The environmental impacts and health co-benefits of climate mitigation measures on household consumption in China

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to the University of Exeter as a thesis for the degree of

Doctor of Philosophy in Sustainable Futures

in September 2022, to be jointly awarded by the University of Exeter and Tsinghua University

I certify that all material in this thesis which is not my own work has been identified and that any material has previously been submitted and approved for the award of a degree by this or any other University has been acknowledged.

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Abstract

Household sector is a key sector for deploying climate mitigation strategy. Previous research has mainly focused on the impact analysis of mitigation measures at supply side. However, how to implement climate mitigation measures for household consumption activities and evaluate health co-benefits among different populations resulting from household consumption changes when conducting mitigation strategies is an unanswered research question. To answer this research question, the household sector is added into an integrated assessment framework, coupling the energy inventory data, a Greenhouse Gas and Air pollution Interactions and Synergies (GAINS) model, a Global Exposure Mortality Model (GEMM), and a Health Economic Model. This integrated assessment framework is used to conduct an analysis of direct and indirect energy consumption of household activities, and health co-benefits of deploying mitigation strategies of household consumption. We then propose suggestions for improving policy making regarding household energy consumption.

Household energy consumption is divided into the direct and indirect. In this thesis, first, an analysis of household direct consumption activities and health co-benefits across age- and gender- specific populations, when deploying the clean energy transition for rural and urban households in China is conducted. Second, household indirect energy consumption is studied, and household consumption activities are classified into eight different categories: food; clothing; housing; household facilities articles and services (abbreviated as facilities); transport and communication services (transport); education; cultural and recreation services (education); medicine and medical services (health) and miscellaneous commodities and services (miscell). These categories are used to identify on which sources of energy consumption to put the emphasis of mitigation strategies, under the ongoing urbanization, in both rural and urban areas. Finally, implementing a mitigation strategy in household transport activities, to better know the potential health co-benefits across subpopulations when households adopt a “greener” mode of transport or switch to electric vehicles. A case study is done in Beijing, China, exploring mitigation scenarios through household transport pattern changes.

The findings of this thesis are: 1) The implementation of climate mitigation strategies in households’ direct and indirect consumption activities can potentially generate large health benefits and economic benefits, but the distribution of these co-benefits shows regional, provincial and gender- and age- heterogeneity. 2) During China's urbanization, energy consumption of household activities related to housing and transport are expected to increase several folds; to better deploy mitigation measures for household consumption activities, regions in the first wealth quintile have the highest average income should take up the responsibility of degrading its own consumption level, especially in the consumption of aspirational and opulent goods and services and improve its own industrial energy efficiency, especially in transport, storage and transport equipment and service sector. 3) When adopting climate mitigation strategies in households’ transport modes, a case study done in Beijing, China, finds that the combination of walking, cycling and use of public transport (abbreviated as “green” transport) and electric vehicles, can generate the largest health co-benefits, with the increased use of green transport having the highest impact.

This study provides new insights into the climate mitigation measures on Chinese household consumption activities and their health co-benefits across different age and gender groups at the national/regional/provincial level. Taking into account different social groups’ benefits and disadvantages for the policy making is necessary to increase the environmental justice.

Keywords: household energy consumption; climate mitigation; health co-benefits; economic benefits; urban and rural

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Author’s Declaration

I, Chenxi Lu, declare that the thesis entitled “The environmental and health impacts and co-benefits of household consumption change in China” and the work presented in the thesis is my own and has been generated by me as the result of my own original research.

I confirm that:

This work was done wholly or mainly while in candidature for a joint Ph.D degree at the University of Exeter and Tsinghua University;

Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;

Where I have consulted the published work of others, this is always clearly attributed;

Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;

I have acknowledged all main sources of help;

Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Abbreviations

AIM	Asia-Pacific Integrated Model
ANCD	Additional nonaccidental noncommunicable diseases
BAU	Business as usual
CEADs	China Emission Accounts and Datasets
CI	Confidence interval
CLA	Consumer lifestyle approach
CO2	Carbon dioxide
COPD	Chronic obstructive pulmonary disease
DALY	Disability-adjusted life-years
ECs.	Electric cars
EE IOA	Environmental extended input-output analysis
EJ	Environmental justice
EVs	Electric vehicles
FYP	Five-year plan
GAINS	Greenhouse Gas and Air pollution Interactions and Synergies
GBD	Global Burden of Disease
GDP	Gross Domestic Product
GEMM	Global Exposure Mortality Model
GHG	Greenhouse gas
IAM	Integrated assessment model
IER	Integrated exposure-response
IGT	Increased green transport
IGT_MEV	Combining IGT and MEV scenarios
IHD	Ischemic heart disease
IIASA	International Institute of Applied System Analysis
IPCC	Intergovernmental Panel on Climate Change

LC	Lung cancer
LEAP	Long-range Energy Alternatives Planning system
LRI	Lower respiratory infections
MARKAL	Market Allocation
MEV	More electric vehicles
MRIO	Greenhouse gas Multi-Regional Input–Output
NAAQ	National ambient air quality standard
NCD	Noncommunicable diseases
NDCs	Nationally Determined Commitments
O3	Ozone
PM2.5	Particular matter 2.5
PM10	Particular matter 10
RR	Relative risk
SCC	Social cost of carbon
SO2	Sulphur dioxide
TMs	Travel modes
UNFCCC	United Nations Framework Convention on Climate Change
US	United States
VSL	Value statistical life
WHO	World Health Organization

Chapter 1 Introduction

1.1 Research background

Global climate change is threatening the earth's ecological safety as well as human survival and development and is one of the major global environmental challenges as well as the global health threat faced by humanity in the 21st century (He, 2016, Costello et al., 2009). Global carbon emissions have increased on an average of 3.1% per year since 2000 mainly due to the global economic growth (Le Quéré et al., 2013, Andres et al., 2012). This has heightened the urgency for economies to make mitigation policies to reduce greenhouse gas (GHG) emissions and to transit to sustainability (Lu et al., 2021, Costello et al., 2009). To avoid warming of 2 ℃ above pre-industrial temperatures by 2030 under the 2015 Paris Climate Agreement, climate change mitigation efforts are required by the United Nations Framework Convention on Climate Change (UNFCCC) committed countries beyond the Nationally Determined Commitments (NDCs) (Chang et al., 2017). The agreement is an important step forward, prompting countries to consider the range of climate policy options and their broader impacts (Chang et al., 2017).

In 2008, due to rapid increase in production and consumption activities in last decades, China become the world's largest carbon emitter (Guan et al., 2009, Yao et al., 2017). China has pledged to cap carbon emissions by 2030 and carbon neutrality by 2060 (Gallagher et al., 2019, Vaughan, 2020), implementing several policies to reduce its GHG emissions as well as promoting environmental sustainability by setting targets for reducing energy intensity, phasing out inefficient power plants and factories, developing renewable and low-carbon energy, etc. (Feng et al., 2011), mainly focusing on certain industrial production sectors (Feng et al., 2011), like iron and steel sector, transport sector, during period of the 11th five-year plan (FYP) (2006-2010),12th FYP (2011-2015) and 13th FYP (2016-2020) (Elzen et al., 2016, Liu et al., 2013b). During these periods, China has achieved some progress on reducing carbon intensity by 29% from 2000 to 2017(Cai et al., 2021a), reducing it's share of coal in the total energy consumption (from 71.4% in 1997 to 57.7% in 2019 (NBSC, 2020)) , increasing the share of low-carbon electricity (hydropower, nuclear, wind, and solar power) (increased by 46.22% between 2000 to 2019; 2019, national low-carbon electricity accounted for 31.13% of the total electricity generation) (Cai et al., 2021a).

However, China's growth in final consumption and associated production process has offset endeavors in mitigation in the production sectors (Guan et al., 2009), resulting in a general increase trend of China's carbon emissions during historical period. In 2012, capital investment accounted for 48%, export contributed to 20% and consumption of products and services by households and governmental institutions was responsible for the remaining carbon emissions (32%), from the consumption-based accounting of carbon emissions (Wiedenhofer et al., 2017). China is transforming domestic consumption-oriented economy instead of export-oriented economy, moving towards carbon- and resource-intensive consumer lifestyles, following the lifestyle of high-income countries (Wiedenhofer et al., 2017, Liu et al., 2021a). It is expected that the China's Gross Domestic Product (GDP) will continue to grow and domestic consumption would play a more significant role in Chinese GDP's growth considering continuous increase in household income, further growth of urbanization and changes in technology and demographic shifts (Skelly, 2017). In 2020, consumption expenditure contributed 54.3% to China's GDP, which hit the highest record in recent years of China (NBSC, 2021). Moreover, the average private consumption level in China is still below the global average. In 2019, China's per capita final consumption expenditure was merely 68.7% of the global average (WB, 2021). With the boom of wealth of Chinese residents and rising of middle class, it is expected that the consumption expenditure of residents would undergo a massive increase, and its attached carbon emissions cannot be put by negligence. Thereafter, it is imperative to put emphasis on mitigation in household consumption.

1.2 Research about household consumption

The analysis of household consumption and related environmental effects is one of the most popular topics in sustainability research in recent decades (Zhang et al., 2015). The most population topic about the household consumption's environmental impacts is about the household carbon emissions, also called as the household carbon footprint (some also studied household energy consumption since the household carbon emissions are from using energy directly or indirectly, below we discuss the progress of household energy/carbon footprint). In last two decades, household energy/carbon footprint and households'/consumers' consumption patterns have attracted increasing attention and discussion among researchers (Bin and Dowlatabadi, 2005). A household not only uses direct energy in the form of gas, electricity and petrol, it also uses indirect energy embodied in consumer goods such as food, furniture and services (Vringer and Blok, 1995), with indirect energy consumption or carbon emissions higher than the direct. Bin and Dowlatabadi (2005) found that over 80% of energy consumption and carbon emissions in United States (US) were attributed to consumer demands and related economic activities and indirect effects of consumer behavior caused by energy consumption and CO_2 emissions were twice those of direct effects. The household sector in Korea resulted in over 60% indirect of the energy requirement (Peters et al., 2007). Wiedenhofer et al. (2017) found that households induced 17% of China's carbon footprint in 2012. Zhang et al. (2017e) concluded that the sum of direct and indirect energy consumption caused by household consumption took up 40% of the total energy consumption in China during 2000-2010, while the CO_2 emission caused by household consumption accounted for 41% of the total on average.

In the late 1980s, research brought the concept of lifestyle (lifestyle is a way of living that influences and is reflected by one's consumption behavior (Bin and Dowlatabadi, 2005)) into the study of personal energy consumption or carbon emissions. As a consequence of this innovation, Schipper et al. (1989) concluded that "about 45–55% of total energy use is influenced by consumers' activities for personal transportation, personal services, and homes. Weber and Perrels (2000) quantified the impact of lifestyle factors on the 1990s and 2010s energy demand and related emissions in West Germany, France and the Netherlands. Bin and Dowlatabadi (2005) found and direct CO_2 emissions of consumers accounted for 41% of US total CO_2 emissions and indirect (such as such as housing operations, transportation operations, food, and apparel) involved more than twice the direct energy use and CO_2 emissions. Wei et al. (2007b) quantified the direct and indirect impact of lifestyle of urban and rural residents on China's energy use and CO_2 emission from 1999 to 2002 and found that Residence; home energy use; food; and education, cultural and recreation services are the most energy-intensive and carbon-emission-intensive activities. Further research by Ding et al. (2017) found the indirect energy consumption of household consumption activities is 1.35 times more than the direct energy consumption. Housing activities cause the most indirect energy consumption.

In general, the research direction of household energy/carbon footprint is primarily about i) how to quantify household energy/carbon footprint; ii) what factors influencing household carbon footprint; iii) how to mitigation household carbon footprint. Various methods have been applied to quantify household carbon footprint, primarily including the input-output model, life cycle assessment, emission coefficient method and consumer lifestyle approach. And consumption data from consumer expenditure survey is also used to quantify household carbon footprint. The adoption of different methods listed above is likely to produce different results (Plassmann et al., 2010) and these methods have their own advantages and disadvantages. For example, the input-output model can provide a standard method of analysis which can be updated or applied to different populations in a uniform manner, but it assumes a fixed technology coefficient which couldn't reflect technological improvement and elasticity, also it lacks reliability when forecasting long-run effects (Zhang et al., 2015). There are many factors influencing household energy or carbon emissions including the socio-economic factors (e.g., household income (Lyons et al., 2012)), household characteristics (e.g., age (Golley and Meng, 2012), gender (Büchs and Schnepf, 2013) , education levels (Golley and Meng, 2012)) and geographic factors (Druckman and Jackson, 2008). For example, Peters et al. (2007) found that household carbon emissions was driven by the increased urban household expenditure and urbanization as household income in most regions continued to rise, more money was spent on recreation activities, education, transportation, communication services, etc. Measures for carbon abatement have been proposed at the policy (Dai et al., 2012), technology(Monahan and Powell, 2011) and consumer levels (Druckman and Jackson, 2010). A reduced consumption scenario in UK found that a minimum income standard can reduce 37% of average household GHG emissions (Druckman and Jackson, 2010). However, few discussed the health co-benefits of mitigating household consumption since the health benefits has gradually recognizing as an important factor in policy making (Hanney, 2003). Zhao et al. (2018) found that if solid fuels by Chinese household had been replaced with clean fuels, it could have saved 33% of the $PM_{2.5}$-induced mortality in 2015.

The research gap of household energy/carbon footprint are the shortage of data reliability; requiring advanced quantification methodologies; the need for more studies of different household consumption activities as well as in regional levels and the need for more studies about health co-benefits of mitigating household energy/carbon footprint.

1.3 Research about climate mitigation measures

Climate change mitigation generally refers to reductions in anthropogenic emission of GHG to limit the magnitude or rate of long-term global warming and its related effects (Fisher et al., 2007, IPCC, 2007). Moreover, mitigation may also be achieved by removing carbon dioxide from Earth's atmosphere (IPCC, 2007), or increasing the capacity of carbon sinks, e.g., through reforestation (IPCC, 2007). Climate mitigation measures to reduce GHG emissions can be categorized as the measures targeting at the supply-side and demand-side. Supply-side mitigation measures include increasing energy efficiency, phasing out fossil fuels by switching to low-carbon energy sources, like solar/wind/nuclear power, applying new energy-efficient technologies, etc. Demand-side mitigation measures are those targeting technology choices, consumption, behavior, lifestyles, coupled production–consumption infrastructures and systems, service provision and associated sociotechnical transitions (Niamir et al., 2020, Creutzig et al., 2018). The exiting literature has the tendency to investigated the supply-side technology solutions and impacts (Creutzig et al., 2018) but few studied about the demand-side mitigation solutions. For a long time, Intergovernmental Panel on Climate Change (IPCC) reports have been working more on the solutions and impacts of enhanced end-use efficiency but provided little attention on the nature, scale, implementation and potential of demand-side solutions, and ignored associated changes in lifestyles, social norms and well-being (Creutzig et al., 2018). Also, the current global scenarios based on the integrated assessment models (IAMs) emphasize on the supply side technologies and carbon dioxide removal options to achieve long-term system transformation to meet the 1.5 °C ambition (Mundaca et al., 2018). But IAMs outcomes have the tendency to heavily rely on carbon dioxide removal and storage technologies, particularly bioenergy with carbon capture and storage (Fuss et al., 2014, Millar et al., 2017) because IAMs have the unique ability to link mitigation strategies and technology choices to emission budgets and warming outcomes (Mundaca et al., 2018). Yet the demand-side solution is neglected in IAMs studies (Kriegler et al., 2018).However, in recent years, academia gradually recognized the important role of demand-side mitigation measures in achieving 1.5 °C ambition. The sixth assessment report, AR6 of the IPCC featured a chapter on demand, services and social aspects of mitigation. And the IPCC special report on 1.5 degrees names “behavioral and lifestyle changes” as a vital climate change mitigation strategy complimentary to technological measures. Literature gradually increased the discussion about demand-side mitigation (Creutzig et al., 2021, Creutzig et al., 2018, Mundaca et al., 2018, Grubler et al., 2018). Modeling studies consistently show that demand-side measures play a critical role in meeting ambitious mitigation targets (Clarke et al. 2014; Riahi et al. 2015). Creutzig et al. (2021) systematically assessed the mitigation potential of demand-side options categorized into avoid, shift and improve, and their human well-being links and found that that these options, bridging socio-behavioral, infrastructural and technological domains, can reduce counterfactual sectoral emissions by 40–80% in end-use sectors as well as achieving large beneficial effects in improvement in well-being.

However, although demand-side mitigation is possibly in line with the 1.5 °C goal and there is a plenty of demand-side measures yet these are not fully been “seen” or captured by current quantitative tools or progress indicators (Mundaca et al., 2018). A comprehensive assessment of the underlying science and methods needed to provide realistic assessments of demand-side potential is still missing (Creutzig et al., 2018). The demand-side solutions require a synthesis of social science and engineering research-- including (but not limited to) contributions from psychology, economics, sociology, political science, industrial ecology, technological innovation studies and energy system modelling to understand the demand-side potential for climate change mitigation (Creutzig et al., 2018).

1.4 Research about health co-benefits of climate mitigation measures

To effectively implement mitigation strategies and provide impetus for countries/area to adopt mitigation strategies, it is also necessary to know the cost and benefits of these strategies. The cost of mitigation efforts is estimated to be several percent of global gross domestic product by the mid-century (Boyd et al., 2015); however these mitigations can deliver additional benefits as well, like improving air quality, lifestyles of humans (Patz and Thomson, 2018). These improvements are referred to as the co-benefits of climate mitigation strategies. In the 4th Assessment Report of the IPCC, co-benefits of climate mitigation are defined as the positive benefits related to the reduction of greenhouse gases (Helgenberger et al., 2019). However, although co-benefits of GHG mitigation can be large, they are often neglected, remaining unquantified by businesses and decision-makers. Appropriate consideration of co-benefits can greatly influence policy decisions concerning the timing and level of mitigation action, and there can be significant advantages to the national economy and technical innovation (Helgenberger et al., 2019). Studying the co-benefits of mitigation measures is vital, not only because it provides an additional rationale to adopt mitigation strategies especially for the UNFCCC committed countries to decrease their GHG emissions.

Over the last three decades, researchers have attempted to quantify the health co-benefits (Chang et al., 2017, Jack and Kinney, 2010, Viscusi et al., 1994, Ayres and Walter, 1991) of climate change mitigation. The Lancet series of papers provide a quantitative and methodological foundation for evaluating the costs and health co-benefits (Chang et al., 2017). Research has found that climate mitigation policies can improve health via improved air quality, physical activities, decreased meat consumption, reduced traffic accidents (Jack and Kinney, 2010, Friel et al., 2009, Woodcock et al., 2009). More specifically, Vennemo et al. (2006) found that China's Clean Development Mechanism potentially could save 3,000-40,000 lives annually through co-benefits of improved air pollution. The Stern Review (Stern, 2007) notes that limiting global mean temperature increase to 2°C and implementing the existing European air pollution control measures would save €10 billion annually and save €16–46 billion in health costs. Reviewing forty-two papers published from 2009-2017, Chang et al. (2017) found that most studies indicated significant, nearer term, local ancillary health benefits; however the studies were not suited to providing specific accurate estimates of health co-benefits. Most mitigation policies are sector-specific, making its co-benefits analysis into sector-specific. Gao et al. (2018) found that public health co-benefits of GHG mitigation was primarily observed in five economic sectors, including energy generation, transportation, agriculture and food, residential and household and industrial sector.

However, most benefits of mitigation studies have assessed benefits solely in terms of their effects on pollutant emissions at the national or local level (Wu et al., 2011) but still the health co-benefits studies are scarce. Globally, previous studies have mostly focused on the total health co-benefit of mitigation measures (Maizlish et al., 2013, Wang et al., 2020, Woodcock et al., 2009, Cai et al., 2018, Liang et al., 2019) but to my best knowledge, few studies have examined the distribution of health co-benefits across subpopulations with mitigation measures, but studying the effects on subpopulations can enhance our knowledge about who is going to benefit or bear the loss of climate mitigation measures; hence, it can promote the climate justice to have just and fair decarbonization transition. What's more, few research studied the impact of implementing climate mitigation strategies at demand-side (Creutzig et al., 2018).

1.5 Research gap and research aim

In Table 1.1, it summaries the research progress and research gap of the study of household consumption, climate mitigation measures and co-benefits of climate mitigation measures as mentioned previously.

From the research gap of the research area in household consumption, climate mitigation measures and health co-benefits of climate mitigation measures, it can be primarily concluded that the i) few literatures studied different household consumption activities' carbon footprint as well as in regional levels; ii) research on climate mitigation measures on demand-side is not sufficient; ii) study on health co-benefits of climate mitigation measures on subpopulations is not fully studied.

It is recognized the possible contribution and position of household sector in climate policies is neither well understood, nor does household sector receive sufficiently high priority in current climate policy strategies (Dubois et al., 2019). Specific issues identified:

(1) Although household energy consumption is one of major anthropogenic contributors of atmospheric pollutants in China, studies on the impact of the household energy consumption on air quality remain limited (Du et al., 2018, Zhao et al., 2019, Yun et al., 2020). The current evidence base has focused on elements of spatial and policy issues (Du et al., 2018, Zhao et al., 2019, Yun et al., 2020, Chen et al., 2018, Zhao et al., 2018) but has not fully accounted for the effect of household consumption on the health profile of different population

groups at different spatial scales or across rural and urban areas. Besides, the study of health co-benefits when adopting climate mitigation measures in the household direct consumption activities in China is limited.

(2) Research on climate mitigation strategies on the demand-side research is limited (Creutzig et al., 2018, Bjørn et al., 2018). Research on the health co-benefits when deploying climate mitigation strategies on the demand-side is limited.

Given that more pronounced effect of China’s household consumption on energy consumption and carbon emissions (Fan et al., 2013), it is necessary to study the household indirect energy consumption in terms of different consumption activities and it is necessary to distinguish different household consumption activities’ embodied energy across regional areas and conduct mitigation strategies with pertinence. Based on the above analysis of research gaps, the research question in this thesis is: how to quantify health co-benefits across subpopulations of climate mitigation measures on household energy consumption (direct and indirect) in rural and urban areas? The aim of this thesis is to understand the energy consumption status caused by household direct and indirect consumption activities and health co-benefits of employing climate mitigation strategies on household direct and indirect consumption activities as well as understanding the health co-benefits across subpopulations to promote climate justice study; at the end, to propose suggestions for improving policy making regarding household energy consumption. Choosing to study the household energy consumption rather than the household carbon footprint, it is because the model I will use for this research is requiring the input of energy data rather than the carbon emission data. I will elaborate the methodology of this study in Chapter 2.

