraction to Guide ARB Policy Choices: The Case of Particulate Matter. Sacramento, CA, California Air Resources Board.

Marshall, J. D., W. J. Riley, et al. (2003). "Intake fraction of primary pollutants: motor vehicle emissions in the South Coast Air Basin." Atmospheric Environment **37**(24): 3455-3468.

Marshall, J. D., S.-K. Teoh, et al. (2005). "Intake fraction of nonreactive vehicle emissions in US urban areas." Atmospheric Environment **39**(7): 1363-1371.

McCarthy, R. and C. Yang (2010). "Determining marginal electricity for near-term plug-in and fuel cell vehicle demands in California: Impacts on vehicle greenhouse gas emissions." Journal of Power Sources **195**(7): 2099-2109.

Meszler, D. (2007). Air Emissions Issues Related to Two and Three-Wheeled Motor Vehicles, ICCT.

Millman, A., D. L. Tang, et al. (2008). "Air pollution threatens the health of children in China." Pediatrics **122**(3): 620-628.

Muller, N. Z. and R. Mendelsohn (2007). "Measuring the damages of air pollution in the United States." Journal of Environmental Economics and Management **54**(1): 1-14.

Nansai, K., S. Tohno, et al. (2002). "Effects of electric vehicles (EV) on environmental loads with consideration of regional differences of electric power generation and charging characteristic of EV users in Japan." Applied Energy **71**(2): 111-125.

NBS (2010). China Data Online, National Bureau of Statistics.

NBS (2012). China Data Online. N. B. o. Statistics.

Ni, J. (2008). Electric Two-Wheelers in China: Analysis of Safety, Luyuan Electric Vehicle Company.

Ni, J. (2011). from http://www.luyuan.cn/html/article/317.html.

Oliver, H., K. Gallagher, et al. (2009). In-use vehicle emissions in China: Beijing study. www.belfercenter.org/energy, Harvard John F. Kennedy School of Government.

Ott, W., A. C. Steinemann, et al., Eds. (2006). Exposure Analysis, Taylor & Francis.

Ou, X., X. Yan, et al. (2010). "Using coal for transportation in China: Life cycle GHG of coal-based fuel and electric vehicle, and policy implications." International Journal of Greenhouse Gas Control **4**(5): 878-887.

Pattanaik, P. K. (1968). "Risk, Impersonality, and the Social Welfare Function." Journal of Political Economy **76**(6): 1152-1169.

Pope, C. A., R. T. Burnett, et al. (2002). "Lung Cancer, Cardiopulmonary Mortality, and Long-term Exposure to Fine Particulate Air Pollution." JAMA: The Journal of the American Medical Association **287**(9): 1132-1141.

Povlsen, L., I. K. Borup, et al. (2011). "The concept of "equity" in health-promotion articles by Nordic authors - A matter of some confusion and misconception." Scandinavian Journal of Public Health **39**: 50-56.

Reid, D. D., P. J. S. Hamilton, et al. (1974). "CARDIORESPIRATORY DISEASE AND DIABETES AMONG MIDDLE-AGED MALE CIVIL SERVANTS: A study of Screening and Intervention." The Lancet **303**(7856): 469-473.

Rose, G. (2012). "E-bikes and urban transportation: emerging issues and unresolved questions." Transportation **39**(1): 81-96.

Rüdisüli, M., T. J. Schildhauer, et al. (2012). "Monte Carlo simulation of the bubble size distribution in a fluidized bed with intrusive probes." International Journal of Multiphase Flow **44**(0): 1-14.

Samaras, C. and K. Meisterling (2008). "Life Cycle Assessment of Greenhouse Gas Emissions from Plug-in Hybrid Vehicles: Implications for Policy." Environmental Science & Technology **42**(9): 3170-3176.

Schoolman, E. D. and C. Ma (2012). "Migration, class and environmental inequality: Exposure to pollution in China's Jiangsu Province." Ecological Economics **75**(0): 140-151.

Silva, C., M. Ross, et al. (2009). "Evaluation of energy consumption, emissions and cost of plug-in hybrid vehicles." Energy Conversion and Management **50**(7): 1635-1643.

Sioshansi, R. and P. Denholm (2009). "Emissions Impacts and Benefits of Plug-In Hybrid Electric Vehicles and Vehicle-to-Grid Services." Environmental Science & Technology **43**(4): 1199-1204.

Sioshansi, R., R. Fagiani, et al. (2010). "Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system." Energy Policy **38**(11): 6703-6712.

Smith, K. R. (1988). "Air Pollution: Assessing Total Exposure in Developing Countries." Environment: Science and Policy for Sustainable Development **30**(10): 16-35.

Smith, K. R. (1993). "Fuel combustion, air-pollution exposure, and health—the situation in developing-countries." Annual Review of Energy and the Environment **18**: 38.

State Council PRC. (2009). "The GHG emissions mitigation target for China in 2020." from http://cn.reuters.com/article/CNEnvNews/idCNCHINA-1207720091127.

Stephan, C. H. and J. Sullivan (2008). "Environmental and Energy Implications of Plug-In Hybrid-Electric Vehicles." Environmental Science & Technology **42**(4): 1185-1190.

Stevens, G., B. de Foy, et al. (2007). "Developing intake fraction estimates with limited data: Comparison of methods in Mexico City." Atmospheric Environment **41**(17): 3672-3683.

Touché, G. E. and G. O. Rogers (2005). "Environmental equity and electric power generation: Disparate community outcomes within Texas?" Journal of Environmental Planning and Management **48**(6): 891-915.

Wallington, T. J., M. Grahn, et al. (2010). "Low-CO2 Electricity and Hydrogen: A Help or Hindrance for Electric and Hydrogen Vehicles?" Environmental Science & Technology **44**(7): 2702-2708.