Table 1.1 Summary of research progress and gap

Research topic	Household consumption	Climate mitigation measures	Co-benefits of climate mitigation measures
Research progress	1. The analysis of household consumption and related environmental effects is one of the most popular topics in sustainability research in recent decades	Research on climate change mitigation tends to focus on supply-side technology solutions (Creutzig et al., 2018) .	1. For thirty years at least, researchers have attempted to quantify co-benefits (Chang et al., 2017, Jack and Kinney, 2010). 2. The Lancet series of papers in 2009 provided a quantitative and methodological foundation for evaluating the costs and health co-benefits

Table 1.1 Summary of research progress and gap (Continued)

Research topic	Household consumption	Climate mitigation measures	Co-benefits of climate mitigation measures
Research progress	(Zhang et al., 2015). 2. The most population topic about the household consumption's environmental impacts is about the household carbon emissions, also called household carbon footprint.		(Chang et al., 2017); the health co-benefits literature has expanded significantly afterwards (Haines et al., 2009).
Research gap	1. The adoption of different quantification methodologies to estimate household carbon footprint is likely to produce different results (Plassmann et al., 2010). 2.Few literature studied different household consumption activities' carbon footprint as well as in regional levels. 3. Few research studied the health effect of mitigating the household carbon footprint.	1. A better understanding of demand-side solutions is missing (Creutzig et al., 2018). 2. A comprehensive assessment of the underlying science and methods needed to provide realistic assessments of demand-side potential is still missing (Creutzig et al., 2018).	1.Most mitigation studies have assessed benefits solely in terms of their effects on pollutant emissions at the national or local level (Wu et al., 2011). 2. The impact of health co-benefits of climate mitigation on subpopulations has not been fully studied. 3. Few research studied the impact of implementing climate mitigation strategies at demand-side (Creutzig et al., 2018).
Conclusion	1. Few literatures studied different household consumption activities' carbon footprint as well as in regional levels 2.Research on climate mitigation measures on demand-side is not sufficient. 3. Study on health co-benefits of climate mitigation measures on subpopulations is not fully studied.		

1.6 Research contents and technical route

The research content to answer for the research question in this thesis is arranged as below:

(1) Study household direct energy consumption across rural and urban areas of China and quantify the adverse health impacts of household direct energy consumption on age- and sex- specific premature deaths from particular matter

2.5 ($PM_{2.5}$) pollution at the Chinese provincial levels for 2015. Also examine the health co-benefits and economic benefits of switching from coal and biomass to electricity in the household direct energy structure. This content will be in Chapter 3.

(2) Study household indirect energy consumption in terms of eight broad consumption activities across rural and urban areas of China. Furthermore, study what consumption activity's indirect energy consumption is going to increase by a large magnitude under the urbanization in China and give suggestions for policymakers for making climate mitigation strategies at the production and demand-side. This content will be in Chapter 4.

(3) Based on the findings of objective 2, conduct a scenario study to study the health co-benefits of switching households' consumption activity into a low-carbon mode. Beijing, China is used as the case study subject to estimate the potential reduction of carbon and $PM_{2.5}$ emission and health co-benefits by age and sex and quantifying the monetary benefits of four mitigation scenarios of passenger travel mode changes compared with the business as usual (BAU) scenario from 2020 to 2050. This content will be in Chapter 5.

Figure 1.1 provides a graphical overview of the objectives of the thesis.

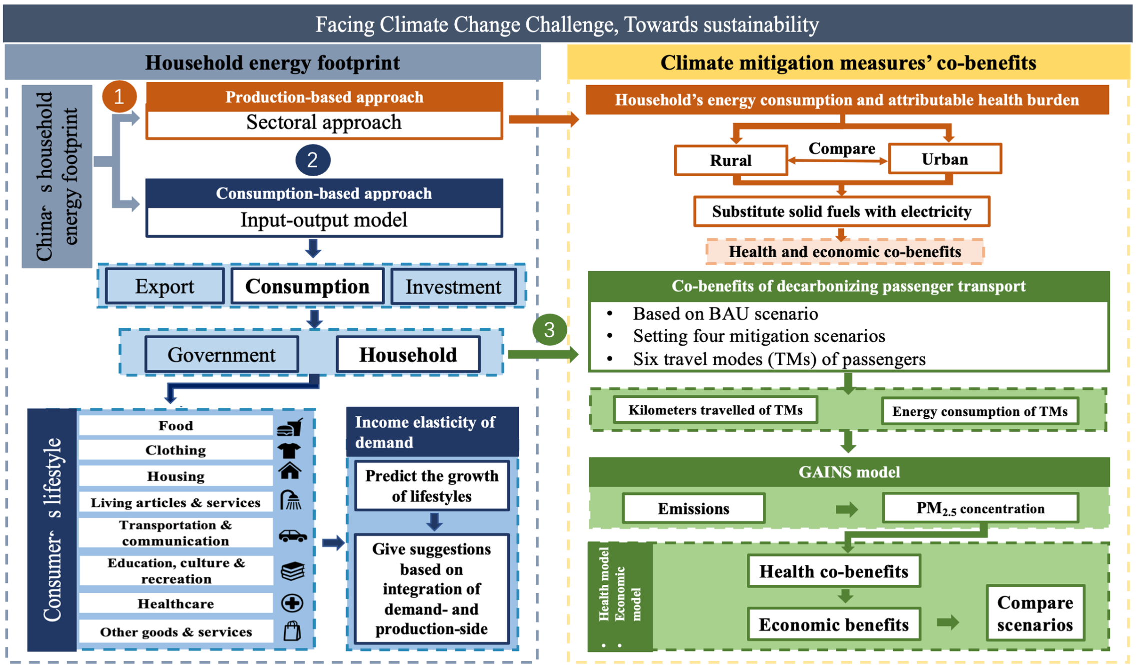


Figure 1.1 Research technical route

1.7 Research significance and innovation

Within this context, this thesis provides research significance and innovation by:

(1) Coupling the household sector analysis into an integrated assessment framework with the energy inventory data with Greenhouse Gas and Air pollution Interactions and Synergies (GAINS) model, Global Exposure Mortality Model (GEMM) and health economic model to access the health co-benefits across different sex- and age- groups and regions when conducting mitigation strategies at one or multiple production or consumption activities.

(2) Quantifying the health co-benefits of household energy consumption activities across different subpopulations in regional levels.

(3) Providing mitigation suggestions for policymakers about what consumption activity ought to be prioritized by climate mitigation measures and implementing them at demand and supply side in regional levels as well as considering different groups to promote just and fair decarbonization transitions.

1.8 Thesis structure

There are six chapters in this thesis. The first chapter is the introduction part to introduce the research background, research question, research gap and research significance. The second chapter is the method part to introduce the methodologies of energy footprint calculations and health co-benefits of climate mitigation measures. Chapter 3 to Chapter 5 are the major research contents which are briefly introduced in the 1.6 Research contents and technical route. Chapter 6 is the conclusion part to summarize the research result and give research implications, limitations and future research prospect as well as giving policy implications.

Chapter 2 Methods

The research content of this thesis can be divided into two parts: i) energy footprint of household consumption activities, corresponding to Chapter 3 and 4 ; ii) health co-benefits of climate mitigation measures in household consumption activities, corresponding to Chapter 3 and 5. Therefore, the method of this thesis can be correspondingly divided into two parts.

2.1 Energy footprint/carbon footprint calculation

The energy footprint calculation is as same as the carbon footprint calculation and carbon footprint is more fully and widely studied in previous studies so for the energy footprint calculation, the carbon footprint calculation is referred.

Carbon footprint is defined as a measure of the exclusive total amount of carbon dioxide emissions that is directly and indirectly caused by an activity or is accumulated over the life stages of a product (Wiedmann and Minx, 2008) so the carbon footprint is divided into the direct and indirect which is calculated by the production-based accounting (PBA) and consumption-based accounting (CBA), individually.

Production-based accounting (PBA) is based on the production activity regardless of where the product is used or who accounts for the final demand (Atkinson et al., 2011, Steininger et al., 2014). It focuses on the direct carbon emissions of national emissions (Zhang and Da, 2015, Liu et al., 2015), regional emissions (Yu et al., 2012, Mi et al., 2015) or sectoral emissions (ie: residential sector (Fan et al., 2015, Fan et al., 2013, Harris et al., 2015), transport sector (Zhang et al., 2016), cement sector (Li et al., 2017a, Shan et al., 2016), steel industry (Wei et al., 2007a, Xu and Lin, 2016)) from domestic production, including exports. PBA is widely applied in protocols pertaining to global climate change (Mi et al., 2019). PBA's result help producers monitor their carbon emissions and emitting behavior and further promote producers to improve the energy efficiency of unit products (Mi et al., 2019). However, PBA doesn't take account of the ultimate destinations and final consumers for goods and services (Steininger et al., 2014). Excluding indirect emissions so that the producer and consumer of goods and services will be geographically separated due to trade, resulting in interregional emission transfer and "carbon leakage" issue (Liu and Fan, 2017). For example, cities with low production but high consumption in China is usually regarded as low-carbon (Feng et al., 2013); consequently, a lack of including indirect failing in depicting the overall picture of carbon emissions will result in unfair assignments of emission reduction task, further affect global emission reduction efficiency and may even adversely affect active participation in reducing emissions (Mi et al., 2019). The method of carbon emissions with PBA is shown as below:

$$C_i = AD_i \times NCV_i \times CC_i \times \ O \qquad (2.1)$$

C_i refers to CO_2 emissions from fossil fuel *i*. AD_i is the combustion volume of fossil fuel *i*. NCV_i represents the net caloric value, that is heat value produced per physical unit of fossil fuel *i* combustion. CC_i is the carbon content of fossil fuel *i* and O refers to "oxygenation efficiency", representing the oxidation ratio during fossil fuel combustion.

Another one is consumption-based accounting (CBA), which takes account of carbon emissions of final consumption including imports, where the responsibility for carbon emissions is borne by consumers (Wiedmann, 2009). This approach attributes direct emission responsibilities to the final consuming sectors; consequently, it characterizes the impact of human consumption choices on climate change. Hence, CBA can be useful to provide plausible indicator for discerning which consumption embodies that largest carbon emissions from the find demand perspective to better assess regional emission mitigation(Larsen and Hertwich, 2009) as well as providing more mitigation options and addressing carbon leakage (Peters and Hertwich, 2008, Peters and Hertwich, 2007). From the perspective of CBA, it also shows that the final demand including export, consumption and investment are the major drivers of carbon emissions (Leng, 2012).

The method of carbon emissions with CBA is shown as below:

The current literature proposes three methods to calculate indirect energy consumption, including the consumer lifestyle approach (CLA) (Feng et al., 2011), environmental extended input-output analysis (EE IOA) (Wiedmann, 2009, Wang and Yang, 2016), and a hybrid method combing CLA and EE IOA (Bin and Dowlatabadi, 2005, Oswald et al., 2020). Input–output analysis has been widely recognized as a popular tool to estimate energy use, greenhouse gas emissions, pollutants embodied in consumer goods and services on a macro-scale (Hertwich and Wood, 2018, Peters et al., 2011, Skelton et al., 2011, Barrett et al., 2013). The Multi-Regional Input–Output (MRIO) analysis is applied in this thesis to do CBA.

The MRIO analysis starts with the monetary flows between sectors and regions:

$$\begin{pmatrix} x^1 \\ x^2 \\ x^3 \\ \vdots \\ x^{30} \end{pmatrix} = \begin{pmatrix} A^{1,1} & A^{1,2} & A^{1,3} & \cdots & A^{1,30} \\ A^{2,1} & A^{2,2} & A^{2,3} & \cdots & A^{2,30} \\ A^{3,1} & A^{3,2} & A^{3,3} & \cdots & A^{3,30} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A^{30,1} & A^{30,2} & A^{30,3} & \cdots & A^{30,30} \end{pmatrix} \begin{pmatrix} x^1 \\ x^2 \\ x^3 \\ \vdots \\ x^{30} \end{pmatrix} + \begin{pmatrix} \sum_s \sum_t y_t^{1,s} \\ \sum_s \sum_t y_t^{2,s} \\ \sum_s \sum_t y_t^{3,s} \\ \vdots \\ \sum_s \sum_t y_t^{30,s} \end{pmatrix} \quad (2.2)$$

Where x^r is the vector of total economic output for each sector in province r; $A^{r,s}$ is the direct requirement coefficient matrix in which the columns reflect the input requirement by sector in region *r* to produce one unit of output of the sector in region s; $y_t^{r,s}$ is the final demand vector of category *t* for each sector that are finally produced in region *r* and consumed in region *s*. Here t = 1, 2···5, means consumption of household and government, capital investment, and exports, respectively. Equation (2.2) can also be abbreviated as:

$$x = Ax + y \qquad (2.3)$$

Where x, A, and y are the block matrix or vector in Equation (2.3). Solving for total output we can get:

$$x = (I - A)^{-1} y \qquad (2.4)$$

Where I is the identity matrix, and $(I - A)^{-1}$ is the Leontief inverse matrix.

Combined with the carbon intensity by sector, pollutant emissions embodied in the trade flow can be calculated as:

$$k = e((I - A)^{-1})y \qquad (2.5)$$

Where e is the diagonalization of the vector of region-specific carbon emissions for unit output by sector (PJ). The region-specific carbon emissions used to produce *e* are calculated by fossil fuel consumption by the corresponding fossil fuel types and sectors multiply by the net caloric value (which is the heat value produced per physical unit of fossil fuel combustion), carbon content of fossil fuel and oxygenation efficiency, which can be find in Shan et al. (2018).

Then, region- and sector-specific carbon emissions attributed to final demand or final use *t* in region *s* can be calculated as:

$$k_t^s = e(I - A)^{-1} \begin{pmatrix} y_t^{1,s} \\ \vdots \\ y_t^{r,s} \\ \vdots \\ y_t^{30,s} \end{pmatrix} \qquad (2.6)$$

Where k_t^s =($e_t^{1,s}, e_t^{2,s}, e_t^{3,s} \cdots e_t^{30,s}$) ; k_t^s is a sector-specific vector for carbon emissions occurred in region *r* caused by final demand *t* in region *s;* $y_t^{r,s}$ is the finished products produced in region *r* consumed in region s belonged to category *t*.

2.2 Health co-benefits of climate mitigation measures

2.2.1 Approaches

Bell et al. (2008) summarized that there were general three key steps to assess the health-related ancillary costs and benefit of climate change policies: 1) estimating changes in air pollutant concentrations, comparing levels in response to GHG mitigation to concentration under a baseline "business-as-usual" scenario; 2) estimating the adverse health impacts avoided from reduced air pollution; 3) for some studies, estimating the monetary benefit from these averted health consequences, often with comparison to the cost of the climate change mitigation measure. Jack and Kinney (2010) concluded any plausible co-benefits study has to take a stand on four questions: 1) what policy scenarios to model? 2) how will firms and individuals respond to climate policy, and how will these responses translate into changes in emissions of non-GHG pollutants? 3) how will emissions translate into exposures? 4) how will exposures affect health? To sum up, the co-benefits study involves four parts: policy scenarios setting, behavioral response, environmental modeling and health modeling.

In many cases, study employed standard sector specific economic, atmospheric, transportation, health impact, and climate models (Chang et al., 2017). To support this study, many models have been developed and applied, like the Asia-Pacific Integrated Model (AIM) (Mittal et al., 2015), Market Allocation (MARKAL) (Mondal et al., 2010)), Long-range Energy Alternatives Planning system (LEAP) model (Pan et al., 2013), etc. The integrate assessment model GAINS developed by International Institute of Applied System Analysis (IIASA) in Laxenburg, Austria, was the most widely used model to evaluate both air quality and related health co-benefits of environmental policies on regional, national or provincial levels (Amann et al., 2011, Rafaj et al., 2012). Using these models, research suggested that greater consistency in selected modeling choices across the health co-benefits of climate mitigation research would facilitate evaluation of mitigation evaluation of mitigation options (Chang et al., 2017, Remais et al., 2014, Liu et al., 2017a). In conclusion, this study needs integration of different models.

In this thesis, an integrated assessment framework is set up to integrate different models, which, in general, couples the energy inventory data with GAINS model, GEMM and health economic model to access the health co-benefits when conducting mitigation measures towards household sector. GAINS model is used to estimate air-pollutants emissions and $PM_{2.5}$ concentration so as to translate emissions into exposures. GEMM is adopted to assess mortality attributable to ambient PM2.5 pollution. Health economic model is applied to assess the health burden or benefits in monetary terms.

2.2.2 Policy scenario setting

Jack and Kinney (2010) summarized that there were three approaches to set policy scenarios. The first approach is to posit a change in emission. The Lancet series of papers assessed health benefits associated with actions to reduce GHG emissions by 50% 2050 versus 1990 in four different sectors, including electricity generation (Markandya et al., 2009), food and agriculture (Friel et al., 2009), household energy (Wilkinson et al., 2009) and transportation (Woodcock et al., 2009). In Chang et al. (2017)'s review, this approached was defined as emission-forced approach. But Jack and Kinney pointed out assuming a change in emissions simplifies the analysis considerably and provides illustrative findings but may lessen the salience of the results in policy discussions. The second approach is to use computable general equilibrium (CGE) models to find the optimal scenarios by using a large number systems of simultaneous equations and data of all model sectors (Jack and Kinney, 2010). Bollen et al. (2009) and Rive (2010) each computed dynamically efficient CO_2 reduction programs with and without health co-benefits for Europe using CGE models. This approach illuminates the synergy between GHG mitigation goals and air quality control, while the policy relevance of the resulting optimal pathways remains untested (Jack and Kinney, 2010). The third approach is to analyze the effects of actual, proposed, or plausible GHG mitigation (Jack and Kinney, 2010). For instance, Groosman et al. (2011) analyzed health benefits for the US related to GHG emissions controls in the electricity and transportation sectors contained in the proposed Warner Lieberman climate legislation.

However, even though researchers try to set up policy scenarios in their study, the tension between policy realism and analytical tractability still exists (Jack and Kinney, 2010). Although policy scenarios positing well-defined changes in emissions are more tractable, it is hard to gain traction in policy debates (Jack and Kinney, 2010). And policy scenarios reflecting the incentive-based policies are generally hard to model and most these policies is adopted in developed economies (Jack and Kinney, 2010). What's more, a GHG mitigation policy scheme is shifting so rapidly in most countries that policy scenarios could be outdated when the research is done (Jack and Kinney, 2010).

Therefore, it is essential that the policy scenarios are well matched to policy debated but not necessarily simulating the benefits of market-based policies and fundamentally researchers get the hang of and respond intelligently to the state of play in the policy domain (Jack and Kinney, 2010).

In this thesis, we apply the third approach mentioned above to analyze the health co-benefits of actual, proposed and plausible mitigation measures. In Chapter 3, plausible mitigation measures about replacing the coal and biomass to electricity for rural and urban households' direct energy usage are applied given that the primary energy tends to be more and more transferred into electricity for usage in China. In Chapter 5, actual and proposed mitigation measures refer to Beijing's government policies, for example, the Beijing City Master Plan (2016-2035), which proposed to increase the share of green transport to over 75% by 2020 and not less than 80% in 2035.

2.2.3 Behavioral response

Since a policy scenario is set, emitters like firms and individuals must respond to this policy scenario environment. But how GHG emitters will respond to these mitigation policies is a critical consideration in studies (Jack and Kinney, 2010). The approaches to this question vary. The Lancet papers simply translated an assumed percentage reduction in GHG emission into emission reduction for health-relevant pollutants (Markandya et al., 2009, Friel et al., 2009, Wilkinson et al., 2009, Woodcock et al., 2009). Bollen et al. (2009) modelled responses to GHG and air pollution control policies based on sector-specific marginal abatement cost curves.

It is necessary to understand baseline and control-scenario emissions of both CO_2 and health-relevant pollutants such as PM, Ozone (O_3) and SO_2 (Sulphur dioxide). Pollution emissions vary widely depending on sources, fuels, combustion processes, emission controls and other factors. Reliable information on emissions is often available in developed countries but largely lacking for developing countries.

In Chapter 3 and 5, we set the baseline scenario in 2015 and the control-scenario is based on the baseline in 2015. In Chapter 3, the control scenario is to assume if rural and urban households replace the amount of coal and biomass used in 2015 to electricity, what benefits would be obtained including reduced CO2, $PM_{2.5}$ pollutants and avoided deaths? In Chapter 5, there are four control scenarios which focus on four facets of urban land passenger travel modes changes. For instance, in the more electric vehicles transport scenarios, it assumes that passengers would use more electric vehicles to replace fossil fuel vehicles or have the preference to buy electric vehicles rather than fossil fuel vehicles in the future.

2.2.4 Environmental modeling

Most air pollution co-benefits work has focused on one or both of two key pollutants, particulate matter (either $PM_{2.5}$ or particular matter 10 (PM_{10})) and ozone (Jack and Kinney, 2010). Once changes in emissions are estimated, it is necessary to analyze how these translate into changes in human exposure to health-relevant pollutants such as $PM_{2.5}$ and/or ozone over space and time.

The human exposure involves the intersection between people and pollution. The science and tools available for ambient air pollution modeling have advanced rapidly in recent decades. Some studies, particularly those based on CGE models, use highly simplified linear equations to scale emission changes to ambient concentration changes (Ezzati et al., 2004, O'Connor et al., 2003, Aunan et al., 2004). With this research field carrying one, it begins to employ global chemical transport models or air quality models to project the policy-induced changes in air quality (West et al., 2013), like regional-scale CMAQ model. However, due to computational costs and complications associated with required data input and processing, using complex air quality models for large suites of scenarios still represents a significant challenge in policy assessment (Xing et al., 2011). To address this challenge, a real-time emission control/air quality response tool, Response Surface Methodology (RSM), has been developed to characterize the relationship between model outputs and input parameters in a relatively economical manner (Xing et al., 2011, Zhu et al., 2015). However, RSM techniques have only been tested and evaluated for a series of $PM_{2.5}$ and ozone assessments and policy analyses in the United States (U.S. Environmental Protection Agency, 2006a, U.S. Environmental Protection Agency, 2006b) but its localizations in other areas like China are still under development (Zhu et al., 2015).

Therefore, an integrate and simplified model for estimating health co-benefits of GHG emissions reduction measures is still needed to translate scientific evidence into policy decisions (Liu et al., 2017a). And other health-relevant pollutants, like black carbon and sulfate aerosols are nearly seldom be studied.

In this thesis, the Greenhouse Gas and Air pollution Interactions and Synergies (GAINS)-ASIA model, which has been developed by International Institute for Applied Systems Analysis (IIASA), has been applied to estimate the CO_2 emissions, pollutant emissions, and $PM_{2.5}$ concentration caused by changes of household consumption activities.

The GAINS model includes all key emission sources, with approx. 2000 end of control options (Amann et al., 2011). The model is applied for estimating air-pollutants and $PM_{2.5}$ concentration based on $E_{f,r,i,t}$ (PJ). Emissions are calculated through a combination of three data categories: activity data, uncontrolled emission factors, the removal efficiency of emission control measures. Equation (2.7) represents the emissions estimates:

$$E_{p,i} = \sum_a \sum_m A_{a,i} ef_{a,m,p,i} X_{a,m,p,i} \qquad (2.7)$$

Where $E_{p,i}$ represents emissions of pollutants p, in province *i*; $A_{a,i}$ is the activity level of type *a* (e.g., coal consumption in residential sector) in province *i*; $ef_{a,m,p,i}$ is the emission factor of pollutant *p* for activity *a* in province *i* after application of control measure *m*; $X_{a,m,p,i}$ is the share of total activity of type *a* in province *i* to which a control measure *m* for pollutant *p* is applied.

The resulting emissions are inputted into an atmospheric dispersion model, the EMEP Chemistry Transport Model (http://webdab.emep.int/) to compute annual mean ambient $PM_{2.5}$ concentration. GAINS employs reduced-form source-receptor relationships that have been derived from the EMEP atmospheric chemistry-transport model with a spatial resolution of 0.1° × 0.1° (Amann et al., 2020). The $PM_{2.5}$ concentration are defined via:

$$C(PM_{2.5})_i = \sum[\pi_i \times Em(PPM) + \sigma_i \times Em(SO_2) + \alpha_i \times Em(NO_X) +. \beta_i \times Em(NH_3) + \gamma_i \times Em(VOC_i)] + \mu_i \qquad (2.8)$$

Where $C(PM_{2.5})_i$ is the $PM_{2.5}$ concentration in grid cell *i*. $Em(PPM)$ represents the total primary $PM_{2.5}$. The constants π, σ, α, β, γ are the source-receptor matrices for the corresponding pollutants contribution to the $PM_{2.5}$ concentration and the constants μ_i are grid cell specific. More details of GAINS model can be found in Amann et al. (2011).

2.2.5 Health modeling

When emissions and concentrations have been estimated, the study will move to adverse health impacts (including premature mortality from cardiorespiratory disease, lung cancer, acute respiratory infection, etc and morbidity resulting from hospital admissions, long-term health care, asthma admissions, etc (Chang et al., 2017)) to exposed population. In this study, we consider the long-term health impacts from $PM_{2.5}$ exposure with the use of the epidemiological relative risk (RR), which can link the concentration of $PM_{2.5}$ to adverse health effects studies. As per the past studies (Lelieveld et al., 2015, Liu et al., 2017b, Maji et al., 2018), the $PM_{2.5}$-induced long-term health impacts of disease-specific are estimated by multiplying the RRs with the baseline disease-specific health impacts rate and the population exposed to $PM_{2.5}$ with a specific age group. The equation is shown as below:

$$HI = [(RR - 1)/RR] \times B \times EP \qquad (2.9)$$

Where HI is the disease-specific health impacts attributable to PM2.5 exposure. Here, the term [(RR − 1)/RR] term is the population attributable risk-potential reduction in the incidence of morbidity or mortality when an entire population would be exposed to pollution with reference concentration. B is the baseline disease-specific mortality rate for population groups. EP is the exposure population.

There are four exposure-response functions to estimate RRs according to past literature: the Integrated Exposure-Response (IER), Global Exposure Mortality Model (GEMM), log-linear (LL) exposure-response function and non-linear power law (NLP) function. IER and LL exposure-response function have mostly been used in the research; GEMM and NLP have been developed recently.

2.2.5.1 Integrated Exposure-Response (IER) function

The integrated exposure risk (IER) function is developed by Burnett et al (2014) which is applied in Global Burden of Disease (GBD) study. The IER function incorporates data from cohort studies of indoor and outdoor pollution including ambient air pollution and second-hand smoking, etc. to describe the exposure-response relationship throughout the full distribution of ambient $PM_{2.5}$. The cause-specific *RR* function is expressed as:

$$RR_{e,a}(C_i) = \begin{cases} 1 & for C_i \leq C_0 \\ 1 + \alpha\{1 - \exp(-\gamma(C_i - C_0)^{\delta}\} & for\ C_i > C_0 \end{cases} \qquad (2.10)$$

Where $RR_{e,a}(C_i)$ is the relative risk of a given $PM_{2.5}$ concentration in grid cell *i for* age specific *a* and health endpoint *e*; C_0 is the threshold $PM_{2.5}$ concentration below which there is no additional risk, in terms of counterfactual $PM_{2.5}$ concentration, which is selected to be a uniform distribution with lower and upper limits of were 2.4 and 5.9 ug/m^3 respectively according to GBD 2017 (Stanaway et al., 2018); and α, γ, and δ are parameters describing the overall shape of the exposure-response curve resulting from a stochastic fitting process. Five causes of deaths (>25 years old) are modelled by the IER model: chronic obstructive pulmonary disease (COPD), lung cancer, ischemic heart disease (IHD), stroke and diabetes mellitus according to GBD 2017 (Stanaway et al., 2018). The RRs in IERs are age-specific for both IHD and stroke (Figure 2.1).

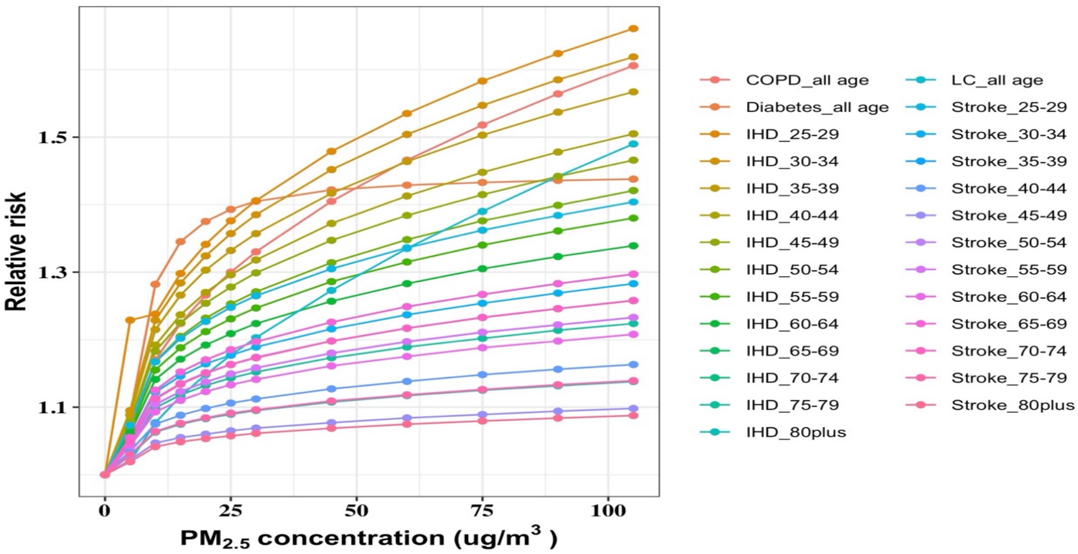


Figure 2.1 Cause and age-specific IER functions with $PM_{2.5}$ concentration ranging from 0 to 120 ug/m^3

2.2.5.2 Global Exposure Mortality Model (GEMM)

The Global Exposure Mortality Model (GEMM) is also developed by Burnett et al., (2018), but it is newly developed. The IER model conducted cohort studies in low-polluted Europe and North America. GEMM which incorporated cohort studies globally, especially added 15 cohorts study of Chinese men with long-term outdoor $PM_{2.5}$ exposures up to 84 μg/m^3, thus greatly extending the range of exposures observed in cohort studies conducted in high-income countries in Europe and North America. Also, GEMM relaxed many strong assumptions required by the IER by relying solely on studies of outdoor $PM_{2.5}$ pollution. The GEMM is expressed as:

$$RR_{e,a}(C_i) = \begin{cases} exp\left\{\frac{\theta_{e,a}\log\left(\frac{C_i - C_0}{\alpha_{e,a}}+1\right)}{1+exp\left\{-\frac{C_i - C_0 - \mu_{e,a}}{V_{e,a}}\right\}}\right\} & if\ C_i > C_0 \\ 1 & if\ C_i \le C_0 \end{cases} \quad (2.11)$$

Where $RR_{e,a}(C_i)$ is the relative risk of a given $PM_{2.5}$ concentration in grid cell *i for* age, *a* and health endpoint, *e*. C_0 is the threshold $PM_{2.5}$ concentration below which there is no additional risk, in terms of counterfactual $PM_{2.5}$ concentration (2.4 ug/m^3 in this study). And $\theta_{e,a}$, $\alpha_{e,a}$, $\mu_{e,a}$ and $V_{e,a}$ are parameters describing the overall shape of the concentration-response curve, provided by Burnett et al. (2018). GEMM considers five causes of deaths: IHD, stroke, COPD, lung cancer, and lower respiratory infections (LRIs), denoted as GEMM 5-COD. And almost all (>99%) nonaccidental deaths in the cohorts were due to noncommunicable diseases (NCD) and LRIs (NCD+ LRI), hence GEMM also considering NCD's health impacts, and it is denoted as GEMM NCD+LRI.

2.2.5.3 Log-linear (LL) function

The log-linear (LL) function has been used to estimate health impacts in high PM2.5 polluted regions (Lelieveld et al., 2013) . The LL function has also been applied in PM2.5-attributed morbidity studies (Maji et al., 2018)。 The calculation of this function is shown as below:

$$RR = \exp\left[ER \times (C_i - C_0)\right] \quad (2.12)$$

Where ER is the exposure-response coefficients obtained from epidemiological studies, representing the incidence change of certain health impact per μg/m^3 of $PM_{2.5}$ increment.

2.2.5.4 Non-linear power law (NLP) function

Based on the global cohort studies exposed from ambient, household air pollution, active and second-hand smoking. Chowdhury and Dey (2016) developed NLP function for four diseases (stroke, IHD, COPD and LC). The function equation is expressed as below:

$$RR = 1 + \alpha \times (C_i - C_0)^{\beta} \qquad (2.13)$$

Where α and β are the two constants, having different values for each cause-specific mortality.

In this thesis, the GEMM model is applied given its advantages on considering more health endpoints including five causes of deaths (IHD, stroke, COPD, lung cancer, and LRIs) and noncommunicable diseases (NCD) as well as its newly cohorts' studies in China. Also, in this research, we would consider the age and sex-specific health impacts and GEMM is also qualified to fulfill this requirement.

2.2.5.5 Economic valuation estimation

For valuation procedures, it means monetize the economic value of changes in health status and if appropriate, it will compare to the costs of mitigation policies. The monetization of mortality relies on non-market valuation methos due to the absence of economic market for human lives. The valuation approaches adopted by past literature include: value of statistical life (VSL) (used in cost/benefit analyses), value of life years lost with mortality analysis by age segmentation, benefits transfer approach, cost of illness (quantifies direct costs of morbidity). The VSL approach is widely applied to estimate the monetary cost of a reduction of mortality (Xie, 2011b). The VSL defines the monetary value of a mortality risk reduction that would prevent one statistical death (Andersson and Treich, 2011). The VSL is calculated in survey studies assessing individuals 'willingness to pay' (∂WTP) for a small reduction of mortality risk ∂R(Andersson and Treich, 2011, Viscusi and Masterman, 2017, Wang and Mullahy, 2006). The function of VSL is:

$$VSL = \partial WTP / \partial R \qquad (2.14)$$

In this thesis, because we would like to improve the accuracy of economic valuation of health impact from PM2.5 exposure, we apply the age and sex-adjusted and regional-specific VSLs of provinces in China in 2015 obtained from Yin et al. (2021), which takes account of the effects of variations in life expectancy, wealth distribution and life quality over the lifecycle (see Figure 2.2).

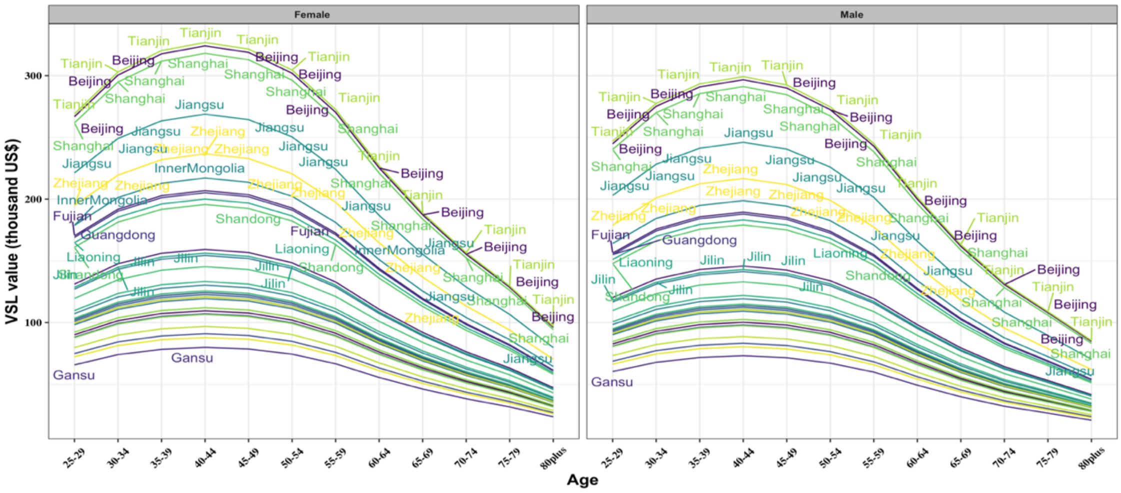


Figure 2.2 VSL values in female and male at different ages of provinces in China in 2015

2.2.6 Conclusion

The health co-benefits of mitigation measures depend on the sources/economic sectors of GHG emissions being reduced. For instance, in energy generation sector, reducing GHG emissions influences on health via corresponding reductions of air pollutants, such as PM, BC, SO_2, and NOx (Chen et al., 2013; Crawford-Brown et al., 2012; Dudek et al., 2003). In the transportation sector, shifting transport from vehicular to active travel can produces many benefits on health not only mortality and morbidity related to air pollution but also decreasing the cardiovascular disease, type 2 diabetes, colon and breast cancer and depression by increasing physical travel, like walking and cycling (Woodcock et al., 2009). Reducing intake of foods from animal sources in high-consumption populations could reduce GHG emissions and substantially benefit public health via reductions in type 2 diabetes, ischemic heart disease, and the prevalence of obesity (Friel et al., 2009). In total, GHG mitigation strategies in different economic sectors could, simultaneously, bring ancillary health benefits, while comprehensive measures across various sectors tend to provide greater health gains (Gao et al., 2018).

The study in health co-benefits of mitigation measures can provide valuable information for central and local governments, non-governmental organizations, policymakers, and other relevant stakeholders concerned with the development and implementation of low carbon technologies and policies. In addition, the potential health co-benefits and cost savings that offset or even outweigh the costs of implementing abatement measures can improve the acceptability of GHG mitigation strategies. This can help policymakers to identify the most cost-effective mitigation measures in achieving the given reduction objectives and to prioritize the use of resources in the fight against climate change.

Nevertheless, to some extents, estimating health co-benefits of GHG emissions reduction is alien to conventional epidemiological approaches and assessment studies, presenting several challenges or uncertainties (Bell et al., 2008, Haines et al., 2009). Health professionals should work closely with those involved in strategic planning and performance appraisals in relevant sectors to ensure that the assumptions and scenarios on which they are based are transparent and founded on the best available evidence (Bell et al., 2008, Haines et al., 2009).Several important sources of uncertainty arise in relation to the key steps of health co-benefits assessment. Given the nature of the information on which the co-benefits assessments must draw, the limitations in data quality and availability and the debate over exposure–response functions for health outcomes, estimating the total health gains from the decrease in air pollution associated with GHG emissions reductions remains a challenge (Bell et al., 2008). Some insufficiencies were summed up as below:

2.2.6.1 Research locations

Most research is still in developed countries/ area, like US and Europe, or on the rapidly developing economies of China and India with rapid urbanization and population growth (Jack and Kinney, 2010, Gao et al., 2018). And it is expected to increase the study in developing countries or areas, particularly in Africa and the Middle East (Gao et al., 2018) and also it is expected that the magnitude of co-benefits in developing countries is to be relatively large for two reasons. First, a given change in relative risk will accrue a larger benefit considering their background rates of disease are higher (Smith and Haigler, 2008). Second, many developing countries wish to simultaneously promote economic growth and at the same time cut pollution, limit GHG emissions, and protect public health concerns (Gao et al., 2018). These goals are not necessarily inconsistent with one another although they are profoundly vital, but health co-benefits of air quality improvement policies can be an incentive for GHG mitigation actions in developing cities (Bollen et al., 2009). Those studies which have studies the co-benefits of GHG reductions in developing regions generally report potentially considerable climate and health benefits (West et al., 2013, Shindell et al., 2012). What's more, the health co-benefits of mitigation measures may contribute to reducing inequality both in GHG emissions reduction responsibilities and in the health consequences of climate change between low and high-income countries (Haines et al., 2009).

2.2.6.2 Failure in policy-making application and difficulty in comparison of different mitigation strategies

The co-benefits literature, while extensive and in some cases quite sophisticated, has so far largely failed to formulate convincing, policy-relevant estimates of co-benefits and been insufficient to inform local decision-makers efficiently for some reasons. First, most prior studies focus on large (regional, national) scales while the small-scale policy assessment requires additional adjustments (Liu et al., 2013a). Second, the findings from existing studies are not consistent (West et al., 2013). Some propose that the co-benefits are substantial, while in other co-benefits account for a small fraction of cost (Markandya et al., 2009, Haines et al., 2009). Among the factors causing the discrepant results, inconsistent methodologies, data sources and study designs seem to be important ones (Bell et al., 2008). Third, the causes of the gap between potential and actual policy impact are complex, and have not been fully elucidated (Jack and Kinney, 2010). Polices need to take into consideration not only scientific evidence, but also competing priorities, interests, and values, and perceptions of equity, fairness, and ethics (Bowen and Zwi, 2005), among other considerations. Therefore, iterative engagement between researchers and policymakers increases the capacity of policymakers to assess, evaluate, and use data in support of complex-policy interventions, and the capacity of researchers to link credible models of economic behavior, environmental processes, and health to provide policy-relevant results (Chang et al., 2017).

2.2.6.3 Equity considerations

Research has already noted that populations in low-income countries are likely to be particularly vulnerable to the adverse effects of climate change and the mitigation policy can improve the health and equity of people in poor countries and assist developing countries in adapting to climate change (Haines et al., 2006). People exposed to higher levels of air pollution tend to be of lower socioeconomic status compared with the population as a whole, likely due to the lower value of homes in close proximity to major road traffic. However, the social distribution of these health benefits across populations, and hence potential for mitigation strategies to enhance and progress social justice, are less well established due to the health equity effects of each factor was difficult to quantify

(Chang et al., 2017). To date, while some air quality models consider regional equity, few research is studying the social distribution of health co-benefits of mitigation measures (Chang et al., 2017). The study by Dhondt et al. (2013) on co-benefits in transport sector by changing travel behavior towards more efficient transport is an exception. It found air quality improvement and increased active travel mainly had an impact at older age, while traffic safety mainly affected younger and middle-aged people (Dhondt et al., 2013), but the transport measure in this study is not aiming for reduce GHG emission.

Hence, the health co-benefits analysis in this thesis is going to consider the above three types of insufficiencies, see Chapter 3 and Chapter 5. We coupled the energy inventory data with GAINS model, GEMM and health economic model to build an integrated assessment framework to conduct the health co-benefits analysis.

Chapter 3 Household direct energy consumption and health co-benefits of cleaner fuel usage

3.1 Introduction

The residential sector is one of largest energy consumers in China (Fan et al., 2013) and as such has a profound impact on the production activities, energy consumption and GHG emissions (Liu et al., 2011). With increasing living standards and wealth across the Chinese population, residential energy consumption is forecast to continually grow in the short and medium term (Fan et al., 2013). In China, solid fuels specifically coal and biomass (mainly wood and crop residues) are still important sources of energy for heating and cooking, largely in rural areas (Archer-Nicholls et al., 2016, Zhang and Smith, 2007, Yun et al., 2020). Combustion of solid fuels by households cause both indoor air pollution (Zhang and Smith, 2007, Clark et al., 2013) and ambient air pollution at a local or regional scale (Chen et al., 2018). The emitted pollutants interact to produce a mixture of hundreds of different and hazardous chemicals known as secondary pollutants through physical processes and chemical reactions in the atmosphere (Li et al., 2017b).

Although household energy consumption is one of major anthropogenic contributors of atmospheric pollutants in China, studies on the impact of the household energy consumption on air quality remain limited (Du et al., 2018, Zhao et al., 2019, Yun et al., 2020). The current evidence base has focused on elements of spatial and policy issues (Du et al., 2018, Zhao et al., 2019, Yun et al., 2020, Chen et al., 2018, Zhao et al., 2018) but has not fully accounted for the effect of household consumption on the health profile of different population groups at different spatial scales or across rural and urban areas. There is some evidence that while rural households have lower energy consumption compared to urban areas, they have higher rates of coal usage. And it is this element of fuel mix that may result in a higher burden for rural areas in terms of emissions and associated economic and public health outcomes. The difference in lifestyles, income, and population distribution between the rural and urban areas of China are pronounced (Hubacek et al., 2009). Hence analyzing the impact of different activities and lifestyles across urban and rural populations, across different demographic groups may help to explain differential health outcomes (Pachauri et al., 2004).

This chapter therefore undertakes an integrated assessment of the adverse impacts of household energy consumption by various fuel types across rural and urban areas on age- and sex- specific premature deaths as a key outcome from $PM_{2.5}$ pollution at the Chinese provincial levels for 2015. It does so through a modelling framework based on an existing integrated assessment model calibrated with data and sub-models for population, spatial distribution of population, and air pollution loading. This chapter then explores the health co-benefits and economic benefits of switching from coal and biomass to electricity since primary energy tend to be more and more transferred into electricity for usage in China.

3.2 Method

The definition of rural and urban households is based on China Bureau of Statistics definition, whereby urban households are those who have been living within the governance of a village (xiang) or town authority over one year and urban households are those who has been living in those areas where local governments of the county level or higher are located (http://www.stats.gov.cn/tjsj/ndsj/2015/html/zb06.htm). Land use in China is predominately rural: 91% of Chinese territory defined as rural. The analysis here focuses on households – these are, following standard definitions, individuals or groups of resident individuals who share the same living accommodation, and consume goods and services collectively (Ding et al., 2017). 56.5% of the total population of China lived in 9.5% of the territory of China, with 775 million urban households and 596 million rural households (excluding Taiwan, Hongkong and Macao) (NBSC, 2016). Sub-national data is provided for 30 provinces, cities and autonomous regions (Tibet is excluded due to a lack of energy inventory data). Fifteen fuel types are included in this study. These include electricity, gasoline, raw coal, heat, natural gas, LPG (liquefied petroleum gas), diesel oil, briquettes, other energy, other washed coal, coke oven gas, other gas, kerosene, fuel oil and coke. Heat as a form of energy usage, is additional energy produced by primary energy, such as coal combustion. Heat as a form of energy usage is predominately the result of coal combustion in China and is recorded in the Chinese energy balance table and as part of the energy inventory collected by China Emission Accounts and Datasets (CEADs, www.ceads.net). All data is from 2015 unless otherwise specified.

3.2.1 Household energy consumption

The calculation of household energy consumption is shown below:

$$E_{f,r,i,t} = \sum_{f=1}^{20} AD_{f,r,i,t} \times NCV_f \qquad (3.1)$$

$E_{f,r,i,t}$ refers to sum of energy consumption from each fuel type *f*, from household in urban or rural area r, at provincial level *i,*in year *t*. The energy unit is petajoule, PJ. $AD_{f,r,i,t}$ refers to the activity data of the combustion volume of each fuel type *f*. NCV_f represents the net caloric value, that is heat value produced per physical unit of fossil fuel combustion. Here, data for the $AD_{f,r,i,t}$ is taken from the energy inventory data from CEADs (www.ceads.net), which is collected from China Energy Statistical Yearbook. Data of NCV_f is taken from Shan et al. (2018).

3.2.2 Pollutant emissions and $PM_{2.5}$ concentration from household consumption activities

Estimates from the household energy consumption model (Equation (3.1)) are treated as the input to the Greenhouse Gas and Air pollution Interactions and Synergies (GAINS)-ASIA model. The equation of GAINS model to output $PM_{2.5}$ concentration is in equation (2.7) and (2.8).