Wang, X., D. Westerdahl, et al. (2011). "On-road emission factor distributions of individual diesel vehicles in and around Beijing, China." Atmospheric Environment **45**(2): 503-513.

Wang, Y. C. (2011). from http://news.bitauto.com/others/20101107/1605238414.html.

WCED (1987). Our Common Future. New York.

Wei, Z., J. Shen, et al. (2006). "Comparative study on life cycle assessment for alternative vehicle fuels." Journal of Transportation Systems Engineering and Information Technology **6**(2): 4.

Weinert, J. (2007). The Rise of Electric Two-wheelers in China. PhD Dissertation, University of California, Davis.

Weinert, J., C. Ma, et al. (2007). "The transition to electric bikes in China: history and key reasons for rapid growth." Transportation **34**(3): 301-318.

Weinert, J., J. Ogden, et al. (2008). "The future of electric two-wheelers and electric vehicles in China." Energy Policy **36**(7): 2544-2555.

Weinert, J. X., C. Ma, et al. (2007). "Electric two-wheelers in China - Effect on travel behavior, mode shift, and user safety perceptions in a medium-sized city." Transportation Research Record(2038): 62-68.

Wheeler, D. and K. Ummel (2008) "Calculating CARMA: Global Estimation of Co2 Emissions from the Power Sector."

Whitehead, M. (1992). "THE CONCEPTS AND PRINCIPLES OF EQUITY AND HEALTH." International Journal of Health Services **22**(3): 429-445.

WHO (2005). 2005 World Summit Outcome.

Xiaohua, W. and F. Zhenming (1997). "Rural household energy consumption in Yangzhong county of Jiangsu province in China." Energy **22**(12): 1159-1162.

Xie, P., X. Liu, et al. (2011). "Human Health Impact of Exposure to Airborne Particulate Matter in Pearl River Delta, China." Water, Air, & Soil Pollution **215**(1): 349-363.

Xie, S. D., X. Y. Song, et al. (2006). "Calculating Vehicular Emission Factors with COPERT III Mode in China." Environmental Science **27**(3): 415-419.

Yan, X. and R. J. Crookes (2010). "Energy demand and emissions from road transportation vehicles in China." Progress in Energy and Combustion Science **36**(6): 651-676.

Yang, C.-J. (2010). "Launching strategy for electric vehicles: Lessons from China and Taiwan." Technological Forecasting and Social Change **77**(5): 831-834.

Yang, C. X., X. W. Peng, et al. (2012). "A time-stratified case-crossover study of fine particulate matter air pollution and mortality in Guangzhou, China." International Archives of Occupational and Environmental Health **85**(5): 579-585.

Yang, Z. Z., B. Yu, et al. (2007). "A parallel ant colony algorithm for bus network optimization." Computer-Aided Civil and Infrastructure Engineering **22**(1): 44-55.

Yao, M., H. Liu, et al. (2011). "The development of low-carbon vehicles in China." Energy Policy **39**(9): 5457-5464.

Yo-Bykes. (2009). "YoEXL Product Specifications." Retrieved June 19, 2009, from http://www.yobykes.in/yo_exl.aspx?pg=prd&sb=yoelec.

Zhang, M., Y. Song, et al. (2007). "A health-based assessment of particulate air pollution in urban areas of Beijing in 2000–2004." Science of The Total Environment **376**(1–3): 100-108.

Zhang, Q., D. G. Streets, et al. (2009). "Asian emissions in 2006 for the NASA INTEX-B mission." Atmospheric Chemistry and Physics **9**(14): 5131-5153.

Zhang, Y., Y. Yu, et al. (2011). "Analyzing public awareness and acceptance of alternative fuel vehicles in China: The case of EV." Energy Policy **39**(11): 7015-7024.

Zhao, Y., S. Wang, et al. (2008). "Primary air pollutant emissions of coal-fired power plants in China: Current status and future prediction." Atmospheric Environment **42**(36): 8442-8452.

Zheng, J., S. Mehndiratta, et al. (2012). "Strategic policies and demonstration program of electric vehicle in China." Transport Policy **19**(1): 17-25.

Zhou, Y., J. S. Fu, et al. (2010). "Risk-Based Prioritization among Air Pollution Control Strategies in the Yangtze River Delta, China." Environmental Health Perspectives **118**(9): 1204-1210.

Zhou, Y., J. I. Levy, et al. (2006). "The influence of geographic location on population exposure to emissions from power plants throughout China." Environment International **32**(3): 365-373.

Zhou, Y., J. I. Levy, et al. (2003). "Estimating population exposure to power plant emissions using CALPUFF: a case study in Beijing, China." Atmospheric Environment **37**(6): 815-826.

Zhu, F., Y. Zheng, et al. (2005). "Environmental impacts and benefits of regional power grid interconnections for China." Energy Policy **33**(14): 1797-1805.

APPENDIX

Table A.1. Emission Factors of Electric Vehicles (g $(100\text{-km})^{-1}$).

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

Table A.1 (Cont.). Emission Factors of Electric Vehicles (g $(100\text{-km})^{-1}$).

City	Vehicle	$PM_{2.5}$	PM_{10}	SO_2	NO_X	VOC	BC	CO	CO_2
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	21.209

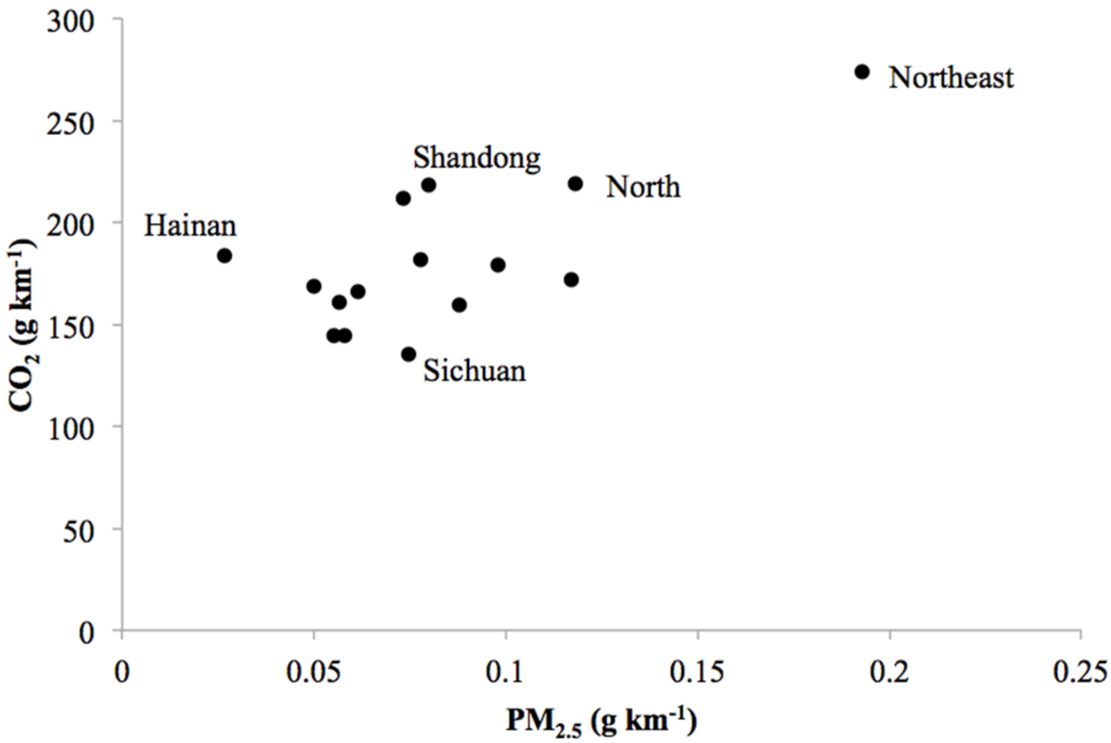


Figure A.1. Average e-car station-to-wheel emission factors for CO_2 and $PM_{2.5}$ for China's 15 electricity grids. In general, points in the lower left represent grids in the southwest and points on the upper right represent grids in the northeast.

Table A.2. Intake Fraction from Urban Tailpipe Emissions in 34 Cities.

City	Urban Population	Urban Area (km^2)	Mix Height*Wind Speed (Harmonic Mean[1]) (m^2 s^{-1})	iF (intake per million)
Beijing	9,290,000	1368.32	575.63	73.2
Changchun	3,289,600	4906.00	608.87	12.9
Changsha	2,305,600	556.33	524.66	31.3
Changzhou	1,800,300	1669.00	612.82	12.1
Chengdu	5,955,600	1418.00	412.61	64.3
Chongqing	8,769,700	82403.00	449.70	11.4
Dalian	3,368,300	2415.00	908.29	12.7
Foshan	3,610,800	77.00	591.45	116.8
Guangzhou	6,935,500	3843.43	591.45	31.7
Guiyang	1,791,200	2403.00	706.47	8.7
Hangzhou	3,237,500	3068.00	576.25	17.0
Harbin	4,769,200	7086.00	635.36	15.0
Huai'an	1,662,600	3218.00	761.74	6.5
Jinan	4,228,600	2119.00	600.64	25.7
Kunming	2,151,700	330.00	905.78	21.9
Lanzhou	1,985,300	1663.00	532.18	15.4
Nanjing	4,813,400	4844.00	607.09	19.1

Table A.2 (Cont.). Intake Fraction from Urban Tailpipe Emissions in 34 Cities.

City	Urban Population	Urban Area (km^2)	Mix Height*Wind Speed (Harmonic Mean[1]) ($m^2\ s^{-1}$)	iF (intake per million)
Ningbo	1,942,100	1033.00	678.18	15.0
Putian	601,100	139.00	776.67	11.0
Qingdao	4,658,200	1159.00	853.22	26.9
Shanghai	11,969,400	2648.60	772.12	50.6
Shenyang	4,557,600	3495.00	582.05	22.2
Shijiazhuang	3,909,700	455.80	591.48	52.0
Suzhou	3,307,700	1650.00	907.47	15.1
Taiyuan	2,563,900	180.00	643.24	49.9
Tangshan	2,362,300	3874.00	576.37	11.1
Tianjin	5,803,400	4334.72	577.87	25.6
Wuhan	5,286,200	1557.00	587.81	38.2
Wuxi	3,344,500	1659.00	863.53	16.0
Xi'an	3,538,500	1066.00	474.72	38.3
Xiangfan	1,933,500	3563.00	507.37	10.7
Zaozhuang	1,212,900	3065.00	584.68	6.3
Zhengzhou	2,978,600	1010.30	505.76	31.1
Zibo	1,835,300	2961.00	587.47	9.6

Table A.3. Average iF (ppm) Comparison – Urban vs. EGUs.

City	iF-Urban (including $PM_{2.5}$)	iF - EGUs							
		$PM_{2.5}$ (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

Table A.3 (Cont.). Average iF (ppm) Comparison – Urban vs. EGUs.

City	iF-Urban (including $PM_{2.5}$)	iF - EGUs $PM_{2.5}$ (Interpolated)	SO_2	PM_1	PM_3	PM_7	PM_{13}	SO_4	NO_3
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

Table A.4. 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		25.2	

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.

Table A.5. Excess Death per 10^{10} Person-km Traveled by Vehicle and City based on Monte Carlo Simulation.