3.2.3 $PM_{2.5}$ related health impact assessment

The long-term exposure to $PM_{2.5}$ concentration on mortality as measured by premature deaths using the GEMM is considered in this study (Burnett et al., 2018). Developed by Burnett et al., (2018), the GEMM assess excess mortality attributable to ambient air pollution on a global scale.

Here. five leading causes of the $PM_{2.5}$-related premature mortality is considered: ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer (LC), and lower respiratory infections (LRI). The premature deaths under scenarios are measured by sex (female and male) and age group (25-29, 30-34, 35-39, 40-44, 45-49,50-54,55-59, 60-64, 65-69,70-74,75-79, 80+). For the purpose of this research, the "elderly" are individuals aged 65 years or more, in line with the World Health Organization (WHO) definition (WHO, 2010b, Orimo et al., 2006).

The number of health outcomes are estimated by multiplying the relative risk (RR) with the population by sex and age and reported cause-specific incidence rate by sex and age, along with the corresponding uncertainties (95% confidence interval (CI)) and normally the percentage of exposed population is assumed to be 1 (Zhang et al., 2017d):

$$M_{k,e,a,g,t}=(RR_{k,e,a}-1)/RR_{k,e,a}\times I_{e,a,g,t}\times P_{a,g,i,t} \qquad (3.2)$$

Where $M_{e,a,g,s,t}$ is mortality in grid cell, *k* for each health endpoint, *e* by age, *a* and sex, *g* in year *t* due to $PM_{2.5}$. $RR_{k,e,a}$ *is* the relative risk of a given $PM_{2.5}$ concentration in grid cell *k* at health endpoint *e* for age specific *a*, which is obtained from the GEMM (Burnett et al., 2018). $I_{e,a,g,t}$ is the mortality rate for health endpoint, *e* by age, *a* and sex, *g* in year *t* obtained from the Global Burden of Disease (GBD) Results Tool **(**http://ghdx.healthdata.org/gbd-results-tool**)** (Figure 3.1). $P_{k,a,g,t}$ is the exposed population for age, *a* and sex, *g* in grid cell *k, in* year *t*. The spatial distribution of the population as a $0.1° \times 0.1°$grid in China in 2015 is taken from Xu (2017). Population data (NBSC, 2011) and death rates (Chen et al., 2020) by age group (5-year-old segments) and sex for 2010 are obtained at the provincial level. Following similar research, $PM_{2.5}$ intake is assumed to be equally harmful irrespective of the $PM_{2.5}$ composition and source and fuel of origin (Liu et al., 2017a).

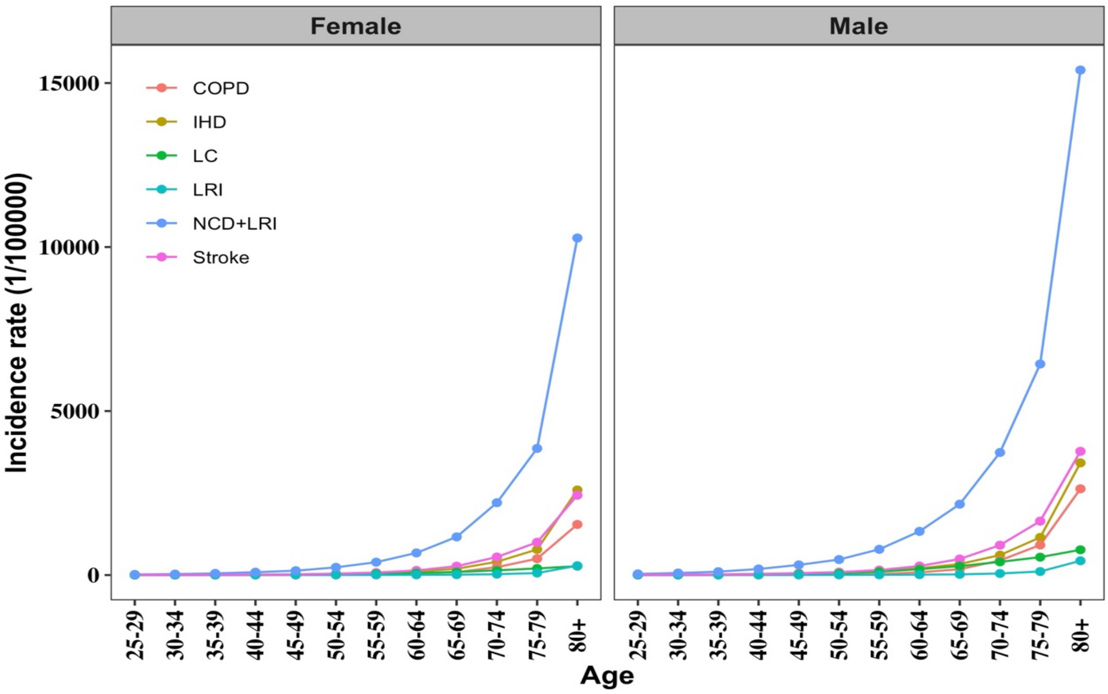


Figure 3.1 Incidence rate of health endpoints by age group and cause

The function of GEMM to estimate RRs is in equation (2.11).

3.2.4 Attribution of premature death to household consumption activities

As per the GBD (2016), given the nonlinear relationship of the GEMM functions, the direct proportional approach was used to estimate premature deaths attributed to the emissions related to a region's production and consumption. The direct proportional approach assumes that the health impact of one pollution source is directly proportional to its contribution to the ambient $PM_{2.5}$ concentration. This proportional approach has also been applied to estimate the pollution health impacts related to household cooking (Chafe et al., 2014), coal consumption (GBD, 2016), road transportation (Anenberg et al., 2017), and international trade (Zhang et al., 2017a). In this research, the proportional approach is applied to estimate health impacts related to household energy consumption.

For a given region, premature deaths due to different activity-based emissions (e.g., household consumption activities) can be calculated by multiplying the contributions of each to baseline ambient $PM_{2.5}$ concentrations by the total $PM_{2.5}$-related mortalities for each grid cell.

$$M_{r,e,a,g,t} = \sum_k M_{k,e,a,g,t,base} \times \frac{C_{k,t,base} - C_{k,t,r}}{C_{k,t,base}} \quad (3.3)$$

$M_{r,e,a,g,t}$ is the premature death of household consumption of rural or urban regions *r* for health endpoint *e* by age, *a* and sex, *g* in year *t*. $M_{k,e,a,g,t}$ is the premature death of baseline scenario for health endpoint *e* by age, *a* and sex, *g* in year *t* in grid cell *k*. The baseline scenario uses modeled $PM_{2.5}$ concentration is taken from the GAINS model which has been validated against $PM_{2.5}$ monitoring data. Please see www.gains.iiasa.ac.at for more information. $C_{k,t,base}$ is the modelled $PM_{2.5}$ concentration for grid cell *k* in the baseline scenario in year *t*. $C_{k,t,r}$ is the modeled $PM_{2.5}$ concentration of grid cell *k* in alternative scenarios where the emissions related to household consumption of rural or urban regions *r* in year *t*.

3.2.5 Avoided premature deaths of replacing coal and biomass fuels into electricity

For the scenario analysis, it is assumed that households replace all coal and biomass fuels including cleaned coal, other washed coal, briquettes, coke, coke oven gas, other gas, other coking products and other energy (large part is biomass) with electricity but the total amount of household energy consumption remained the same. The GAINS model was used to calculate the number of avoided premature deaths across urban and rural area if current levels of coal and biomass consumption shifted to electricity consumption:

$$A_{r,e,a,g,t}=\sum_k M_{k,e,a,g,t,base}-R_{k,e,a,g,t,r} \qquad (3.4)$$

Where $A_{r,e,a,g,t}$ is avoided premature death by rural or urban populations, *r* for health endpoint *e,* by age, *a* and sex, *g* in year *t*. $R_{k,e,a,g,t,r}$ is the premature death attributable to household energy consumption without coal and biomass consumption but more electricity consumption of rural or urban regions *r* for health endpoint *e* by age *a* and sex *g* in year *t* in grid cell *k*.

3.2.6 Economic benefit of replacing coal and biomass fuels into electricity

This research uses the monetary value statistical life (VSL) approach to reflect health gains in monetary terms. The VSL defines the monetary value of a mortality risk reduction that would prevent one statistical death (Andersson and Treich, 2011). The provincial age and sex-adjusted VSL for 2015 is obtained from Yin et al. (2021) (see Figure 2.2). The calculation of economic benefit is shown:

$$B_{r,e,a,g,k,t} = VSL_{a,g,i,t} \times A_{r,e,a,g,t} \qquad (3.5)$$

Where B is the economic benefit value of household consumption of rural or urban regions *r* in grid cell *k* for each health endpoint, *e* by age *a* and sex *g* in year *t*. $VSL_{a,g,i,t}$ is the value of a statistical life for age *a* and sex *g* in province *i* in year *t*. The exchange rate for US dollar and Chinese Yuan for 2015 was taken as 1 US dollar equals 6.2284 Chinese Yuan (https://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A060J&sj=2019).

3.2.7 Uncertainty analysis

Uncertainty in this analysis emerges in three areas:

(1) The value of annual mean ambient $PM_{2.5}$ concentration in China in 2015 from the GAINS. To validate the performance of the $PM_{2.5}$ concentration results from the GAINS, the linear regression model between observed results from 366 overserving sites in China and results from GAINS is applied.

(2) Uncertainty based on the RRs of GEMM. For the GEMM, estimates of $\theta_{e,a}$ and its standard errors are obtained by using standard computer software that fit the Cox proportional hazards model. Bootstrap methods were used to obtain 95% uncertainty intervals. Details can be seen in Burnett et al. (2018)(Burnett et al., 2018). Moreover, there are two versions of GEMM. One is GEMM 5-COD which comprises five causes of death: IHD, stroke, COPD, LC, and LRI, and this one is applied in this research. Another one is GEMM NCD+LRI which covers risks from noncommunicable diseases (NCD) and LRI. Since the total mortality burden from $PM_{2.5}$ exposure is represented by nonaccidental mortality and all almost all nonaccidental deaths were due to NCD and LRI. Therefore, the results from GEMM NCD+LRI would represent more health burden from $PM_{2.5}$ so that premature deaths from these two versions of GEMM are compared to know the difference.

(3) In this research, the variant VSL by age and sex is taken account of. However, in most research, they mostly adopt invariant VSL, which means VSLs don't vary by risk characteristics. So, the invariant VSL is applied to do the uncertainty analysis. Because the contingent valuation for VSL is limited in China, the VSL value from some Contingent valuation studies for Beijing is collected (Table 3.1). The VSL was 2027,866 RMB (US$ 325,583.8) in 2015 for Beijing. As household income is positively correlated with people's WTP (Sun et al., 2016), the value-transfer method from Reference Case Guidelines for Benefit-Cost Analysis in Global Health and Development is adopted (Robinson et al., 2019) to adjust VSL from Beijing to other provinces in China . Here the VSL is represented as the income ratio between Beijing and the other regions of interest using the following equation:

$$VSL_i = VSL_{Beijing} \times \left(I_i / I_{Beijing}\right)^e \qquad (3.6)$$

Where VSL_i and $VSL_{Beijing}$ are value of a statistical life year for people in other provinces and Beijing in 2015 respectively; VSL_i and $VSL_{Beijing}$ is GDP per capita in other provinces and Beijing in 2015 respectively. *e* is the income elasticity in VSL (*e* is about 1.0 for non-US countries (Viscusi and Masterman, 2017)).

Table 3.1 Contingent valuation estimates of VSL for Beijing

Study	Fieldwork: city and year	VSL (RMB)	
		Mean	Median
Zhang (2002)	Beijing 1999	2,357,953	N/A
Hammitt and Zhou (2006)	Beijing 1999	1,929,725	358,204
Gao et al. (2015)	Beijing 2011	N/A	660,204
Xie (2011a)	Beijing 2010	1,795,920	N/A
Average (in 2015 value)		2,027,866	509203.72

3.3 Results

3.3.1 Household energy consumption

In 2015, the total household energy consumption in China was 10,500 PJ; nearly 1.6 times greater than rural household energy consumption (6,700 PJ) (Figure 3.2a). Heat (21.1%), electricity (21%), and gasoline (20.5%) accounted for 63 % of total urban household energy consumption. In contrast, raw coal accounted for 34% of the total rural household energy consumption (1,300 PJ), representing 2.8 times the amount of coal consumed by urban households. Electricity was the second largest fuel type used by both rural and urban households, that accounted for 1,100 PJ and 1,400 PJ, respectively (Figure 3.2b). Figure 3.2b indicates that fuel type usage is more homogenous than urban households, with the top three fuel types representing 77% of the total rural household energy consumption, whereas in urban areas, the top three fuel types represented 63% of the fuel used.

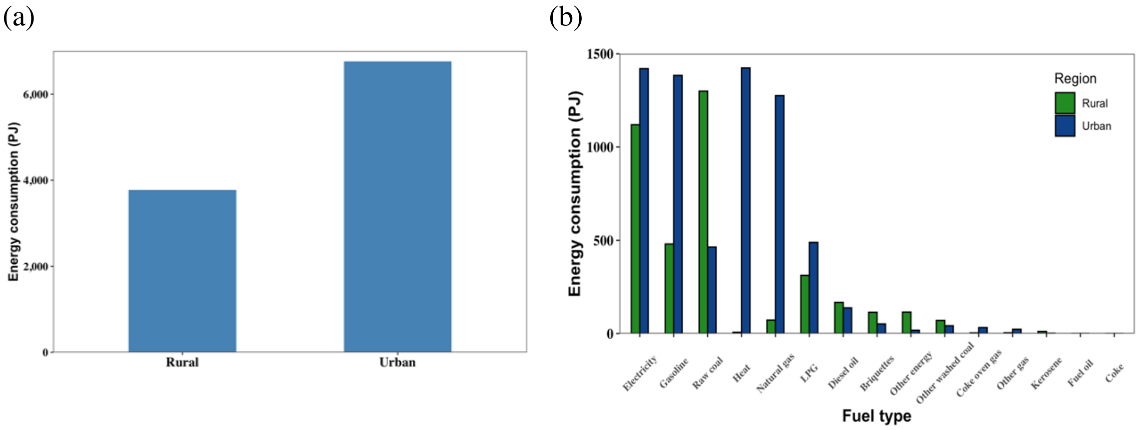


Figure 3.2 Energy consumption of rural and urban household in China in 2015

(a) The total energy consumption (PJ) (b) Different fuel types of energy consumption of household

To examine regional differences between urban and rural dominated regions, China is divided into eight economic zones according to a definition developed by the Development Research Center of the State Council (Wu, 2014) (Table

3.2) . These eight zones comprise the Northern coastal, Eastern coastal, Southern coastal, Northeastern, Northwestern, and Southwestern economic zones, as well as two economic zones defined to cover the middle reaches of the Yellow River and the middle reaches of the Yangtze River. Higher household energy consumption is more located in the Northern coastal, Eastern costal, Southern coastal and middle reaches of the Yellow River economic zone (Figure 3.3a and 3.3b). Rural household energy consumption is highest in Hebei, Guangdong, Shandong, Henan and Hunan, that were 448, 293, 265, 243 and 202 PJ, respectively. For urban household energy consumption, consumption is highest in Guangdong, Liaoning, Shandong, Hunan and Heilongjiang, 553, 472, 433, 392 and 386 PJ, respectively. Regrading energy intensity，on average, energy intensity of rural households are larger than urban households and Northern coastal, Northeastern, Northwestern and Eastern coastal had higher energy intensities of household consumption.

Table 3.2 Description of eight economic zones (Unit: for the population it is 10000 population; aging ratio is 100%; population weighted $PM_{2.5}$ concentration is ug/m^3)

Economic zone	Province	Urban population	Rural population	Aging ratio	Deaths	Premature deaths in per 100,000 people	Population weighted $PM_{2.5}$ concentration
Northern coastal economic zone	Beijing, Tianjin, Hebei, Shandong	12581.4	8408.6	12%	31916	20.4	63.7
Eastern coastal economic zone	Shanghai, Jiangsu, Zhejiang	11065.8	4864.2	14%	51914	41.4	47.4
Southern coastal economic zone	Fujian, Guangdong, Hainan	10359.7	5239.3	10%	23347	21.1	21.4

Table 3.3 Description of eight economic zones (Unit: for the population it is 10000 population; aging ratio is 100%; population weighted $PM_{2.5}$ concentration is ug/m^3) (Continued)

Economic zone	Province	Urban population	Rural population	Aging ratio	Deaths	Premature deaths in per 100,000 people	Population weighted $PM_{2.5}$ concentration
Middle reaches of the Yellow River economic zone	Shanxi, Inner Mongolia, Henan, Shaanxi	10017	9431	12%	24380	17.4	46.2
Middle reaches of the Yangtze River economic zone	Anhui, Jiangxi, Hubei, Hunan	12238.4	11107	13%	59771	35.4	43.4
Southwestern economic zone	Guangxi, Chongqing, Sichuan, Guizhou, Yunnan	11545.7	12743	13%	55443	32.8	29.1
Northwestern economic zone	Gansu, Qinghai, Ningxia, Xinjiang	2902.3	3313.7	10%	752	1.8	25.2

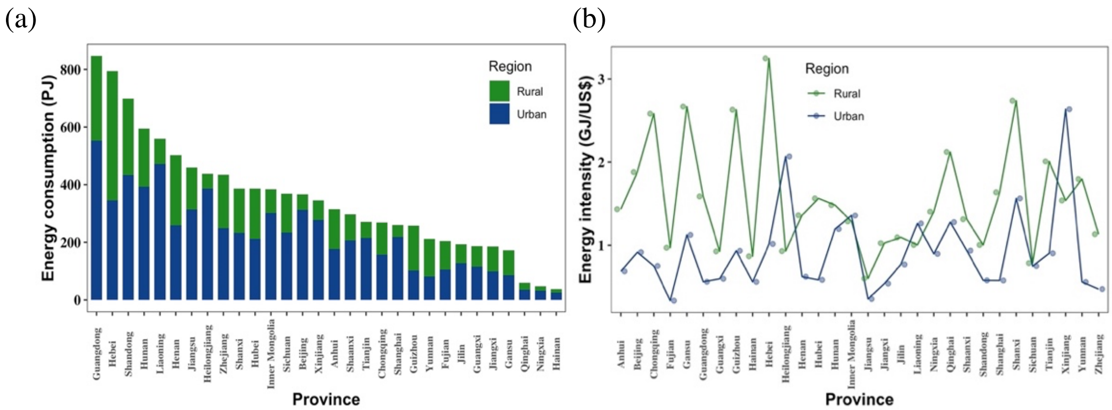


Figure 3.3 Energy consumption and energy intensity of provinces of rural and urban households in China in 2015

(a) Energy consumption of 30 provinces of rural and urban households (b) Energy intensity of 30 provinces of rural and urban households; the energy intensity of rural or urban households = energy consumption of households in the rural or urban area /GDP in the rural or urban area in 2015

3.3.2 $PM_{2.5}$ concentration of China

The average population weighted $PM_{2.5}$ concentration calculated by the GAINS model. The average population weighted concentration of $PM_{2.5}$ was 37 ug/m^3 in China in 2015, which has exceeded the national ambient air quality standard (NAAQ) (35 ug/m^3) of China (MEE, 2012) and WHO air quality guideline (10 ug/m^3). $PM_{2.5}$ concentration was generally higher the Northern coastal economic zone (Jing-Jin-Ji area) with the highest average population weighted $PM_{2.5}$ concentration, middle reaches of the Yellow River economic zone, middle reaches of the Yangtze River economic zone, Eastern coastal economic zone, Southern coastal economic zone, Sichuan Basin area in the Southwestern economic zone and Tarim Basin in the Northwestern economic zone and especially in urban areas. The five provinces with the highest population weighted $PM_{2.5}$ concentration were Henan (68 ug/m^3), Hebei (67 ug/m^3), Beijing (66 ug/m^3), Tianjin (65 ug/m^3) and Shandong (58 ug/m^3). 55% of the population is exposed to annual average $PM_{2.5}$ concentration of more than 35 μg/m^3 in 2015.

3.3.3 Premature deaths of household consumption

The total premature mortality attributable to $PM_{2.5}$ concentration in China across five health endpoints of interest, COPD, IHD, LC, LRI and Stroke were 1540,000 (95% CI：1270,000-1789,000). Rural household energy consumption activities resulted in 133,000 (95% CI: 104,476-159,389) premature deaths, representing 9% of the total premature deaths in China in 2015. Although, the total energy consumption of urban households was higher than that of rural households (Figure 3.2)，urban household energy consumption was associated with fewer premature deaths, 123,000 (95% CI: 96,136-147,450) premature deaths (Figure 3.4). In total, 256, 000 (95% CI: 200,612-306,839) premature deaths was lost due to household consumption in China in 2015 (Figure 3.4).

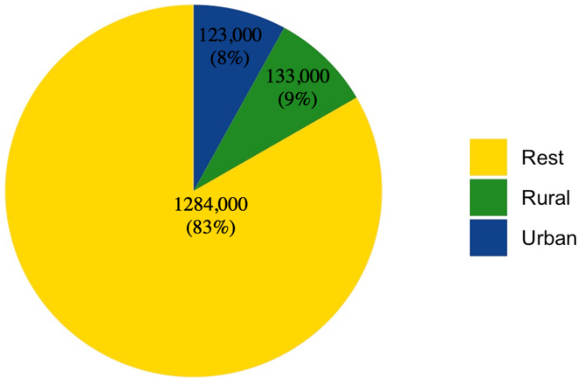
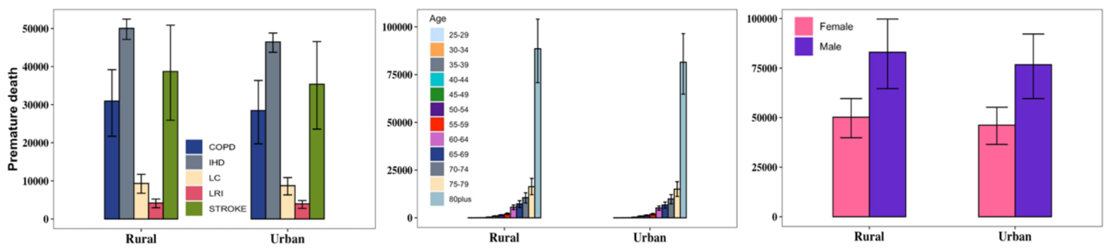


Figure 3.4 Premature deaths attributable to $PM_{2.5}$ concentration and $PM_{2.5}$-related premature deaths attributable to rural and urban household energy consumption in China in 2015

The age- and sex-specific premature deaths attributable to $PM_{2.5}$ pollution associated with household energy consumption to varies across rural and urban areas. Premature deaths attributable to $PM_{2.5}$ pollution are greater in rural than urban households (Figure 3.5a). Figure 3.9 shows that IHD was the largest health burden attributable to household sourced $PM_{2.5}$ exposure (between 37.5% and 37.8% premature deaths). The population aged over 80-year-old accounted for over half the total household energy consumption-$PM_{2.5}$-related premature deaths (66.3% to 66.5%), with the age category 25 to 29-year-old recording the lowest (Figure 3.5b). Premature mortality is higher among the male population compared to the female population, ranging from 62.3% to 62.4% of household energy consumption $PM_{2.5}$-related premature deaths (Figure 3.5b).

(a)



(b)

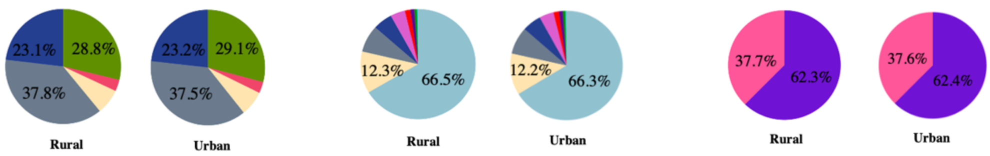


Figure 3.5 Health endpoint-, age- and sex-specific premature deaths attributable to $PM_{2.5}$ pollution by rural and urban household energy consumption in China in 2015

(a) Value of health endpoint-, age- and sex-specific premature deaths attributable to $PM_{2.5}$ pollution by rural and urban household energy consumption in China in 2015 (b) Percentage of health endpoint-, age- and sex-specific premature deaths of the total premature deaths attributable to $PM_{2.5}$ pollution by rural and urban household energy consumption in China in 2015

The number of premature deaths per 100,000 people had a positive correlation with $PM_{2.5}$ concentration, as shown in Figure 3.6, with rural household energy consumption attributable to a larger number of premature deaths per 100,000 people compared to urban household. When the $PM_{2.5}$ concentration was less than 45 ug/m^3, premature deaths was less than 20 per 100,000. Thirteen provinces (Henan, Hebei, Beijing, Tianjin, Shandong, Anhui, Shanghai, Jiangsu, Hubei, Chongqing, Shaanxi, Shanxi and Sichuan) had $PM_{2.5}$ concentration over 45 ug/m^3, with associated premature deaths per 100,000 people, ranging from 65.9 (Chongqing) to 2.6 (Shanxi). The number of premature deaths associate with rural household energy consumption per 100,000 of the population were highest in Chongqing, Shanghai, Beijing, Hubei and Tianjin (65.9, 31.7, 28.8, 22.1 and 21.5, respectively); while the number of premature deaths per 100,000 associated with urban energy consumption was highest in Chongqing, Shanghai, Beijing, Hubei and Sichuan (65.7, 31, 22.5, 21.5 and 21, respectively). Although the highest levels of $PM_{2.5}$ concentration were in the Northern coastal economic zone of China, the highest numbers of premature deaths per 100,000 people were more located in the Southern area of China which include the Southern coastal, the middle reaches of the Yangtze River and Yellow River, Eastern coastal economic zones, and the Sichuan Basin area in the Southwestern economic zone. Provincial level premature deaths per 100,000 attributable to $PM_{2.5}$ pollution by age- and sex-specific health endpoint (Figure 3.6).

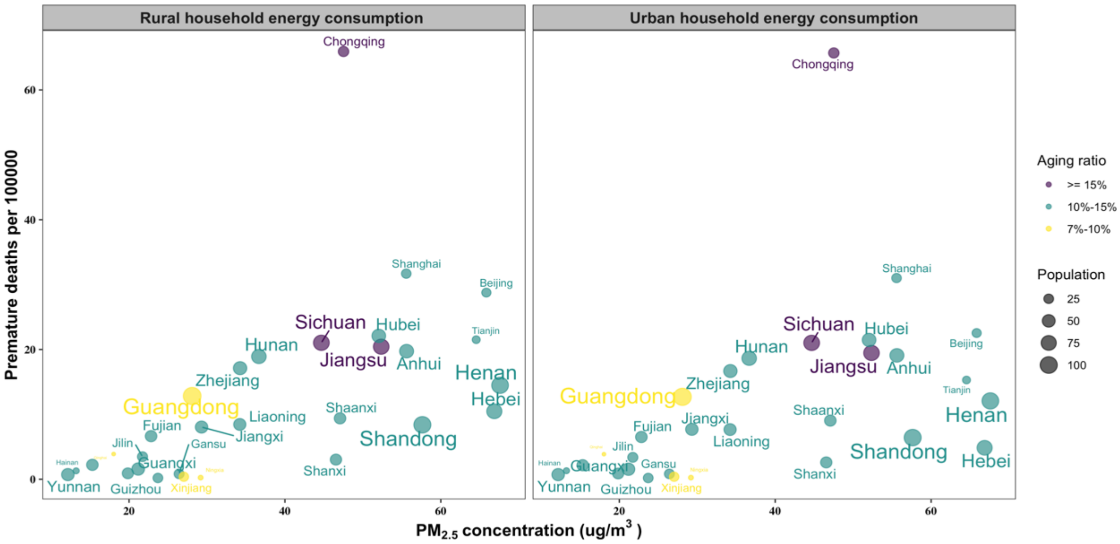


Figure 3.6 Provincial-level premature deaths per 100,000 people and population weighted $PM_{2.5}$ concentration by rural and urban household energy consumption in China in 2015

The colorful dots show the aging ratio of population over 65-year-old and grey dots represents the size of population (million population) in 30 provinces in China in 2015

3.3.4 Avoided premature deaths and economic benefits from reduced direct coal consumption

If rural and urban households in China substituted electricity for coal and biomass, the model suggests that this could result in a significant reduction in deaths: such substitution could save 37,400 (95% CI: 31,800-41,800) deaths attributable to rural household consumption and 6,900 (95% CI; 6,100-7,900) lives attributable to urban household consumption, meaning on average 3 lives per 100,000 people can be saved in 2015. This corresponds to 28% and 6% of the total premature deaths caused by rural and urban household consumption in 2015. Economically, such a shift would result in US$ 2.5 billion (95% CI: 2.1 -2.7) economic benefits for rural households, equaling 0.09% (95% CI: 0.08%-0.1%) of GDP of the rural region of China in 2015, and it could create 522 (95% CI: 468-

594) million US$ economic benefits by urban household consumption, equaling 0.006% (0.005%-0.007%) of GDP of the urban region of China in 2015. A shift to electricity by rural households would result in the largest economic benefits in Beijing (282: 252-307 US$), the highest number of deaths avoided in Hebei did (5,000: 4,400-5,450). A shift to electricity by urban households, would witness the Jiangsu area receive the largest economic benefits (75: 65-82 US$) and Sichuan recoding the largest reduction in premature motilities (697: 696-868) (Figure 3.7).

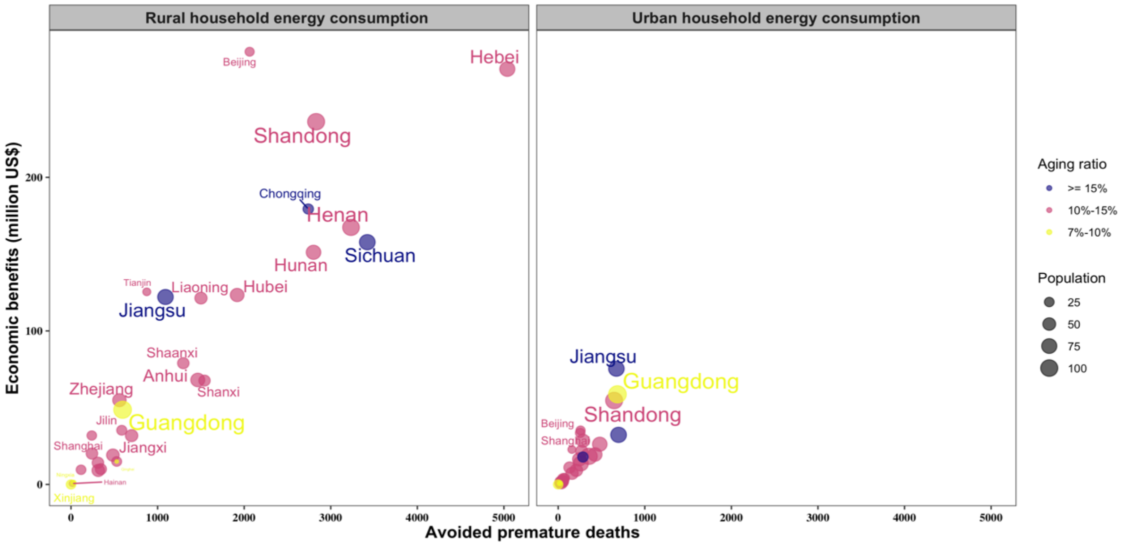


Figure 3.7 Provincial-level economic benefits and avoided premature deaths by rural and urban household energy consumption in China in 2015

The colorful dots show the aging ratio of population over 65-year-old and grey dots represents the size of population (million population) in 30 provinces in China in 2015

3.3.5 Uncertainty analysis result

Compared to the premature deaths from GEMM 5-COD, the premature deaths from GEMM NCD+LRI was approx. 1.9 times larger. In 2015, the rural household energy consumption resulted in 253,529 (95% CI: 228,299-276,707) deaths resulted from NCD and LRI while the urban household energy consumption led to 235,828 (95% CI: 212,030-257,786). From the results of the uncertainty analysis (Figure 3.8 and Figure 3.9), it finds that premature deaths from the five health endpoints is underestimated compared to results from GEMM

NCD+LRI (Figure 3.8). The economic benefits from changing household coal consumption into the electricity is also underestimated by the variant VSL approach relative to invariant VSL approach (Figure 3.8). Compared to the invariant VSL approach, results from invariant VSL were around 2.4 times larger. In 2015, the rural household energy consumption resulted in 5,966 (95% CI: 5,092-6,627.8) million US$ while the urban household energy consumption led to 1,255.6 (95% CI: 1,108.3-1,429.3) million US$.

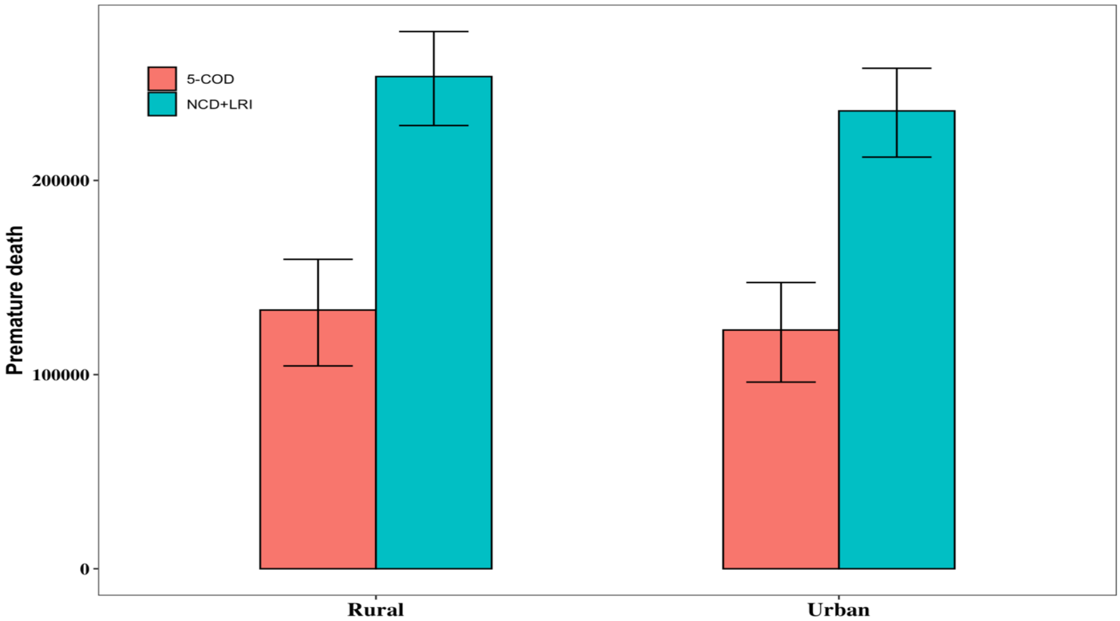


Figure 3.8 Premature deaths from GEMM 5-COD and GEMM NCD+LRI from rural and urban household consumption in China in 2015

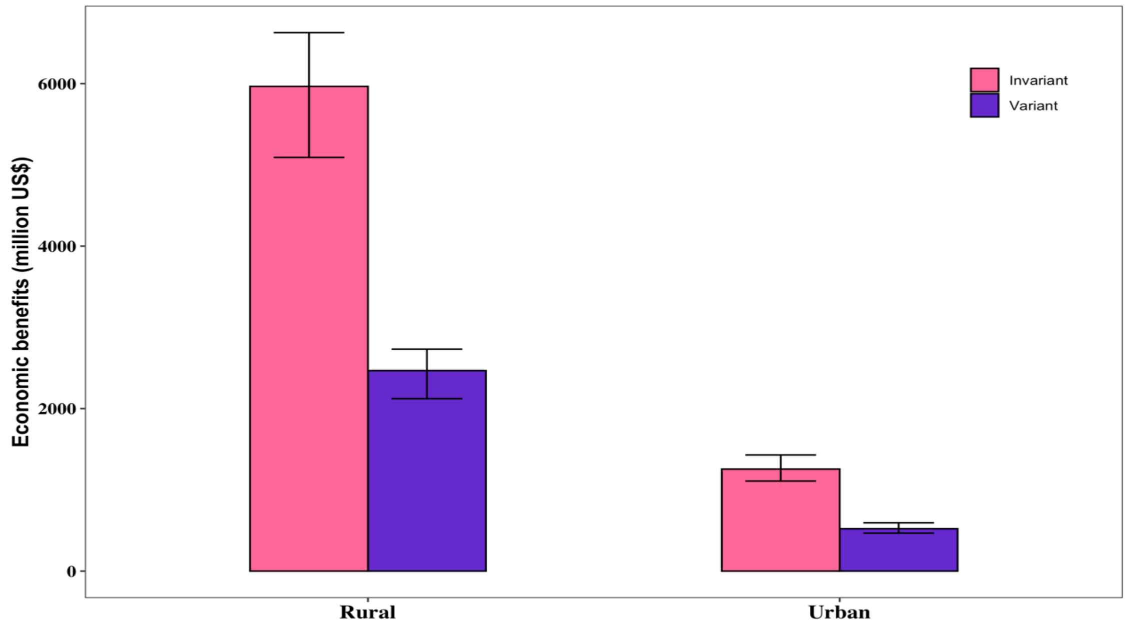


Figure 3.9 Economic benefits of variant VSL and invariant VSL from rural and urban household consumption in China in 2015

3.4 Discussion

A number of recent studies have examined the health burden attributable to $PM_{2.5}$ exposure in China (Maji et al., 2018, Liu et al., 2021b, Li et al., 2018a, Li et al., 2021, Song et al., 2017), and shown the scale of the challenge. This study confirms the scope and scale of the challenge and focuses specifically on the direct role of household energy consumption specifically. The contribution here builds on knowledge of household energy use (Chen et al., 2018, Yun et al., 2020, Zhao et al., 2018) to implement an integrated assessment approach connecting energy, emission, air pollution and health outcomes. Hence, the adverse impacts of household energy consumption by various fuel types across rural and urban areas on $PM_{2.5}$ related age- and sex- specific premature deaths at provincial levels for 2015 are investigated. This provides new insights by estimating the premature death associated with each of the 15 fuel types used by households in China across different age and sex groups at the national/ regional/ provincial levels for China. Further, a scenario analysis is applied to calculate the economic benefits from switching solid fuels into electricity.

Our estimates found that in 2015, 17% of national premature deaths could be attributed to outdoor $PM_{2.5}$ from residential energy sector. Although urban households consumed nearly 1.6 times energy than rural households, premature deaths attributable to $PM_{2.5}$ exposure from household energy was 1.1 times higher from rural household consumption compared to urban households due to rural households' use of solid fuel products. Regarding urban-rural differences, these findings are consistent with a similar study by Zhao et al. (2019) using data from 2012. However, Zhao et al. (2019) reported higher estimates for premature deaths for rural areas compared to our study (18% vs 8.7%). Direct energy consumption was higher in 2012 than 2015, but the difference may also be underpinned by to cleaner energy sources in rural. In 2012, raw coal energy usage corresponded to 50% and 1.3% of the total energy consumption in rural and urban households, whereas in 2015, the proportion of raw coal proportion had decreased to 46% and 0.9% for respectively rural and urban households (NBSC, 2013, NBSC, 2016).

Analysis at the regional level incorporating differences between urban and rural areas and age-sex specific mortality rates by five health outcomes, finds that between 37.5% and 37.8% premature deaths attributable to household energy consumption were due to IHD. Importantly, the analysis found that the distribution of household energy consumption-related premature deaths is not just a product of energy consumption and outdoor $PM_{2.5}$ concentration, but also population density and demographic structure (Figure 3.8). The population aged over 80-year-old accounts for over half the total household energy consumption-$PM_{2.5}$-related premature deaths (66.3% to 66.5%), with the age category 25 to 29-year-old recording the lowest. Premature mortality was higher among the male population compared to the female population, ranging from 62.3% to 62.4% of household energy consumption $PM_{2.5}$-related premature deaths. Household energy consumption-related premature deaths are shown to be highest in the Southern area of China, explained by a combination of high population density and an aging population. For example, Chongqing has the highest number of premature deaths as well as premature deaths per 100,000 and this was mainly attributable to its aging population (highest among the 30 provinces), population density (listed as 11/30) and $PM_{2.5}$ concentration (listed as 10/30).

The scenario analysis finds that if coal and biomass had been replaced with electricity in both urban and rural households, 28% (rural) and 6% (urban) premature deaths would have been avoided. Previous research by Zhao et al. (2018) similarly found that if solid fuels by Chinese household had been replaced with clean fuels, it could have saved 33% of the $PM_{2.5}$-induced mortality in 2015. With regard to the lower estimates presented here, Zhao et al. (2018) also calculated the avoid deaths from indoor air pollution. This is equivalent to US$ 2.5 billion (95% CI: 2.1-2.7) economic benefits for rural households and US$ 522 million (95% CI: 468-594) for urban household consumption. The estimates presented here are also lower than those by Yun et al. (2020), who found that the residential sector contributed to 71% of the indoor $PM_{2.5}$ concentrations and 67% of $PM_{2.5}$-induced premature deaths in 2014 in China. However, once again our model may underestimate pre-mature deaths as indoor household energy consumption is not accounted for.

This research suggests that households in Beijing would receive the largest economic benefits from cleaner air. However, it is important to note that the value of statistical life approach inevitably gives disproportionate weight to wealthier regions because of the innate characteristics of the method. Larger potential economic benefits of cleaner air to regions with high concentrations of wealth and income remains a significant challenge in policy and decision-making, not least in the context of just and fair decarbonization transitions (Friel et al., 2008). This study illustrates the large positive health and economic impacts that would be obtained from a shift to cleaner energy types within households in China, particularly regarding rural households.

From a policy perspective, this analysis suggests that mitigation measures such as promoting cleaner household fuel, through the subsidization of modern stoves within rural household will have large health and economic impacts, particularly in rural China. Li et al. (2019b) found that switching from solid fuels into carbonized fuels (higher thermal efficiencies and lower pollutant emissions) can generate environmental benefits for household residents. However, the health impacts of such a switch need to be more fully explored. For example, a recent clinical trial in the US found that cookstoves emitting lower $PM_{2.5}$ emissions still had a negative impact on cardiac health (Cole-Hunter et al., 2021). Irrespective of measures, the role of local municipalities will be crucial for the promotion and operationalization of new technologies, especially communities in poorer areas with resources are fewer higher baseline health risks than those in richer areas (Liu et al., 2021b).

There are two major limitations in this research which can lead to further research. First, our estimates do not account for indoor household energy consumption. Indeed research by Yun et al. (2020) found that the residential sector contributed to 71% of the indoor $PM_{2.5}$ concentrations and 67% of $PM_{2.5}$-induced premature deaths in 2014. As such this analysis is (i) a lower bound estimate of total premature deaths from direct household energy consumption and (ii) likely underestimates the impact on women as they may well have higher exposure to indoor air pollution due to their longer duration indoors in residential settings, as suggested by Hashim and Boffetta (2014). Secondly, we do not consider fuel sources of power producing in our scenario analysis as electricity supplies are mostly from coal power plants in China (Hubacek et al., 2009), hence the health co-benefits from fuel switching and decarbonizing in our research may be even more significant than portrayed. Also, in this research, although we consider the health burden and health co-benefits across different age and sex groups, but we didn’t discuss the environmental justice issues in the household energy consumption and energy transition. It will be good to analyze who benefits the most/ least from the energy transition among household consumption and then give policy suggestions to subside or support household groups who benefits the least from the energy transition.

The Chapter 3 has analyzed the status of household direct energy consumption and heath co-benefits of its proposed energy transition. The next Chapter 4 is going to analyze the status of household indirect energy consumption in China in 2015.

Chapter 4 Climate mitigation for household indirect/embodied energy consumption of consumption activities

4.1 Introduction

Climate mitigation strategies tend to focus on supply-side technology, underemphasizing the significant potential for mitigation through managing consumption practices(Creutzig et al., 2018, Bjørn et al., 2018) or using interactions between demand-side and supply systems to leverage mitigation action (Creutzig et al., 2018, Ding et al., 2017). The household/residential sector is a major source of energy consumption, impacting even in countries with large manufacturing sectors such as China (Fan et al., 2013). Direct and indirect CO_2 emissions, related to household consumption accounted for 41% of the total CO_2 emissions in China between 2000-2010, with household energy consumption accounting for 40% of the total (Zhang et al., 2017e). With increasing living standards and wealth across the Chinese population, residential energy consumption is forecast to continually grow in the short and medium term (Fan et al., 2013). To achieve stated climate change mitigation goals, previous research for China has found that the energy intensity of household expenditure, and indeed the aggregate levels of consumption may have to decrease significantly in areas such as housing, food and transport activities (Ding et al., 2017).

At the individual household level, the total amount of indirect energy consumption is not only affected by the energy intensity but also household income, with households with higher income or the anticipation of higher income, consuming more goods and services. As such, the income elasticity of different products and services will vary depending on household income. The economy of China is diverse across rural and urban regions: households in rural and urban regions have divergent profiles in terms of income, income elasticity and the ability to meet basic household needs. Hence any mitigation strategy for the household sector in China needs to account for the continued economic development of poorer households and convergence between regions of China.

There has been a long-standing debate that consumption practices drive unsustainability, notably in the consumption of goods and services with high emissions intensity that become more desirable with higher levels of income. If income elasticity of demand for type of goods and services is positively correlated with their emissions intensity, economic convergence within and across countries will increase consumption and thus emissions (Ivanova and Wood, 2020, Clune et al., 2017, Thøgersen, 2021). Already, there is evidence for this relationship in, for example, demand for leisure travel and emission-intensive diets (Ivanova and Wood, 2020, Clune et al., 2017, Thøgersen, 2021)). In response, a rich literature is emerging around the concept of sustainable consumption and economic development, specifically the definition of the necessary versus luxury consumption (Thøgersen, 2021, Lee and Ahn, 2016, Oswald et al., 2020, Kantenbacher et al., 2017). However, consumption activities and their classification as necessary or luxury will depend on societal conditions in which the consumption occurs, what is considered as a necessity in one country or region, may be viewed as a luxury good in another. From an economic perspective, basic and luxury goods and services are defined according to their income elasticity of demand.