City	E-bike	E-Car	Diesel Car	Gasoline Car	Bus
Beijing	2.1 (3.2)	15.2 (25.7)	61.5 (104.7)	6.4 (12.2)	16.4 (41.2)
Changchun	3.6 (8.6)	24.9 (51.7)	21.7 (4.76)	2.3 (5.9)	6.0 (23.4)
Changsha	3.4 (6.0)	23.7 (41.0)	54.1 (117.3)	5.7 (14.1)	14.8 (53.1)
Changzhou	3.1 (5.8)	21.7 (43.0)	20.0 (32.7)	2.1 (3.8)	5.4 (13.4)
Chengdu	2.3 (4.4)	16.0 (31.3)	54.2 (86.7)	5.6 (10.0)	14.4 (29.0)
Chongqing	4.2 (8.6)	30.7 (69.1)	19.0 (36)	2.0 (4.2)	5.1 (13.4)
Dalian	3.7 (7.2)	25.6 (39.7)	21.5 (44.9)	2.3 (5.5)	5.9 (21.4)
Foshan	2.0 (3.6)	13.8 (26.5)	96.7 (165.1)	10.1 (18.0)	25.9 (49.9)
Guangzhou	2.0 (3.5)	14.3 (26.5)	53.4 (92.5)	5.6 (10.5)	14.3 (33.3)
Guiyang	1.4 (2.7)	10.2 (21.0)	14.7 (28.2)	1.5 (3.2)	4.0 (10.4)
Hangzhou	3.0 (5.3)	21.7 (43.8)	29.6 (61.0)	3.1 (7.0)	8.1 (25.3)
Harbin	3.7 (7.0)	25.2 (46.2)	25.3 (39.7)	2.7 (4.7)	6.9 (15.9)
Huai'an	3.1 (6.1)	21.6 (41.5)	10.8 (22.8)	1.1 (2.5)	2.9 (8.2)
Jinan	2.7 (5.3)	18.9 (34.5)	44.3 (79.6)	4.7 (9.5)	12.0 (33.5)
Kunming	1.3 (0.28)	8.6 (16.3)	37.2 (65.8)	3.8 (7.3)	9.9 (23.7)

Table A.5 (Cont.). Excess Death per 10^{10} Person-km Traveled by Vehicle and City based on Monte Carlo Simulation.

City	E-bike	E-Car	Diesel Car	Gasoline Car	Bus
Lanzhou	2.2 (5.6)	15.9 (41.3)	25.8 (48.6)	2.7 (5.3)	6.9 (17.4)
Nanjing	3.1 (5.6)	21.2 (37.8)	32.2 (60.2)	3.4 (7.3)	8.9 (27.6)
Ningbo	3.1 (6.6)	22.3 (40.9)	25.3 (45.7)	2.6 (5.4)	6.8 (19.0)
Putian	2.4 (4.9)	17.0 (31.3)	19.4 (37.4)	2.0 (4.4)	5.3 (15.8)
Qingdao	2.8 (6.4)	19.6 (37.6)	46.3 (102.5)	4.8 (12.3)	12.6 (46.5)
Shanghai	3.0 (5.9)	21.9 (46.8)	46.3 (113.4)	4.8 (13.5)	12.4 (50.5)
Shenyang	3.7 (7.5)	26.0 (53.3)	38.2 (83.6)	4.0 (9.9)	10.5 (36.6)
Shijiazhuang	2.3 (0.56)	16.3 (34.9)	45.7 (96.9)	4.8 (10.8)	12.4 (35.5)
Suzhou	3.0 (4.7)	21.3 (37.0)	25.7 (54.9)	2.7 (6.7)	7.0 (25.3)
Taiyuan	2.2 (3.5)	15.6 (29.9)	43.4 (73.6)	4.5 (8.1)	11.6 (23.5)
Tangshan	2.2 (4.0)	15.4 (28.3)	18.9 (33.2)	2.0 (3.7)	5.0 (12.2)
Tianjin	2.2 (4.2)	16.0 (3.17)	43.9 (85.8)	4.6 (9.8)	11.9 (33.0)
Wuhan	3.6 (7.1)	24.7 (52.0)	63.7 (118.7)	6.6 (13.8)	17.2 (50.3)
Wuxi	3.0 (5.2)	20.8 (32.1)	27.3 (54.2)	2.9 (6.6)	7.5 (25.1)
Xi’an	2.2 (4.4)	16.1 (38.5)	65.0 (144.9)	6.9 (17.5)	18.0 (67.3)

Table A.5 (Cont.). Excess Death per 10^{10} Person-km Traveled by Vehicle and City based on Monte Carlo Simulation.

City	E-bike	E-Car	Diesel Car	Gasoline Car	Bus
Xiangfan	3.5 (7.3)	24.5 (48.1)	18.3 (41.4)	1.9 (5.1)	5.1 (19.8)
Zaozhuang	2.6 (4.5)	18.1 (29.9)	10.3 (19.3)	1.1 (2.2)	2.8 (8.0)
Zhengzhou	3.4 (5.9)	24.3 (46.5)	51.6 (90.2)	5.4 (10.9)	14.2 (41.2)
Zibo	2.7 (4.4)	18.7 (31.3)	16.9 (36.6)	1.8 (4.3)	4.6 (15.5)

1. Numbers in parenthesis are the standard deviation of results.
2. Emission factors used for gasoline and diesel cars are based on Euro III emission standards.