This research seeks to decompose embodied household consumption by urban and rural residency to understand where the greatest embodied energy savings may be made without compromising the continued economic convergence between Chinese regions. Specifically, data on household consumption patterns, an energy and expenditure extended input-output model and income elasticity of demand analysis is used, to examine embodied energy usage across eight broad consumption activities (food, clothing, housing, household facilities, articles and services (abbreviated as facilities), transport and communication services (transport), education, cultural and recreation services (education), medicine and medical services (health) and miscellaneous commodities and services (miscell)). Given the large regional and urban/rural differentials in standards of living in China, this research disaggregates the notion of necessary (income elasticity less than 1) and luxury (income elasticity greater than 1) emissions by extending this classification to four income elasticity of demand categories. This classification is based on the ranges of income elasticity of demand of eight consumption activities to categorize them into four dimensions:

- Households with subsistence demand (goods and services are demanded at a level that does not meet basic needs), income elasticity of demand between 0-0.8;
- Households with essential demand (goods and services are consumed at a level that meets basic needs), income elasticity of demand between 0.8-1;
- Households with aspirational demand (goods and services are consumed at a level above that necessary for their daily life), income elasticity of demand between 1-1.2, and;
- Households with opulent demand (goods and services are consumed at a level to reach a luxurious life), income elasticity of demand >1.2.

Chinese regions produce and consume household goods and services at much different rates. To capture inter-regional trade, 31 provinces, cities, autonomous regions into five quintiles are classified according to their provincial average household income per capita in 2015. Then, regional demand-side and supply-side to account for inter-regional trade and supply chains are decomposed (Feng et al., 2013, Meng et al., 2013).

To address the above research questions, the Consumer Lifestyle Analysis (CLA), an energy and expenditure extended input-output model and the income elasticity of demand concept in the microeconomics are applied to estimate the embodied energy consumption of eight broad household consumption activities across urban and rural China in 2015 and to distinguish these eight household consumption activities into the subsistence, essential, to aspirational and opulent categories and further to predicate the potential increasing category among eight consumption activities under the urbanization in China. Further, via building an integrated framework with CLA and input-output model, the demand-side consumption and supply-side production across eight broad household consumption activities of urban and rural China are combined.

4.2 Method

4.2.1 Data on embodied household energy consumption

The definition of direct and indirect household energy consumption for the purpose of this research is shown in Table 4.1.

Table 4.1 The goods and services; category of household consumption (Feng et al., 2011, NBSC, 2016-2020)

Consumption activities categorization	Consumer expenditure	Goods and services
Direct influence	Home energy	Space heating; air conditioning; water heating; refrigeration; other appliances and lighting; personal travel
Indirect influence	Food	Food; starch and potatoes; dried beans and soy products; grease; meat and poultry and products; eggs; aquatic products; vegetables; condiments; sugar; tobacco; wine and beverages; dried and fresh; melons and fruits; pastry; milk and diary products; other food; dinning out; food processing service fee
	Clothing	Garments; clothing material; footwear; clothing processing service fee
	Residence	Housing construction; electricity use; heat use; fuel gas us; water use; leasing and business service

Table 4.1 The goods and services; category of household consumption (Feng et al., 2011, NBSC, 2016-2020) (Continued)

Consumption activities categorization	Consumer expenditure	Goods and services
Indirect influence	Household facilities, articles and services	Home equipment; supplies and services; consumer durables; interior decorations; bedding; household daily use; furniture materials; household services; miscellaneous goods
	Transport and communication services	Road transport; rail transport; water transport; air transport; private cars; auto parts and accessories; electronic and telecommunications equipment; transportation equipment
	Education, cultural and recreation services	Papermaking and paper products; printing and record medium reproduction; education (educational cost, personal tutors/studying exchanges, etc) ; cultural education and sports articles (recreational costs)
	Medicine and medical services	Medical and pharmaceutical products; health and social work
	Miscellaneous commodities and services	Wholesale, retail trade and catering; other goods and goods

4.2.2 Calculating embodied household energy consumption

The current literature proposes three methods to calculate indirect energy consumption, including the consumer lifestyle approach (CLA) (Feng et al., 2011), environmental extended input-output analysis (EE IOA) (Wiedmann, 2009, Wang and Yang, 2016), and a hybrid method combing CLA and EE IOA (Bin and Dowlatabadi, 2005, Oswald et al., 2020). For CLA, the term “consumer” represents those who purchase and use products for individual or household consumption and lifestyle is a way of living and is reflected in consumption behavior (Bin and Dowlatabadi, 2005). Input–output analysis has been widely recognized as a popular tool to estimate energy use, greenhouse gas emissions, pollutants embodied in consumer goods and services on a macro-scale (Hertwich and Wood, 2018, Peters et al., 2011, Skelton et al., 2011, Barrett et al., 2013).

The energy intensity of an economic sector is :

$$\mathrm{e} = \mathrm{f}x^{-1} \quad (4.1)$$

Where f is the direct energy consumption of a sector, which are from Energy Inventory or Carbon Emissions Inventory from CEADs, and x is the total sector output in monetary term, which is from MRIO tables of China. The Leontief inverse matrix is given by:

$$\mathrm{L} = (I - A)^{-1} \quad (4.2)$$

Where I is the identity matrix and A is the matrix block of normalized matrix of intermediate coefficients where the columns reflect the input from each sector in a region r required to produce one unit from each sector. The indirect energy intensity of each sector is produced as below:

$$\mathrm{f} = \mathrm{eL} \quad (4.3)$$

To map the indirect energy of each sector and each consumption activities, this research follows Liu et al. (2019) and links consumption activities with the sectors of the Chinese 2015 MRIO table (Zheng et al., 2020) . The MRIO 2015 includes 31 provinces, cities and autonomous regions (Macao, Hong Kong, and Taiwan are not included) and 42 sectors.

Three different linkages are possible including one-to-one correspondence between consumption activities and industrial sectors. In this case, the energy/carbon intensity of each consumption activity is equal to the indirect energy/carbon emission intensity of the corresponding sector; many-to-one correspondence between consumption activities and sectors. In this case, it is assumed that all consumption activities have the same energy/carbon emission factor which is equal to indirect carbon emission intensity of this sector; and finally, one-to-many correspondence between consumption activities and sectors. In this case, the energy/carbon emission factor of a household activity was equal to the weighted sum of corresponding industrial sectors' indirect carbon intensities. Please see Table 4.2 for an overview of the linkages for each sector and activities and Table 4.3 for the details of mapping among energy inventory data, MRIO table and household consumption activities.

Table 4.2 Sectors in the MRIO tables related to consumption activities

Consumer expenditure	Related sectors
Food	Agriculture; food processing and tobaccos; hotel and restaurant
Clothing	Textile; clothing, leather, fur, etc.; resident services, repairs and other services
Residence	Coal mining; electricity and heat production and supply; gas and water production and supply; water production and supply; construction; real estate; leasing and commercial services; hotel and restaurant
Household facilities, articles and services	Wood processing and furnishing; chemical industry; nonmetal products; nonmetal products; metal products; electrical equipment; other manufacturing; resident services, repairs and other services
Transport and communication services	Petroleum refining, coking, etc.; transport equipment; electronic equipment; transport and storage; information transmission, software and information technology services
Education, cultural and recreation services	Paper making, printing, stationery, etc.; education; culture, sports and entertainment
Medicine and medical services	Specialist machinery; chemical industry; health and social work
Miscellaneous commodities and services	General machinery; specialist machinery; instrument and meter; resident services, repairs and other services; financial; scientific research; wholesale and retailing; water conservancy, environment and public facilities management; public management, social security and social organization

Table 4.3 Mapping sectors among energy inventory data, sectors from MRIO table and household consumption activities

Consumption activities	MRIO 42 sector	Energy inventory 45 sectors
Food	Agriculture; food processing and tobaccos; hotel and restaurant	Farming, forestry, animal husbandry, fishery & water conservancy; food processing; food production; beverage production; tobacco processing; other
Transport and communication services	Petroleum refining, coking, etc.; transport equipment; electronic equipment; transport and storage; information transmission, software and information technology services	Petroleum processing and coking; transportation equipment; electronic and telecommunications equipment; transport, storage, postal & telecommunications services telecommunications services; other
Education, cultural and recreation services; Medicine and medical services	Paper making, printing, stationery, etc.; education; culture, sports and entertainment; specialist machinery; chemical sector; health and social work	Papermaking and paper products; printing and record medium reproduction; cultural, educational and sports articles; raw chemical materials and chemical products; medical and pharmaceutical products; chemical Fiber; rubber products; plastic products; equipment for special purpose; ordinary machinery; other

Table 4.3 Mapping sectors among energy inventory data, sectors from MRIO table and household consumption activities (Continued)

Consumption activities	MRIO 42 sector	Energy inventory 45 sectors
Clothing; Housing; Household facilities, articles and services; Miscellaneous commodities and services	Textile; clothing, leather, fur, etc.; resident services, repairs and other services; coal mining; electricity and heat production and supply; gas and water production and supply; water production and supply; construction; real estate; leasing and commercial services; hotel and restaurant; wood processing and furnishing; chemical sector; nonmetal products; nonmetal products; metal products; electrical equipment; other manufacturing; resident services, repairs and other services; general machinery; specialist machinery; instrument and meter; resident services, repairs and other services; financial; scientific research; wholesale and retailing; water conservancy, environment and public facilities management; public management, social security and social organization	Coal mining and dressing; logging and transport of wood and bamboo; textile industry; garments and other fiber products; leather, furs, down and related products; timber processing, bamboo, cane, palm & straw products; furniture manufacturing; raw chemical materials and chemical products; medical and pharmaceutical products; chemical fiber; rubber products; plastic products; nonmetal mineral products; metal products; ordinary machinery; equipment for special purpose; electric equipment and machinery; instruments, meters cultural and office Machinery; other manufacturing industry; electric power, steam and hot water production and supply; gas production and supply; tap water production and supply; construction; wholesale, retail trade and catering service; other
	Petroleum and gas; Metal mining; Nonmetal mining; Metallurgy; Scrap	Petroleum and natural gas extraction; ferrous metals mining and dressing; nonferrous metals mining and dressing; nonmetal minerals mining and dressing; other minerals mining and dressing; smelting and pressing of ferrous metals; smelting and pressing of nonferrous metals; scrap and waste

It supposes that s (s > 1) sectors were related to activity c, and the carbon emission factor of consumption activity can be estimated as follows:

$$g_{c,t} = \sum_1^p w_{s,t} \times f_{s,t} \quad (4.4)$$

$$w_{s,t} = c_{s,t}/\sum_{1}^{p} c_{s,t} \qquad (4.5)$$

Where $f_{s,t}$ represents the embodied energy intensity in sector *s* in year *t*; $f_{s,t}$ is the household final demand in sector *s* in the MRIO table； $w_{s,t}$ shows the percentage of one sector's household final demand on the sum of some (stands for *p*) sectors' household final demand which are related to one consumption activity.

The total embodied energy consumption of households can be computed by:

$$Eembodied_{a,r,i,t} = \sum_{f=1}^{20} g_{c,t} Y_{r,i,t} \quad (4.6)$$

$Eembodied_{f,r,i,t}$ is embodied energy consumption of rural or urban households (represented by r) in province *i* and in year *t*; respectively. $g_{c,t}$ is the vector of indirect energy intensities of household consumption activities *c* in year t. $Y_{r,i,t}$ is the household expenditure matrix of rural or urban households (represented by r) in province *i* and in year *t*, which is the product of household expenditure per capita and rural or urban population number in China. And $Y_{r,i,t}$ is adjusted by a balanced concordance matrix that maps the eight consumption activities identified in Table 1 and the 42 MRIO sectors.

4.2.3 Income elasticity of demand

The total amount of indirect energy consumption of the eight consumption activities is not only affected by the energy intensity but also the amount of money spent on each activity. As expenditure/demand is affected by income level, more money or anticipation of income, will result in more goods purchased by consumers. However, the income elasticity of demand (which is a measurement of the sensitivity of demand to changes in income, showing how the quantity purchased changes in response to a change in the consumer's income) of different products varies. Here, the income elasticity of demand of different consumption activities is calculated by employing a log-log regression of expenditure per capita of eight categories of provinces from 2010 to 2015 and income per capita of provinces during the same period.

$$\log\left(expenditure_{a,i,t,r}\right) = b\log\left(income_{i,t,r}\right) + a \quad (4.7)$$

r represents rural or urban households. Where $expenditure_{a,i,t,r}$ is the expenditure of a consumption activity by rural or urban households (r) in province *i* and in year *t*. $income_{i,t,r}$ is the income of rural or urban households (r) in province *i* and in year *t*. The coefficient b of the modelled log-log regression is the required value of income elasticity of demand. If the income elasticity of demand is over 1, which means the change in the quantity demanded is greater than the change in consumer income, this demand is deemed as income elastic; if it is less than 1, it is said to be income inelastic.

4.2.4 Consumption-based and production-based household energy consumption

China is a vast country and the goods and services produced in one region may not be produced in that region. Production-based household energy consumption, that is the energy used in one region can be quantitatively decomposed into the components linked with consumption activities in that region as well as in other regions (Equation (4.8)). And the consumption-based household energy consumption, associated with regional consumption can be decomposed into the components generated within the region's geographical boundary and those embodied in imports from outside of it, caused by region's household consumption activities (Equation (4.9)).

$$EP_c^r = E_c^{rr} + \sum_s^{30} E_c^{rs} \quad (4.8)$$

$$EC_c^r = E_c^{rr} + \sum_s^{30} E_c^{sr} \quad (4.9)$$

Where EP_c^r and EC_c^r represent energy use relevant to household consumption activities *c* related to produced and consumed in a region *r*, respectively. s stands for 30 Chinese provinces. E_c^{rr} represents household energy consumption activities c produced and consumed locally. E_c^{rs} represents household energy consumption activities *c* produced in *r* but consumed in other Chinese provinces s. E_c^{sr} represents household energy consumption activities *c* consumed in *r* but produced in other Chinese provinces s.

4.3 Results

4.3.1 Embodied energy consumption and expenditure of household consumption activities

Household consumption is categorized into eight broad categories: food, clothing, housing, household facilities, articles and services (abbreviated as facilities), transport and communication services (transport), education, cultural and recreation services (education), medicine and medical services (health) and miscellaneous commodities and services (miscell). Total embodied energy consumption by urban households' (15,000 PJ) is approx. 3 times that of rural household's (5,000 PJ); corresponding to 17.6% and 6.1% of the total final energy consumption or 19.9 GJ/person and 9 GJ/person, respectively. Embodied energy consumption was highest across the food (24.7% in rural and 22.9% in urban), housing (20.2% in rural and 20.9% in urban) and transport (18.6% in rural and 19.6% in urban) consumer sectors in both rural and urban households. These three activities represented the largest share of household expenditure per capita (Table 4.4).

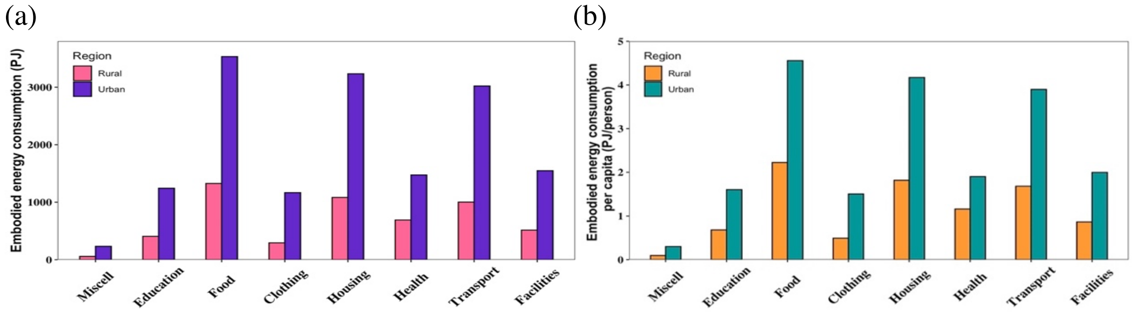


Figure 4.1 Embodied energy consumption and embodied energy consumption per capita of households in China in 2015

(a) The total embodied energy consumption of household lifestyles in China in 2015 (b) The embodied energy consumption per capita of household lifestyles in China in 2015

Table 4.4 Energy intensity of consumption activities and contributions to rural and urban household indirect energy consumption

Consumption activities	Embodied energy intensity (MJ/US$)	Proportion of rural household expenditure per capita	Proportion of urban household expenditure per capita	Proportion of rural household embodied energy consumption	Proportion of urban household embodied energy consumption
Food	4.5	33.00%	29.90%	24.70%	22.90%
Clothing	5.53	6.10%	8.20%	5.50%	7.50%
Housing	5.63	21.10%	21.80%	20.20%	20.90%
Facilities	9.64	5.70%	6.00%	9.60%	10.00%
Transport	8.58	12.80%	13.40%	18.60%	19.60%
Education	4.26	10%	11.00%	7.60%	8.00%
Health	8.34	9.20%	7.10%	12.90%	9.50%
Miscell	3.3	1.90%	2.60%	1.10%	1.50%

4.3.2 Matrix of income elasticity of demand and embodied energy intensity and projection of household consumption lifestyles under urbanization

A two-dimension matrix is built to relate activities' status as subsistence, essential, aspirational and opulent to embodied energy intensity for respective rural and urban households. The matrix is segmented into eight quadrants defined by an elasticity of 0.8, 1 and 1.2 (below 0.8 is seen as the subsistent products; between 0.8 and 1 is the essential products and over 1 is viewed as luxury products) in the y-dimension and the median of embodied energy intensity (in the x-dimension (Figure 4.2). Figure 4.2 indicates that for rural and urban households' consumption activities regarding facilities and transport activity can be classified as essential and aspirational, respectively. For rural households, essential goods include goods consumed in the food, clothing and facilities activities; aspirational goods include goods consumed in the housing, transport, health, and miscell activities; opulent goods include goods consumed in the education activity. For urban household, subsistence goods include goods consumed in the food, clothing and health activities; essential goods include goods consumed in the facilities and miscell activities; aspirational goods include goods consumed in the transport and education activities; opulent goods include goods consumed in the housing activity.

Figure 4.2 indicates that the ranking of embodied energy intensity for the eight categories is as follows: facilities > transport > health> housing>clothing >food>education> miscell. And facilities, transport, health and housing activities are represented as the high intensity activities and the rest of four are the low intensity activities.

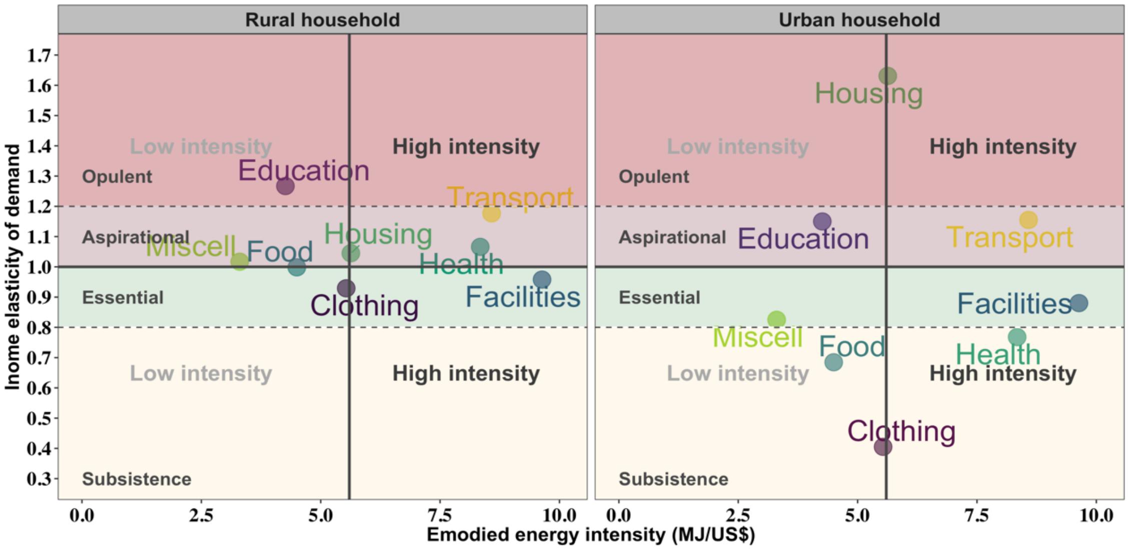


Figure 4.2 A matrix of income elasticity of demand (y-dimension) and embodied energy intensity (x-dimension) for rural and urban households

4.3.3 Scenario analysis of urbanization

As per our findings in Figure 4.2, a further scenario analysis is conducted to know what consumption activities are going to increase by a larger magnitude by households under the urbanization in China in the near future. The urbanization process in China will have two effects on household embodied energy consumption: (i) more rural household transferring into urban households; (ii) the increase of income for rural and urban households (Liu and Lei, 2018, Al-mulali et al., 2013, Verma et al., 2021, Liu et al., 2011). The continued increase in household income will stimulate large increase of expenditure on luxury products compared to necessary products if the effect of income on expenditure is primarily considered. For urban households, expenditure on education, transport activities as the aspirational demand will increase at a higher rate relative to other activities while expenditure on housing activity will increase more than the education and transport activities. And for rural households, expenditure on the housing, health, transport and miscell activities as the aspirational demand will increase by a high rate while the increase rate of expenditure on the education activity will increase even higher. Comparing the rural and urban households, expenditure on the clothing, food and health for urban households is lacking elasticity but to fulfill their minimal subsistence demand while for rural households, food and clothing activities are to fulfill their essential demand and health activity is to satisfy their aspirational demand; and rural and urban households regard the education and housing activities differently so that for the housing activity, expenditure of rural households will increase less than that of urban households, while for the education activity, the circumstance is on the contrary.

Among the aspirational and opulent consumption activity categories, transport, housing and health activities have the highest intensity activity. Moreover, the largest share of Chinese households' expenditure is on housing (21.1%-21.8%), transport (12.8%-13.4%) and health (7.1%-9.2%) (Table 4.4). The scenario analysis suggests that driven by continued urbanization, transport and housing consumption activities will produce the largest amount of embodied energy for urban households. For rural households, embodied energy usage will increase across transport, housing and health consumption activities.

4.3.4 Effect of inter-regional trade on energy flow among regions by household consumption

Regarding inter-regional trade, 31 provinces, cities, autonomous regions into five quintiles are classified according to their provincial average household income per capita in 2015 (see Table 4.4). The first quintile is the highest income and the fifth is the lowest. Also, the order of lifestyle activities according to their embodied energy intensity is ranked. Figure 4.3 presents the embodied energy consumption /production-based energy consumption per capita across the five regional income quintiles. Here it shows that embodied energy consumption is consistent with the region's income levels except for the fourth quintile region, whereby the fourth quintile region is the largest energy producer and the second largest energy consumer (Figure 4.3a). it also finds that production-based energy was greater than its consumption-based energy (6,052 PJ > 4,667 PJ) in quintile

4, making it a net energy exporter. Food, housing and transport activities were the largest exporting categories for the fourth quintile region (Figure 4.4). In contrast, the second quintile region was the net importer for all eight categories (Figure 4.4).