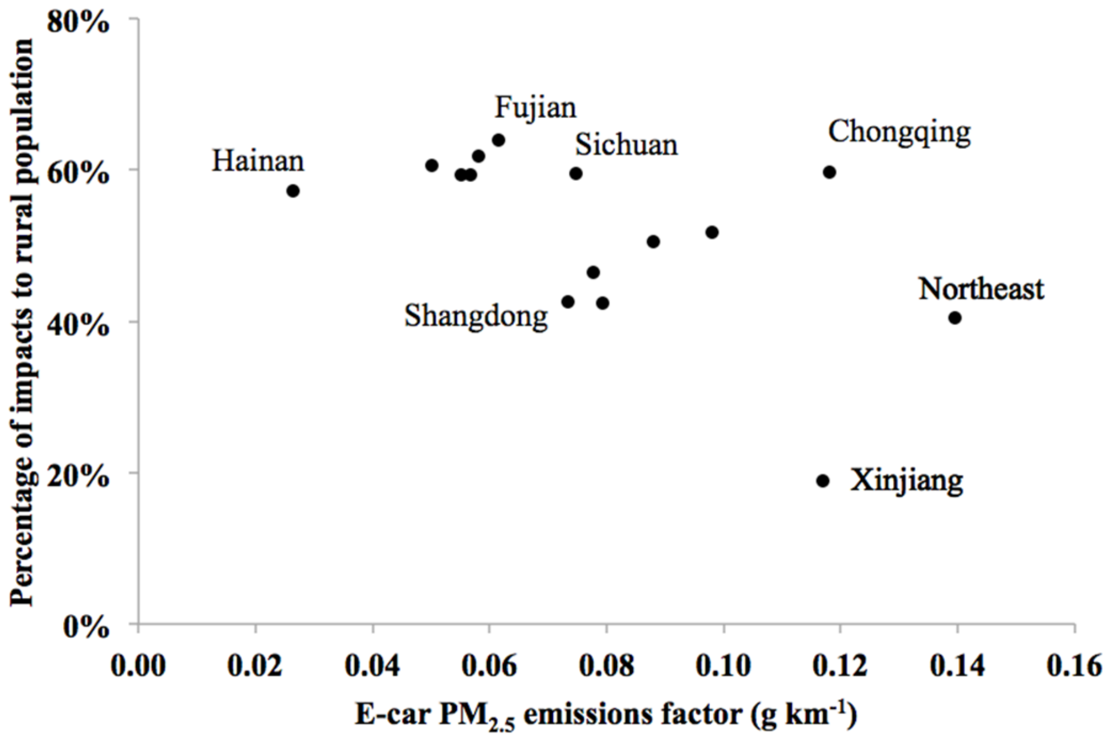


Figure A.2. E-car $PM_{2.5}$ station-to-wheel emission factors and proportion of impacts of urban EV use to non-urban populations. In general, urban use of EVs rather than CVs moves emissions and health impacts to rural locations. The data exhibit a weak negative relationship between emission factors and proportion of health impacts born by rural populations, implying that grids with higher emission factors are more urbanized.

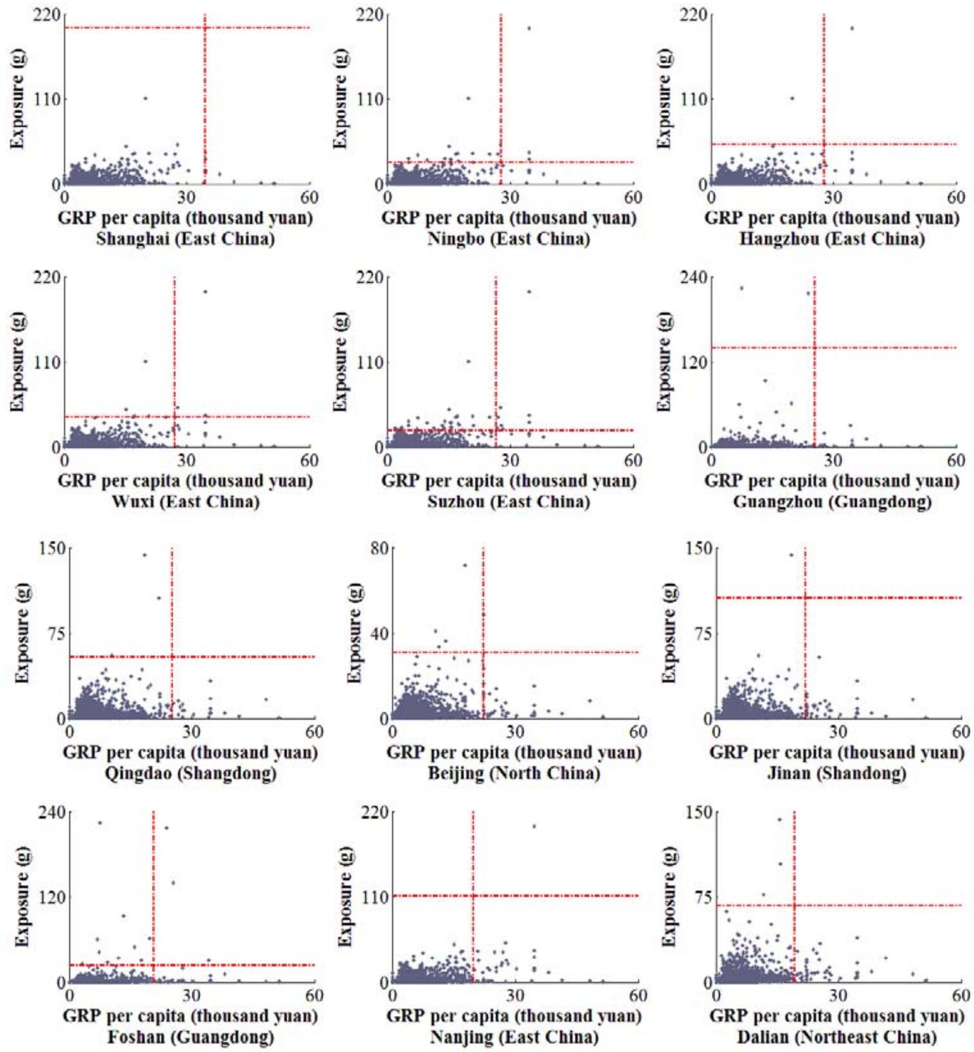


Figure A.3. Exposure to primary $PM_{2.5}$ emissions from EV shift. The red dash lines divide counties into four groups - low income with low exposure (bottom left), low income with high exposure (top left), high income with low exposure (bottom right), and high income with high exposure (top right). The cross point (marked as asterisk) of dash lines represents city using e-cars.

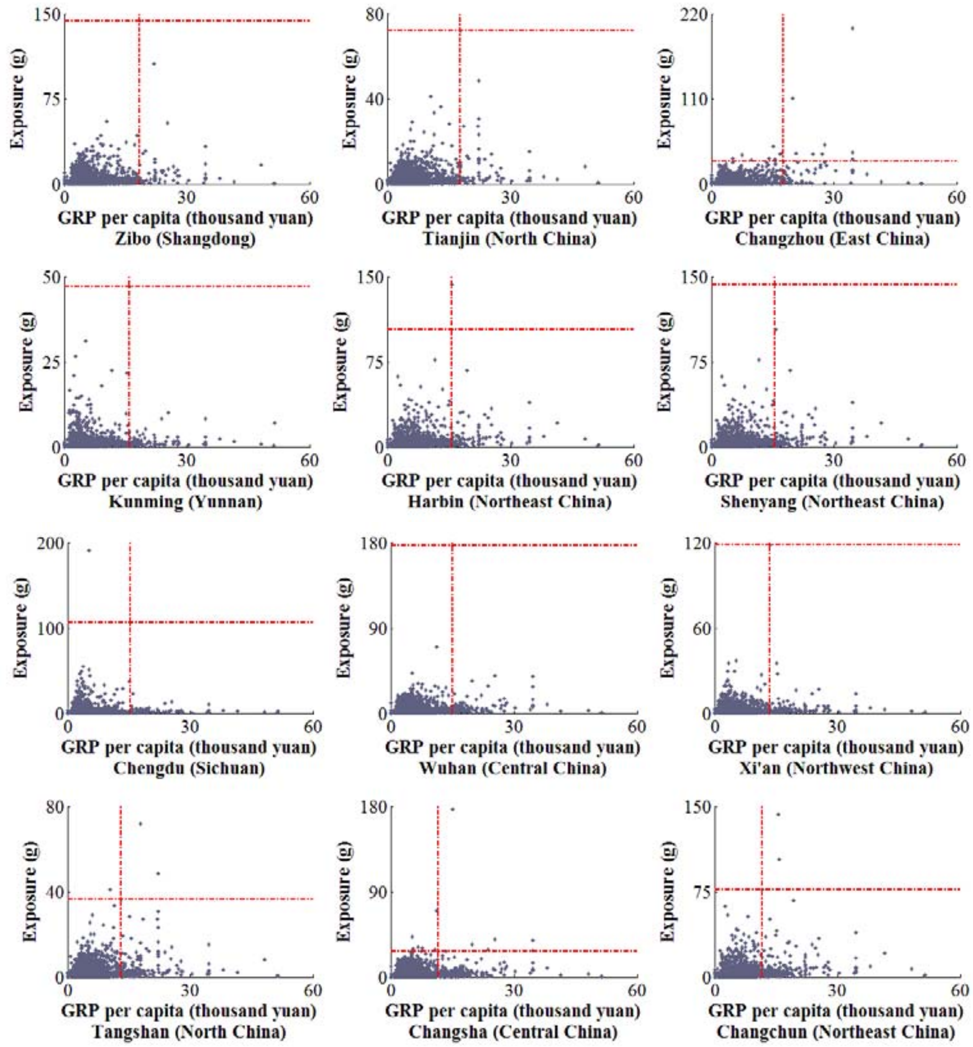


Figure A.3 (Cont.). Exposure to primary $PM_{2.5}$ emissions due to EV shift. The red dash lines divide counties into four groups -- low income with low exposure (bottom left), low income with high exposure (top left), high income with low exposure (bottom right), and high income with high exposure (top right). The cross point (marked as asterisk) of dash lines represents city using e-cars.