Table 4.3 Division of 31 provinces of China based on disposable income per capita of households

Division	Disposable income range (US$)	Provinces
First quintile, high income	8006-4473	Shanghai, Beijing, Zhejiang, Tianjin, Jiangsu, Guangdong
Second quintile, middle high	3215-4473	Fujian, Liaoning, Shandong, Inner Mongolia, Chongqing, Hubei
Third quintile, middle	2948-3215	Hunan, Hainan, Jilin, Heilongjiang, Jiangxi, Anhui
Fourth quintile, middle low	2749-2948	Hebei, Shanxi, Shaanxi, Ningxia, Sichuan, Henan
Fifth quintile, low	1967-2749	Guangxi, Xinjiang, Qinghai, Yunnan, Guizhou, Gansu, Tibet

(a) (b)

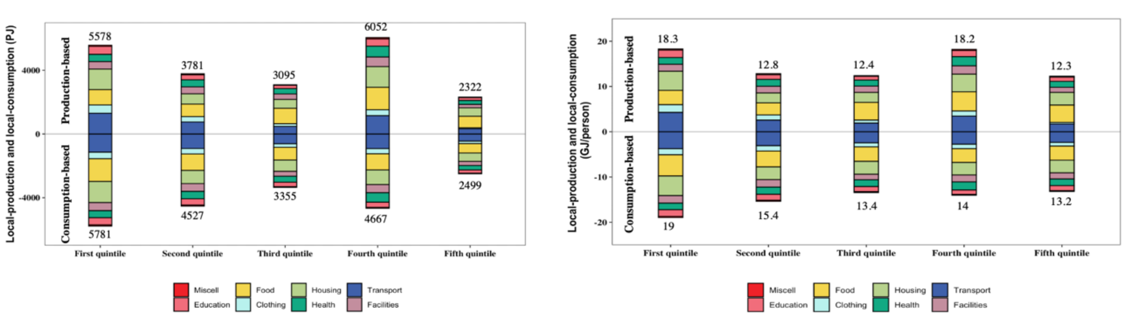


Figure 4.3 Discrepancy of energy consumption from local production (production-based) and consumption activities (consumption-based)

(a) The total amount (b) per-capita number of production-based and consumption-based energy consumption of eight lifestyle activities of five income level regions of household energy consumption in China in 2015

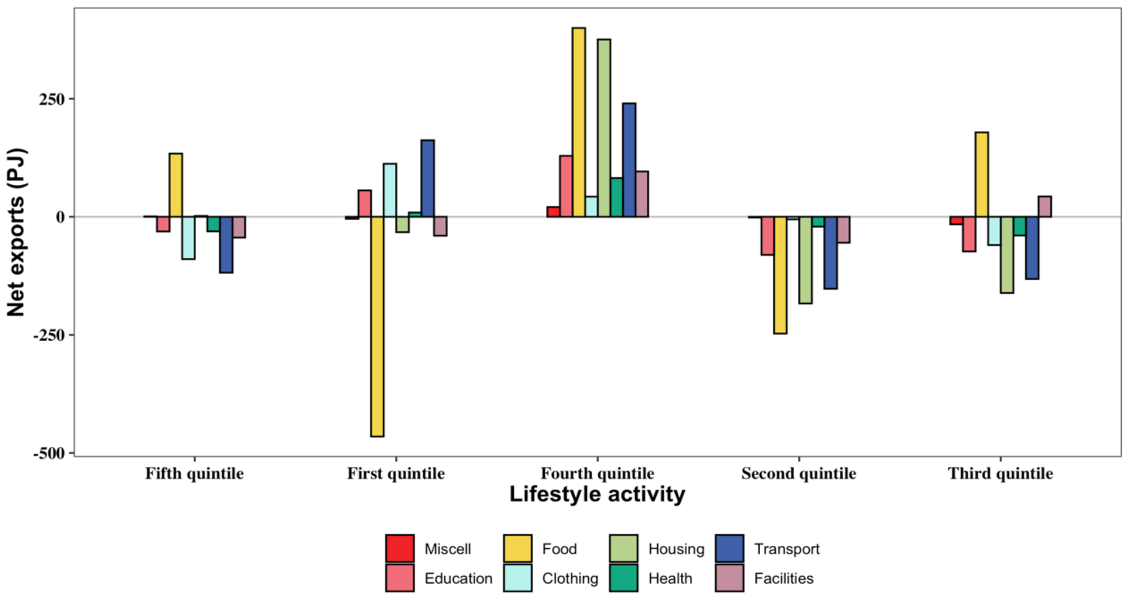


Figure 4.4 Net energy exporter of five income level regions in eight lifestyle activities

Examining the energy flow of food, housing, transport and activities (Figure 4.5), the first regional income quintile was the largest consumer of all consumption activities except for the consumption of health activities, and the largest producer of transport and education related consumption. The fourth quantile region was the largest consumer of health relevant consumption activity and the largest producer of food, housing and health relevant consumption activities.

(a)

Food activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	891.0	60.6	247.6	121.6	107.8	1428.6	4.68	-465.2
Second quintile	18.1	679.8	70.8	235.6	29.2	1033.5	3.51	-247.2
Third quintile	18.7	17.1	538.8	192.6	29.4	796.6	3.19	178.7
Fourth quintile	26.8	21.4	87.7	845.9	28.1	1009.9	3.04	399.8
Fifth quintile	8.8	7.4	30.4	14.1	529.5	590.1	3.12	133.9
Production-based	963.4	786.3	975.3	1409.7	724.0	4858.7		

(b)

Housing activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	1204.5	35.2	22.8	43.0	19.0	1324.5	4.34	-32.5
Second quintile	32.4	577.1	13.3	194.4	10.7	828.0	2.81	-183.6
Third quintile	21.8	13.4	503.5	165.8	7.5	712.0	2.85	-161.3
Fourth quintile	18.2	9.9	5.9	883.9	5.5	923.4	2.78	375.5
Fifth quintile	15.1	8.7	5.2	11.9	488.0	528.9	2.79	1.9
Production-based	1292.0	644.4	550.7	1298.9	530.8	4316.8		

(c)

Transport activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	961.2	67.4	36.7	58.3	17.8	1141.3	3.74	162.1
Second quintile	97.0	577.8	29.0	193.4	11.6	908.8	3.09	-152.3
Third quintile	78.7	37.6	364.5	123.8	8.2	612.8	2.45	-131.6
Fourth quintile	93.8	34.2	26.3	751.0	9.0	914.4	2.75	240.1
Fifth quintile	72.8	39.5	24.7	27.9	281.6	446.6	2.36	-118.3
Production-based	1303.5	756.5	481.2	1154.5	328.2	4024.0		

(d)

Education activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	420.0	12.3	3.1	7.5	3.6	446.6	1.38	55.9
Second quintile	19.6	264.5	5.0	96.2	3.4	388.6	0.07	-80.5
Third quintile	22.4	9.5	183.5	59.2	5.5	280.2	0.09	-73.3
Fourth quintile	19.0	11.2	8.6	283.8	3.1	325.6	0.06	129.1
Fifth quintile	21.4	10.6	6.7	8.0	162.5	209.1	0.11	-31.0
Production-based	502.5	308.0	206.9	454.7	178.0			

(e)

Health activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	335.5	37.1	34.8	25.8	12.6	445.8	1.46	9.1
Second quintile	17.8	332.9	12.6	100.6	4.9	468.9	1.59	-20.8
Third quintile	31.4	22.9	239.5	73.5	7.7	374.9	1.50	-39.5
Fourth quintile	47.2	38.4	32.8	464.8	13.4	596.6	1.80	82.1
Fifth quintile	23.0	16.8	15.7	14.0	210.0	279.5	1.48	-30.8
Production-based	454.8	448.1	335.4	678.7	248.6	2165.7		

(f)

Facilities activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	371.0	37.9	53.8	31.6	12.5	506.7	1.66	-40.0
Second quintile	17.0	337.0	17.4	111.0	4.7	487.1	1.65	-54.9
Third quintile	16.7	9.9	205.7	68.9	3.7	304.9	1.22	43.0
Fourth quintile	40.3	31.7	46.7	377.3	11.9	507.8	1.53	95.9
Fifth quintile	21.7	15.8	24.4	14.9	180.1	256.9	1.36	-44.0
Production-based	466.7	432.3	347.8	603.7	212.9	2063.4		

(g)

Clothing activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	337.7	32.5	13.1	23.7	2.6	409.6	1.11	112.2
Second quintile	37.9	226.5	9.4	69.5	1.3	344.5	0.13	-5.3
Third quintile	36.2	19.3	114.2	52.6	1.1	223.4	0.14	-59.8
Fourth quintile	65.5	36.1	16.2	208.4	2.3	328.5	0.20	42.6
Fifth quintile	44.6	24.8	10.8	16.8	56.9	153.8	0.24	-89.6
Production-based	521.8	339.1	163.6	371.1	64.2	1459.8		

(h)

Miscell activity	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	66.6	4.8	2.1	2.5	1.7	77.8	0.22	-4.2
Second quintile	1.3	55.6	0.7	9.6	0.8	67.9	0.00	-1.5
Third quintile	3.3	3.4	30.5	12.5	0.7	50.4	0.01	-16.0
Fourth quintile	1.5	1.7	0.8	55.9	0.4	60.3	0.00	20.7
Fifth quintile	0.9	0.9	0.4	0.5	31.3	34.1	0.00	0.9
Production-based	73.6	66.4	34.5	81.0	35.0	290.5		

(i)

Eight activities	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	Consumption-based	Consumption-based per capita	Production-based minus consumption-based
First quintile	4587.4	287.8	414.1	314.0	177.6	5780.9	15.04	-202.6
Second quintile	241.0	3051.2	158.1	1010.3	66.7	4527.3	0.82	-746.2
Third quintile	229.2	133.1	2180.1	748.9	64.0	3355.3	0.92	-259.9
Fourth quintile	312.4	184.6	224.9	3871.1	73.6	4666.7	0.94	1385.7
Fifth quintile	208.3	124.4	118.2	108.1	1939.8	2498.8	1.10	-177.0
Production-based	5578.3	3781.1	3095.4	6052.4	2321.8	20829.0		

Figure 4.5 Consumption-based (horizonal direction) and production-based (vertical direction) energy consumption by eight household consumption activities

(a) food activity (b) housing activity (c) transport activity (d) education activity (e) health activity (f) facilities activity (g) clothing activity (h) miscell activity (i) eight activities within five regions

A Sankey diagram is drawn to show the energy flow from eight categories of household consumption activities at the regional levels traced back to the production side at regional levels (Figure 4.6 and Table 4.5). Based on results above and the income elasticity of demand analysis, household health consumption activities will increase at a rapid pace. Health and social work sector, chemical sector and machinery sector provided 1284.8 PJ (59.3%), 870.1 PJ (40.2%) and 10.8 PJ (0.5%) to fulfil household's health activity. For food activity, the amount of energy provided by food processing and tobaccos sector accounted for 57.1% of the total energy consumed by food activity followed by agriculture sector (30.2%) and service sector (12.6%). For the housing activity, the service sector and electricity, heat, gas and water production and supply sector and other sector accounted for 44.1%, 43.4% and 12.5%, respectively. For transport activity, transport, storage, and transport equipment sector accounted for 56.6%, followed by petroleum refining, coking, etc. sector (21.1%), service sector (16%) and machinery sector (6.3%). In sum, the service sector, food processing and tobaccos sector, transport, storage, and transport equipment sector, electricity, heat, gas and water production and supply sector and chemical sector were the top five sectors affected by household consumption activities, accounting for 25.9%, 13.3%, 10.9%, 9% and 8.3% of the total embodied energy consumption, respectively.

The supply chain analysis indicates that the service sector consumed 43.5% goods from itself and 12.1% from electricity, heat, gas and water production and supply sector. For the food processing and tobacco sector, 30.4% was provided by itself followed by agriculture sector (15.6%) in terms of energy amount. For the transport, storage, and transport equipment sector, 51.6% was provided by within itself, followed by petroleum refining, coking, etc. sector (13.1%). Electricity, heat, gas and water production and supply sector largely consumed 68.4% goods from itself and imported 13.2% goods from the other sector. For the chemical sector, 60.7% was provided by itself and 11.5% was provided by electricity, heat, gas and water production sector. In summary, the five major industrial sectors consumed between 30.4%-68.4% of its own energy. What's more, embodied intensities of household activity tend to be relatively large compared to the rest of activities and chemical sector is the largest suppliers to this activity. For the chemical sector, 60.7% was provided by itself and 11.5% was provided by electricity, heat, gas and water production and supply sector. Herein, the chemical sector was the major reason for resulting in higher embodied intensity of household activity.

Finally, what regions provide the production of these five major industrial sectors is analyzed. For the first quintile region contributed the largest production to the transport, storage, and transport equipment sector (34.2%) and service sector (28%) while the fourth quintile region provided the largest production to the food processing and tobaccos sector (27.1%), electricity, heat, gas and water production and supply sector (30.1%) and chemical sector (28.7%).

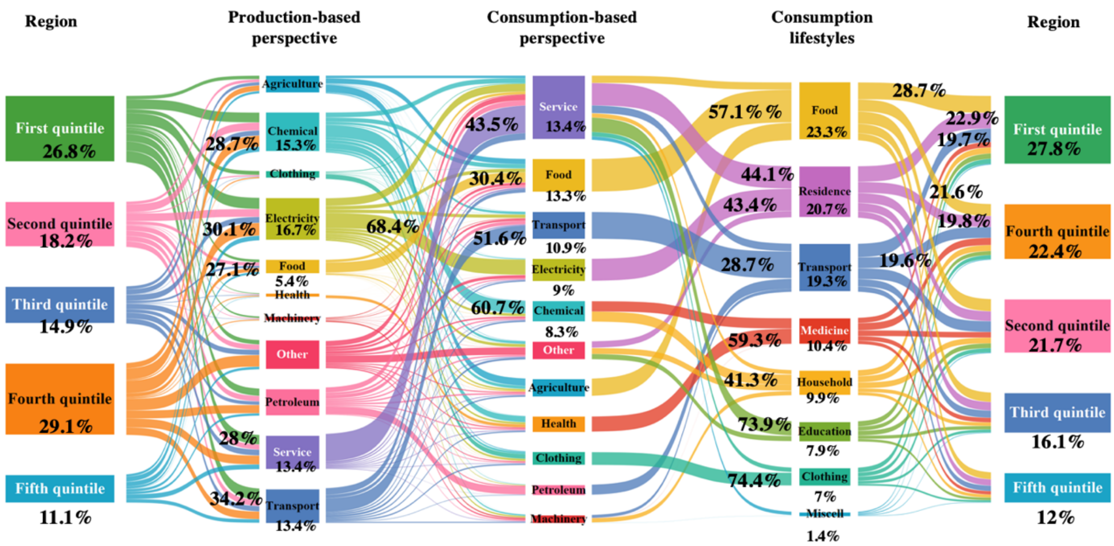


Figure 4.6 Energy flow from household lifestyle activities tracing back to production activities by supply chain

Table 4.4 Explanation of abbreviation of industrial sectors in the left part in Figure 4.6

Abbreviation	Detailed sectors
Agriculture	Agriculture
Food	Food processing and tobaccos
Clothing	Textile
	Clothing, leather, fur, etc.
Electricity	Electricity and heat production and supply
	Gas and water production and supply
	Water production and supply
Transport	Transport and storage
	Transport equipment
Health	Health and social work
Machinery	General machinery
	Specialist machinery
	Electrical equipment
	Electronic equipment
	Instrument and meter
	Other manufacturing
Service	Wholesale and retailing
	Information transmission, software and information technology services
	Financial
	Leasing and commercial services
	Scientific research
	Water conservancy, environment and public facilities management
	Culture, sports and entertainment
	Public management, social security and social organization
	Hotel and restaurant
	Real estate
	Resident services, repairs and other services
	Education
Other	Coal mining
	Wood processing and furnishing
	Nonmetal products
	Metal products

Table 4.4 Explanation of abbreviation of industrial sectors in the left part in Figure 4.6 (Continued)

Abbreviation	Detailed sectors
Other	Paper making, printing, stationery, etc. Construction
Petroleum	Petroleum refining, coking, etc.
Chemical	Chemical sector

4.4 Discussion

This study develops an integrated frame to connect demand-side consumption and supply-side production for Chinese households across eight broad consumption activities applying a Consumer Lifestyle Analysis (CLA) with an energy and expenditure extended input-output model. A matrix of income elasticity is built to distinguish eight discrete need/usage categories depending on household need for the product or service and the amount of energy the sector consumes. Four categories are (i) subsistence and low intensity; (ii) subsistence but high intensity; (iii) essential and low intensity; (iv) essential but high intensity; (v) aspirational and high intensity; (vi) aspirational but low intensity; (vii) opulent and high intensity; (viii) opulent but low intensity.

Previous research of household consumption has predominately focused on studying direct and indirect energy consumption or carbon emissions at the national(Ding et al., 2017, Goldstein et al., 2020, Druckman and Jackson, 2009) or regional (Chen et al., 2019) level. This research extends this research by incorporating an urban/rural income elasticity of demand analysis to examine the impact of ongoing urbanization on future embodied energy consumption. The analysis finds that Chinese households' expenditure on four consumption categories, housing, education, cultural and recreation services (education), transport and communication services (transport), and medicine and medical services (health) are set to increase at a considerable rate compared to other consumption activities. Categorized as aspirational, opulent and high energy intensity activities, consumption relating to housing and transport is estimated to increase by the largest magnitude. This finding are similar to recent work by McKinsey Consumer & Shopper Insights report: Meet the 2020 Chinese consumers (Atsmon et al., 2012) which predicted that higher than average growth rates across the housing, transport and recreation sectors. While data from China National Bureau of Statistics showed that average annual increase rates of per-capita expenditure on health, education, housing and transport activities were 12.4%, 9.3%, 9.1% and 8.3%, respectively during 2015-2019 whereas the annual increase rates of per-capita expenditure on food, clothing, facilities and miscell activities were 5.6%，3.5%，7.5% and 8.5%, individually (NBSC, 2016-2020).

Regarding rural and urban households, this analysis also found that per-capita expenditure of urban households will be higher than that of rural households. Although food and clothing activities belong to the necessary demand, rural and urban households treat these two activities differently, showing that expenditure on the food and clothing activities is more sensitive for rural households than for urban households to changes in income. This indicates that households in rural areas still have difficulties meeting their essential daily demand. For education activity, rural households are willing to spend relatively more than urban household relative to their change of income, indicating that rural households have a stronger desire to fulfill their educational than urban households. And for the health activity, it shows the similar meaning as the education activity but health activity more reflects the demand for personal care and well-being (Kaplan et al., 1976). For housing activity, the income elasticity is higher for urban households than the rural households, showing that urban households are more eager to experience higher quality of living (Hubacek et al., 2009).

Regarding recent academic literature, Ding et al. (2017) found that housing, food and transport activities cause the most household embodied energy consumption in China in 2012 and in our study, it found the food, housing and transport activities contributed the largest share to household embodied energy consumption in 2015. The average annual increase of per-capita expenditure on food was 4.6% while housing was 27.2% during 2012-2015 but the overall spending on food was over than the housing during these years meanwhile the embodied energy intensity of food activity has dropped by 14.3% from 2012-2015 while for housing, it has increased by 18.5% so that from analyzing the factors of activity expenditure and energy intensity which both affect the final embodied energy consumption, it shows that energy intensity plays a vital role in reducing the embodied energy consumption and this finding is supported by Ding et al. (2017). From their scenario analysis, it found that the accelerated decrease of energy intensity play a more vital role on energy conservation than the role of low-carbon consumption pattern (Ding et al., 2017).

From an inter-regional trade perspective, it finds that household embodied energy consumption is positively related to household income/expenditure except for the fourth regional income quintile. However, this pattern is mainly because of its higher self-supplement rate (83%) (Appendices Figure A.1) and higher energy intensity of its local production which are majorly heavy industries like iron and steel production, coal mining, petroleum refining, coking, etc. On the other hand, although the first quintile region is the largest household embodied energy consumer (as its self-supplement rate ranked the second with 79% (Figure 4.3)) it did not import the largest energy. Instead, the second regional income quintile had the highest imports (Figure 4.4)). This is an interesting result, as although rich regions induced higher consumption-based energy usage (Wiedenhofer et al., 2017), regional self-sufficiency can decrease inter-regional differentials.

Since it finds that embodied household energy consumption from housing and transport are expected to rise at a large magnitude, it is necessary to reduce the expenditure on these two categories for five income level regions, especially for the first quintile region and reduce the energy intensity of industrial sectors (primarily are service sector, transport, storage, and transport equipment sector, electricity, heat, gas and water production and supply sector) related to housing, transport and health activities. And these industrial sectors are majorly produced in different regions. For instance, to enhance the energy intensity of households' transport activities, it is vital to cut down the energy intensity of transport, storage, and transport equipment sector, and this sector is primarily produced in the first quintile region so that decreasing this sector's energy intensity in the first quintile region is crucial. As the largest energy consumer, the first quintile plays a decisive role to reduce its own industrial sectors' energy intensities since its self-sufficient rate was in the second rank. What's more, the fourth quintile region is the largest net energy exporter so that reducing this region's energy intensity is essential, especially in the food processing and tobaccos sector, electricity, heat, gas and water production and supply sector.

Reducing the consumption level on aspirational and opulent and high intensity consumption activities is a natural and rational conclusion from our analysis and other research also indicated less consumption on energy-consuming lifestyle replacing with low-carbon lifestyle (Ding et al., 2017, Lee and Ahn, 2016) . However, suggesting consumers to adopt a frugal lifestyle in housing and transport activities is not easy. But behavioral economics suggests that subjective factors like beliefs and preferences, can affect individual decision-making (Kahneman, 1979). It shows that consumer environmental knowledge can affect behaviors (Frick et al., 2004) and environmental knowledge can lead to sustainable consumption (Press and Arnould, 2009). Also environmental beliefs and self-efficacy can indirectly effect on pro-environmental behavior, including accommodating, promotional and proactive behavior through media use (television, newspapers and the Internet) since most people nowadays rely on the media to acquire information about climate change and global warming(Huang, 2016). Therefore, China's government and environmental organizations can use the media to spread the knowledge about environmental protection and low-carbon lifestyles through various media channels to induce low-carbon and frugal lifestyles of individuals, like using the public transport to do commuting rather than private vehicles, reducing travel times and travel by public transport as often as possible, using energy efficient home applicants, not buying energy-consuming houses, turning off electronic devices when not using them, etc. Also, government can incentivize this kind of lifestyle, like giving incentives for individuals/groups who buy low-caron houses and electric cars and adopt low-carbon lifestyles. Generally, policymakers can adopt the 'avoid–shift–improve' approach, a well-established framework in the sustainable transport community (Creutzig et al., 2018), which provides a categorization of policy options so as to finally incentivize the public to take those low-carbon lifestyles in daily life.

However, the existing of awareness-behavior gap also called as value - action gap (Parkinson et al., 2014) may sabotage the intension of these efforts (Li et al., 2019a, Owens and Driffill, 2008, Bai and Liu, 2013). A method that has recently come to prominence in the last decade to influence behavior change is Nudge Theory(Thaler and Sunstein, 2008). Nudging works on the principle that small actions can have a substantial impact on the way people behave – and it creates 'choice architectures' for these actions that encourage (but don't force) people to make better decisions. There are some nudging techniques which has been proved efficient: (i) optimize the defaulting options. For example, it was found that a greater number of consumers chose the renewable energy option for electricity when it was offered as the default option (Pichert and Katsikopoulos, 2008); (ii) provide visible information. Individuals tend to be more active in taking action at things which can be measured and get quick feedbacks. For example, Meituan, a Chinese shopping platform, has released individuals' cycling carbon reduction transcript on 17th September, 2021 so that their users who are using Meituan Bikes can know the number of carbon reduction they have contributed to by cycling(Ma, 2021); (iii) provide convenience of using facilities. The percentage of families who do recycling classifications when they receive garbagy can providing classification functions was nearly 50% higher than that of families who receive brochures about recycling classification; (iv) game design. A city painted giant and beautiful patterns on steps at its subways and it has increased the frequency of individuals to walk on steps rather than by elevators by 25% during peak times and 140% at non-peak times. There are many other techniques in nudging. In our research, although reducing individuals' consumption on food is not easy since it is the basic need for individuals, using the nudging can avoid people eat excessive meat and encourage green diet by providing smaller plates at restaurants and putting low-caron food at salient places in a menu or relocating green food next to the cash register (Kroese et al., 2016), etc.