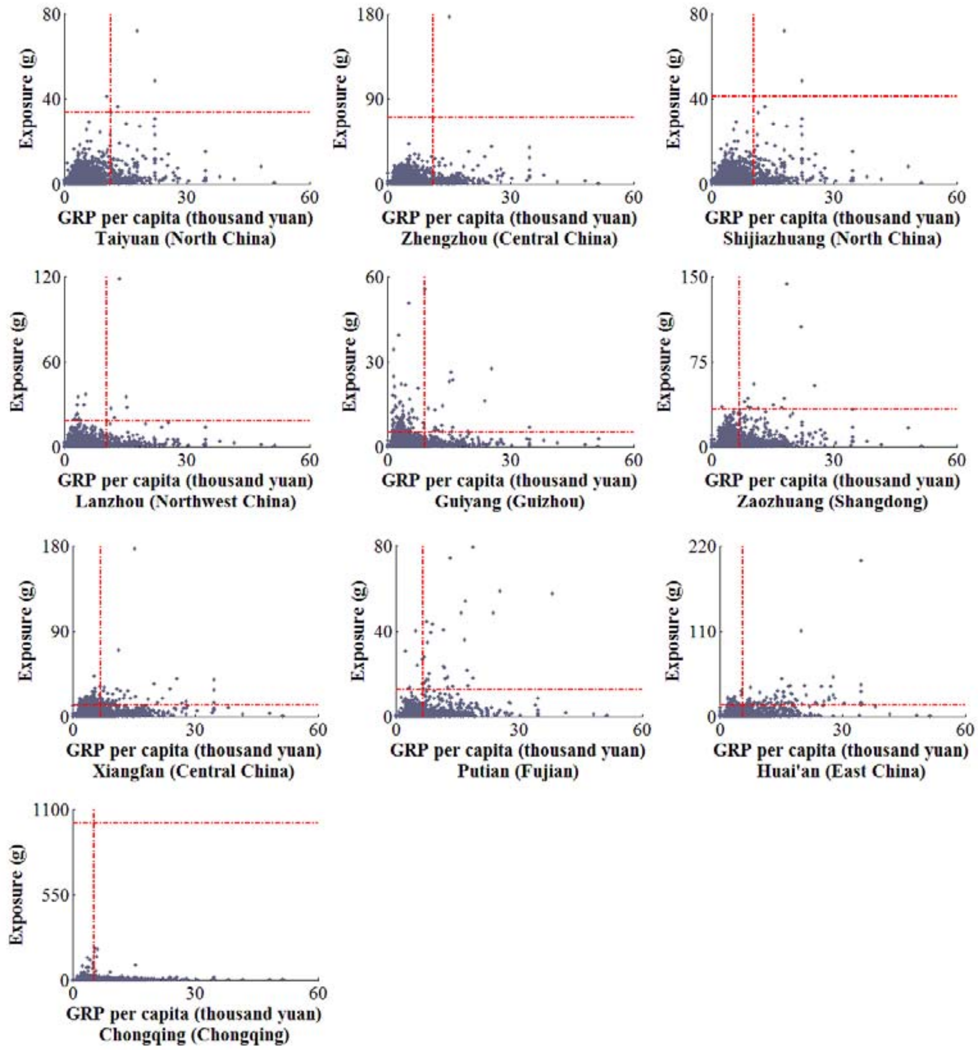
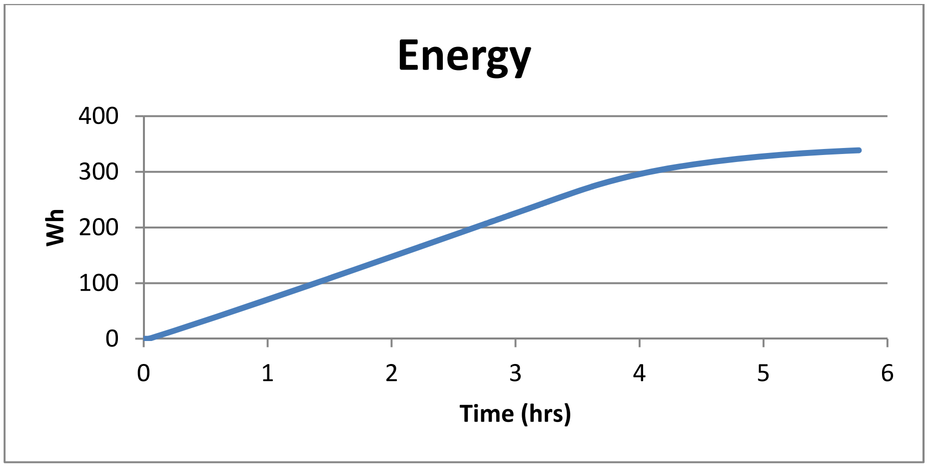
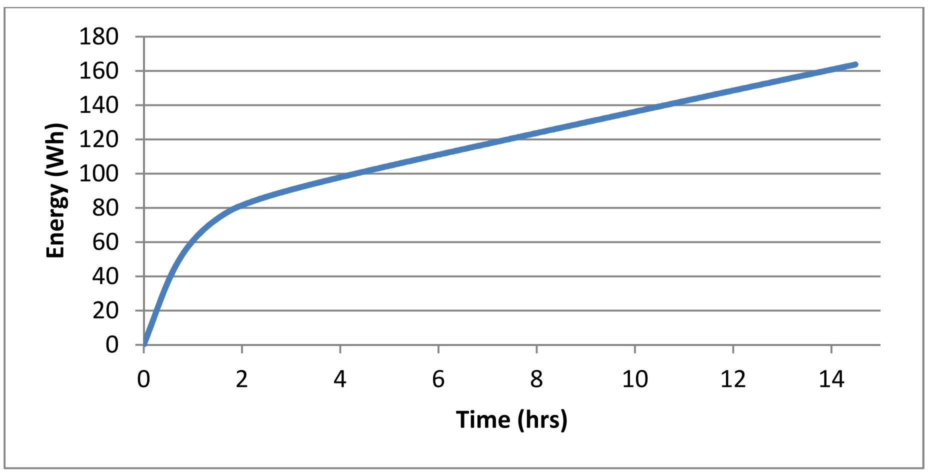


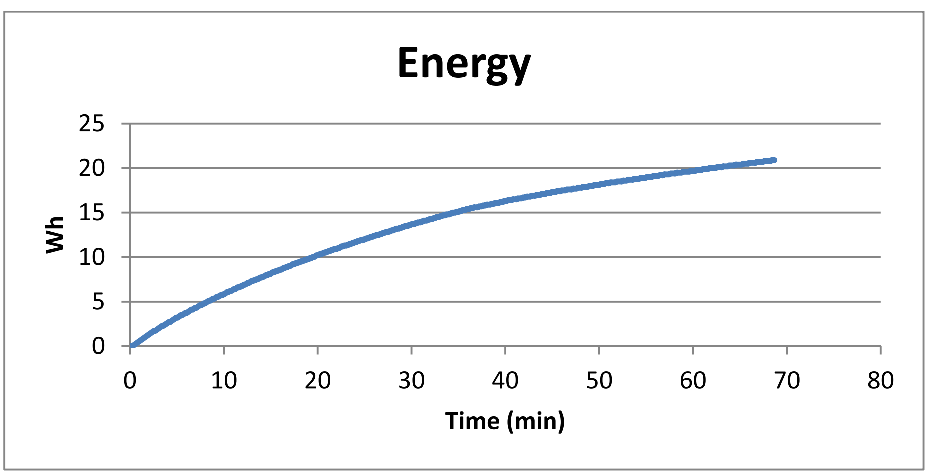
Figure A.3 (Cont.). Exposure to primary $PM_{2.5}$ emissions due to EV shift. The red dash lines divide counties into four groups -- low income with low exposure (bottom left), low income with high exposure (top left), high income with low exposure (bottom right), and high income with high exposure (top right). The cross point (marked as asterisk) of dash lines represents city using e-cars.



(a)



(b)



(c)

Figure A.4. Recharging profiles of e-bike battery.

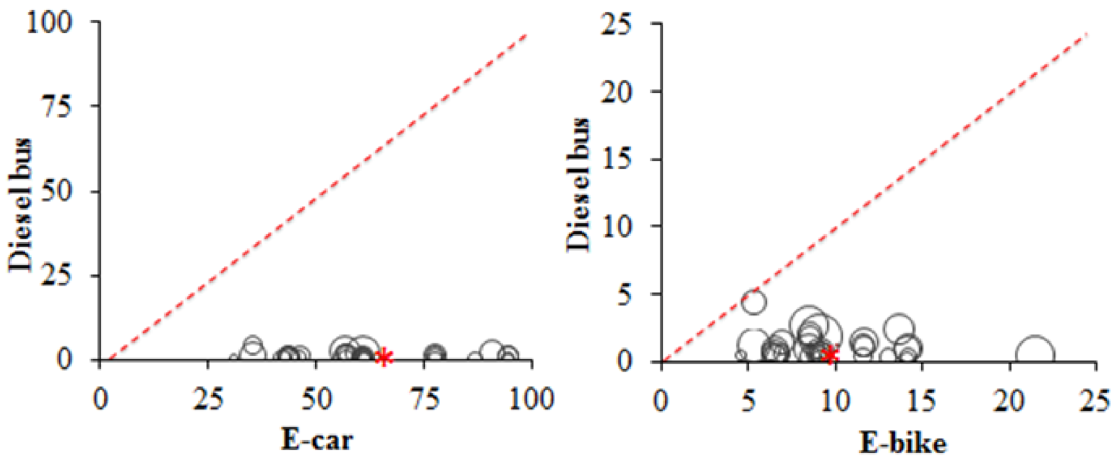


Figure A.5. SO_2 excess deaths per 10^{10} passenger-km, for the 34 cities considered.

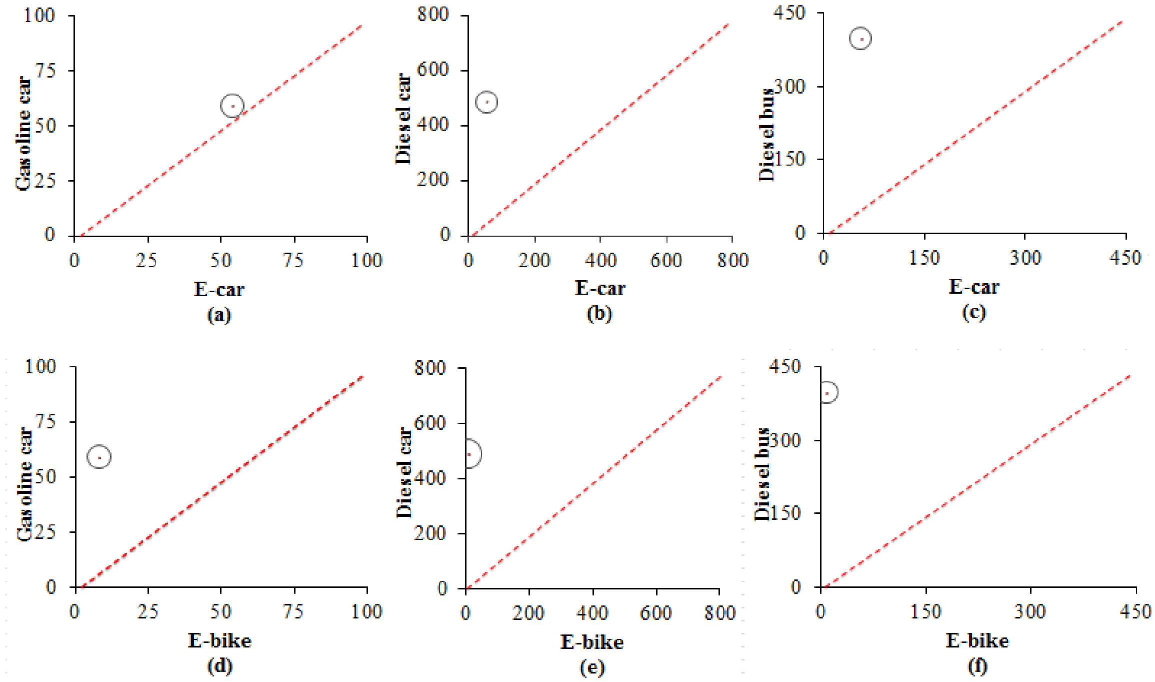


Figure A.6. NOx excess deaths per 10^{10} passenger-km for Beijing.

VITA

Mr. Shuguang Ji was born in Dalian, China. He completed his Bachelor's and Master's degrees in Transportation Engineering at Dalian Maritime University.

Mr. Ji continued his study at University of Tennessee at Knoxville and works as doctoral student with Dr. Christopher Cherry. His major is Civil Engineering with concentration on Transportation Engineering. At the same time, he is in the Master program of Business Administration with concentration on Statistics. He also minors in Computational Science. He holds Engineer-in-Training certificate.

Mr. Ji's research interests include transportation and the environment, transportation and energy policy, statistics and non-linear mathematics, marine transportation, high performance computation, and remote sensing.

Mr. Ji is member of ITE, ASA, ASCE, AREMA, TCI, PACE, and ENCSS. He serves as secretary of ITE student chapter at University of Tennessee, Knoxville from 2008. He has received the McClure scholarship, Chancellor's Honor: Extraordinary Contributions to Campus Life, and Baker Policy Center research funding at University of Tennessee, Knoxville. His research on electric vehicles in China has received ample media coverage worldwide.