In our research, although reducing the industrial energy intensity is more important at this stage than decreasing the consumption level, it should not be neglected that the demand-side solution can have a profound effect on production activities and push the industrial production to do more technology innovation. Also it has been proved that conserving energy from the demand-side is more cost-effective both for the government and the public (Ding et al., 2017). And government should develop more policies on demand-side innovations, for example, carbon tax for goods and services is one of instruments which can be implemented to reduce the demand of high carbon-emitting goods and services with high carbon taxes.

There are two major limitations in this study. First, due to the data availability and limitation of input-output model, products in the same activity category consumed by rural and urban households are not distinguished, for example, rural and urban maybe tend to consumer different quality of food products, which then embrace different energy intensities. Second, the scenario analysis to model the effect of urbanization in China on households' embodied energy consumption is not applied, but this is an area of further research.

The Chapter 4 is about the status of household indirect energy consumption within eight consumption categories. Since we find that household indirect energy consumption related to housing and transport categories are about to increase in a large amount. Hence, based on this result, in Chapter 5, we will conduct a case study in Beijing city to estimate the health co-benefits of households' travel pattern changes under four climate mitigation scenarios.

Chapter 5 Health co-benefits from decarbonizing passenger transport: a scenario study

5.1 Introduction

There are recognized to be significant benefits from tackling transport pollution for both climate change and more localized pollutants. Carbon emissions are rising faster than emissions from other sectors and are projected to be 80% higher than current levels by 2030 (Kahn Ribeiro et al., 2007). At the same time, urban air pollution from the transport sector has been linked to approximately 0.8 million deaths per year globally with a further 1.2 million deaths per year due to road traffic and 1.9 million deaths per year by physical inactivity (WHO, 2002). Within this area, the distributional impact of air pollution across sections of exposed populations is widely recognized and well-established (Burnett and Cohen, 2020, Burnett et al., 2018, Burnett et al., 2014). For example, children, the elderly and those with predisposed respiratory and cardiovascular disease, are known to be more susceptible to the health impacts from air pollution due to their increased biological sensitivities and different exposure patterns (WHO, 2010a, Sun et al., 2013, Chen and Kan, 2008, Li et al., 2018b, Simoni et al., 2015, Bell et al., 2013). From a socioeconomic perspective, the distributional impacts of air pollution are amplified by historical patterns of segregated neighborhoods in cities and other legacies (Schell et al., 2020), and ability to afford cleaner technologies (Holland et al., 2019). Promoting a transition to low-carbon transport is therefore a priority for climate change mitigation as well as reducing risk to many sections of the population.

GHG mitigation measures in the transport sector include decreased use of motor vehicles, electrification of vehicles, increased levels of active travel (walking and cycling) and increased use of public transport (Haines et al., 2009, WHO, 2010a, Zhang and Fujimori, 2020). Recent research has examined several mitigation measures or potential mitigation scenarios in the transport sector regarding energy consumption, GHG emission, atmospheric pollution and public health, etc (Wang et al., 2020, Wu et al., 2016b, Shindell et al., 2011, Wu et al., 2011, Saikawa et al., 2011, Woodcock et al., 2009, Maizlish et al., 2013, Huo et al., 2014). Each of these impacts will have direct and indirect positive impacts on human health (Xue et al., 2015). Referred to as health co-benefits (Pan et al., 2016), improvements in health outcomes from transport mitigation measures may include: reduction in mortality and morbidity attributable to air pollution exposure; reduced burden of obesity and chronic non-communicable diseases through increasing physical exercise from active travel; and reduced danger from road traffic (Woodcock et al., 2009, Perez et al., 2015, Maizlish et al., 2013, Shaw et al., 2014). Wang et al. (2020) studied vehicle emission control measures in China from 2000 to 2015 and found that without these control measures vehicular emissions during 1998–2015 would have been 2-3 times larger, and in 2015 average concentration of $PM_{2.5}$ and O_3 would have been higher by 11.7 μg/m3 and 8.3 parts per billion, respectively, and the number of deaths attributable to 2015 air pollution would have been higher by 510 thousand (95% CI: 360 to 730). Liang et al. (2019) developed multiple scenarios by considering various electric vehicles (EVs) penetration levels in China and found higher fleet electrification ratios can synergistically deliver greater air quality, climate and health benefits; estimating that the electrification of 27% of private vehicles could reduce the number of annual premature deaths nationwide by 17,456 (95% CI: 10,656–22,160).

Beijing, the capital of China, is an international metropolis with 21.5 million people in 2019 (BMBS, 2016-2020, UN, 2019). Accommodating the transport needs of this population, the energy consumption of Beijing's transport sector is increasing year on year (BMBS, 2016-2020), while rapid socioeconomic development has resulted in personal motor vehicle ownership in Beijing increasing by 146.4% (BTRC, 2012-2020) from 2005 to 2019. The rapid increase of passenger vehicles rapidly increases the energy consumption, GHG emission (He et al., 2016) as well as exacerbating traffic congestion and air pollution. Particulate pollution especially high concentrations of $PM_{2.5}$ pollution, have been the foremost environmental problem for Beijing (Yang et al., 2013). In response, the Beijing government has implemented transport policy packages to tackle these problems (Appendices 1.2) to create a better living environment for citizens as well as reducing GHG and pollution emissions. However, to date, the majority studies of traffic pollution mitigation studies in China have assessed benefits solely in terms of their impacts on pollutant emissions at the national (Huo et al., 2014, Wu et al., 2017) or local level (Wu et al., 2011, Zhang et al., 2017c) and a small number of studies have evaluated vehicular emissions' impact on air quality in China (Li et al., 2015, Ke et al., 2017, Saikawa et al., 2011). This research seeks to build comprehensive insights into the impact of transport mitigation measures on population health, and on the distributional impact of such measures on different sub-populations. Furthermore, there is limited evidence on the economic benefits of mitigation measures in the transport sector in China (He and Qiu, 2016).

To optimize the social and economic benefits of transport mitigation strategies as well as achieving socially progressive outcomes akin to environmental justice, it is necessary to also study the health co-benefits of mitigation measures across different populations. In response, the objective of this research is to estimate the potential emission reduction and health co-benefits by age and sex, as well as quantifying the monetary benefits of four mitigation scenarios for Beijing in the urban land passenger sector compared with the BAU scenario from 2020 to 2050. An integrated assessment model with a Grey Forecast model, a low carbon traffic development model, the Greenhouse Gas and Air pollution Interactions and Synergies (GAINS)-ASIA model, a GEMM and a health economic model are applied. Results at a spatial resolution of 0.1°× 0.1°across Beijing's central area are performed. This study therefore fills the current gap on detailed knowledge of the benefits of transport mitigation strategies studies for China at the city level. It also provides a reference for policymakers to compare different transport mitigation strategies or prioritizing a certain strategy so as to implement integrated climate mitigation measures that decreases carbon emission but also improves health outcomes for residents. The age-sex distributional analysis provides insights on the policy needs for different segments of the population.

5.2 Methods

5.2.1 Integrated transport and health model

This study applies an integrated model framework on the basis of combining a Grey Forecast model, a low carbon traffic development model, the GAINS-ASIA model, a health assessment model (GEMM), and a health economic model (Figure 5.1).

The Grey Forecast model is used to forecast the resident trips in the central area of Beijing per day from 2020 to 2050. The low carbon traffic development model is applied to calculate travel distances and energy consumption of different travel modes (TMs). The GAINS-ASIA model estimates future air pollutants emissions using data on energy consumption, industrial production and proposed environmental regulations under different scenarios. The GEMM model is used to examine premature deaths and avoided deaths attributable to ambient $PM_{2.5}$ caused by emissions related to regional production and consumption activities. Finally, the health economic model is to evaluate the related economic benefits from saving lives from mitigation in transport.

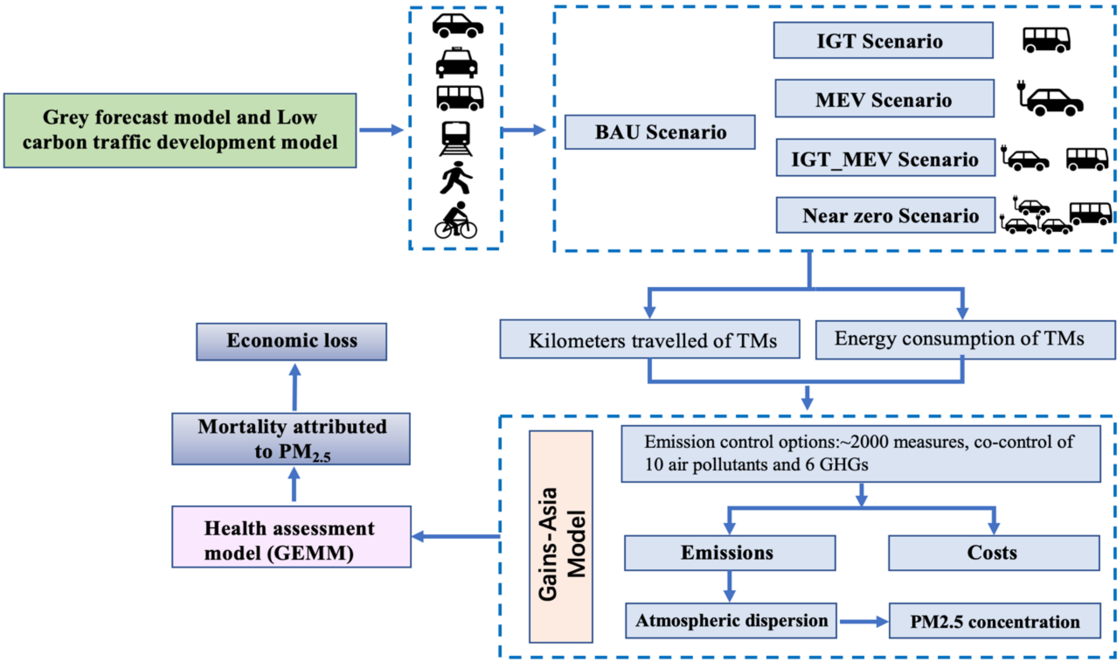


Figure 5.1 Research framework for assessment of health and economic outcomes of transport scenarios for Beijing

5.2.2 Scenario description and research scope

Due to data availability from Beijing Transport Annual Report (BTRC, 2012-2020), the research area is the central area of Beijing, China, including Dongcheng, Xicheng, Chaoyang, Haidian, Shijingshan and Fengtai Districts. The transport sector was divided into freight, intercity passenger and urban passenger transport according to the classification of national statistical systems (Liu et al., 2018). Data on urban land passenger transport defined as public passenger transport (buses, subway, walking and cycling) and private passenger transport (private cars and taxis) was used. The year 2015 was selected as the base year for this study and this baseline year data is from the Beijing Transport Annual Report (BTRC, 2016).

A BAU scenario is used as the reference scenario, with four alternative mitigation scenarios proposed: IGT (increased green transport), MEV (more EVs), IGT_MEV (combining IGT and MEV scenarios) and Near zero CO_2 emissions scenarios. Description of scenarios are in Table 5.1, basis for setting parameters are in Table 5.2 (I majorly set scenarios according to climate mitigation measures of transport sector from the Beijing City Master Plan (2016-2035) (PGBM, 2017)) and detailed assumption parameters for scenario setting are in Table 5.3.

Table 5.1 Principal features of BAU scenario and for progressive transport scenarios for Beijing

Scenario	Description
BAU	Improve transport structure and energy structure; increase the share of green transport (including walking, cycling, subway and buses) in the central area of Beijing to 75% in 2020 as per 2020 Beijing Transport Annual Report(BTRC, 2012-2020)); reduce share of passenger cars and taxis
IGT	Increase share of green transport in the central area of Beijing, increasing the share of green transport to over 75% by 2020 and not less than 80% in 2035 according to Beijing City Master Plan (2016-2035)(PGBM, 2017)
MEV	Based on BAU, focus on decarbonizing motor vehicles; increase diffusion of electric cars (ECs) according to Beijing Municipality regulations on quantifying the number of passenger cars and restricting usage of gasoline cars according to Beijing City Master Plan (2016-2035)(PGBM, 2017)
IGT_MEV	Aggregates the IGT and MEV scenario
Near zero	Based on the IGT_MEV scenario, 100% achieve electronification of passenger vehicles in Beijing by 2050; eliminate gasoline cars by time, making the total gasoline cars' population reduce by time and the total passenger vehicles' population gets less by time

The BAU scenario takes account of transport structure improvement over time as well as any energy structure improvements in the transport sector. Historical share of different land passenger TMs in Beijing from 2007 to 2019 is shown in supplementary figure 1. In 2019, share of green transport in the central area of Beijing was 74.1%, with walking ranking the first (30.2%), followed by car (23.3%), subway (16.5%), bus (15.3%), cycling (12.1%) and taxi (2.6%) (Figure 5.2). The IGT and MEV scenarios refer to policies of associated with Beijing's transport development: Beijing City Master Plan (2016-2035) (PGBM, 2017). The IGT emphasizes increasing the share of green transport (walking, cycling and public transport) in Beijing, increasing the share of green transport to over 75% by 2020 and not less than 80% in 2035 (PGBM, 2017). The MEV scenario emphasizes the decarbonization of vehicles, which will affect the fuel consumption of vehicles. In this study, for passenger cars, two types of cars are considered -- gasoline cars and ECs. There are three major types of ECs used by consumers in Beijing--battery EV, plug-in hybrid EV and range-extended EV (DaaS-Auto, 2015-2020). In this study, it is assumed that all EVs are carbon-free EVs (note: carbon-free EVs means they are carbon-free on a direct basis not on a well-to-wheel basis) like battery EVs and range-extended EV under the five relevant scenarios. This assumption is based on the current status of EVs' populations in Beijing from 2015-2020 (Table 5.4) and projected industry trends in supply and demand towards using carbon-free EVs in the near future (Winton, 2021). For example, Volkswagen declared 70% of its total European vehicle sales will be battery EVs by 2030 and investment bank UBS predicted that new cares would be 20% electric in 2025, 50% by 2030 and 100% by 2040 (Winton, 2021). In this context, China is in a competitive market position for production and distribution of EVs, especially in battery EVs (Dabelstein et al., 2021). Therefore, 100% using carbon-free EVs appears to be a justifiable and realistic assumption in these scenarios.

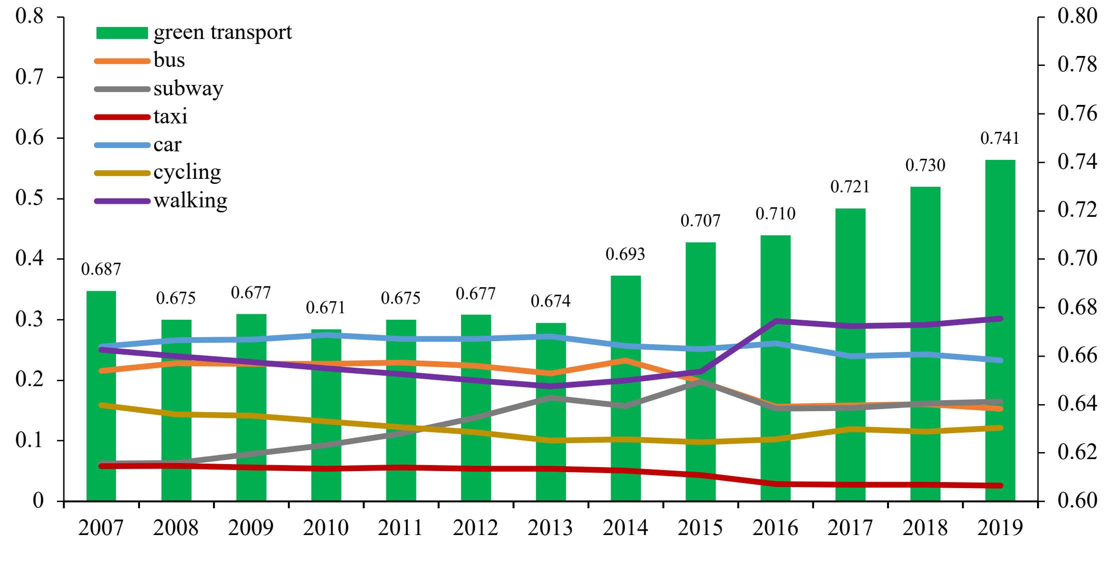


Figure 5.2 Share of green transport and different shares of urban passenger travel modes in the central area of Beijing from 2007 to 2019

The IGT_MEV scenario aggregates the IGT and MEV scenarios.

In 2020, China pledged to achieve carbon neutral by 2060 (Watkins, 2020). To align with the goals of the Paris Agreement and the China government a “Near zero” CO_2 emissions scenario is set up. This scenario is based on IGT_MEV, but it further promotes 100% electronification of Beijing’s passenger transport including passenger cars, taxis, and buses by 2050.

To compare results between scenarios the following five common assumptions are used:

Annual total resident trips under the five scenarios are the same.

Except for data for the transport sector, the data underpinning each scenario in the GAINS-ASIA model remains the same.

All scenarios consider current policy to improve the gasoline and diesel fuels standard to China national VI standard and energy intensity of different fuels of vehicles stays as the China national VI standard in the studying period.

All scenarios have same population number and demographic structure per year.

Table 5.2 Dimensions of private and public vehicle use in scenarios and sources for their parametrization

Basis for setting parameters	Passenger car	Taxis	Bus	Green transport share
13th FYP (2016-2020)			Replaced the old public buses to renewable buses every year and the percentage of renewable buses population of the total public buses was over 90%(Chen, 2018)	
Beijing City Master Plan (2016-2035)	In 2018, 2019 and 2020, the total quota for new cars was 100,000 with 60,000 allocated for electric cars (PGBM, 2017, PGBM, 2017-2020)			Increased the share of green transport to over 75% by 2020 and not less than 80% in 2035[51]

Table 5.2 Dimensions of private and public vehicle use in scenarios and sources for their parametrization (Continued)

Basis for setting parameters	Passenger car	Taxis	Bus	Green transport share
Assumptions	Two types of cars: gasoline and electric cars and all the electric cars are carbon-free; the total quota for new cars will stay 100,000 per year from 2020 to 2050 and since 2025, all the total quota will be for electric cars (Zhuang and Jiang, 2012) and population of gasoline cars stay unchanged; eliminate gasoline cars by 8% since 2030, which is only applied in the Near zero scenario	The percentages of populations of gasoline and electric taxis are kept as same as that of cars	From 2025 to 2050, its percentage is 100%, achieving100% electrification	
Applied scenario	MEV, IGT_MEV, Near zero	BAU, IGT, MEV, IGT_MEV, Near zero	BAU, IGT, MEV, IGT_MEV, Near zero	IGT

Table 5.3 Principal parameters of five transport scenarios for Beijing, 2020 to 2050

Parameter	TM	BAU	IGT	MEV	IGT_MEV	Near zero
Share of TM	Goals of share of TM	Share of green transport reaches 75% in 2020(BTRC, 2012-2020)	Share of green transport reaches > 75% in 2020 and <= 80% in 2035(PGBM, 2017)	Same as BAU	Same as IGT	Same as IGT
Share of TM	Bus	Increase by 0.1% annually	Increase by 0.2% annually	Same as BAU	Same as IGT	Same as IGT
	Subway	Increase by 0.1% annually	Increase by 0.2% annually	Same as BAU	Same as IGT	Same as IGT
	Taxi	Decrease by 0.05% annually	Decrease by 0.08% annually	Same as BAU	Same as IGT	Same as IGT
	Cycling	Increase by 0.01% annually	Increase by 0.02% annually	Same as BAU	Same as IGT	Same as IGT
	Walking	Increase by 0.01% annually	Increase by 0.02% annually	Same as BAU	Same as IGT	Same as IGT
Percentages of different fuel-type vehicles	Car	The percentages of gasoline and electric cars are 99.3% and 0.7%, respectively	Same as BAU	Since 2025, all of the quotas will be for electric cars(Zhuang and Jiang, 2012) and quota will be 100,000 per year, and population of gasoline cars stay unchanged	Same as MEV	Based on MEV before 2030, but eliminate gasoline cars by 8% since 2030; in 2050, achieving100% electronification of passenger cars

Table 5.3 Principal parameters of five transport scenarios for Beijing, 2020 to 2050 (Continued)

Parameter	TM	BAU	IGT	MEV	IGT_MEV	Near zero
Percentages of different fuel-type vehicles	Bus	In 2020, the percentage of electric bus is 90%; from 2025 to 2050, its percentage is 100%, achieving100% electronification	Same as BAU	Same as BAU	Same as BAU	Same as BAU
	Subway	Use electricity	Same as BAU	Same as BAU	Same as BAU	Same as BAU
	Taxi	The percentages of gasoline and electric taxis are 99.3% and 0.7%, respectively	Same as BAU	Keep the same percentage as cars	Same as MEV	Keep the same percentage as cars

Note: Assumption of shares of different TMs under scenarios is based on historical data of and trend of changes in different TMs from Beijing Transport Annual Report (BTRC, 2012-2020). Generally, shares of bus, subway, cycling will increase in Beijing, while taxi and cars will decrease in the future. The annual 8% elimination rate of present gasoline cars is set according to the BTRC 2018(BTRC, 2012-2020).

Table 5.4 Population of electric cars (EVs) in Beijing from 2015 to 2020 (DaaS-Auto, 2015-2020)

Type	2015	2016	2017	2018	2019	2020
Battery EV	338	63,058	118,618	190,757	268,569	356,777
Range-extended EV		7	23	25	193	3,868
Plug-in hybrid EV		612	1,777	3,420	5,941	7,474
Total	338	63,677	120,418	194,202	274,703	368,119

5.2.3 Modelling air pollutants emissions, scope of travel modes (TMs) and $PM_{2.5}$ concentration

The low carbon traffic development model is used to calculate the travel distance of each TMs under the five scenarios multiplying the energy intensity of different fuel vehicles. The IPCC (2006)'s bottom-up approach calculating GHG is used (IPCC, 2006). The equation for calculating the energy consumption of different TMs is shown as below:

$$E_{i,t,s,f} = N_{t,s} \times S_{i,t,s} \times TD_{i,t,s} \times P_{i,t,s,f} \times I_{i,f} \quad (5.1)$$

Where $E_{i,t,s,f}$ (PJ) is the energy consumption (PJ) of different fuels *f* (GSL(gasoline), MD (diesel), CNG (compressed natural gas), ELE (electricity)) of TMs *i* (bus, subway, taxis, car, cycling and walking) in year *t* under a scenario *s* ; $N_{t,s}$ (10^4 times) is the total resident trips in year *t* under a scenario *s*; $S_{i,t,s}$ is the share of TMs *i* in year *t* under a scenario *s* (Table 5.5); $TD_{i,t,s}$ (km) is the per trip distance of TM *i* in year *t* under a scenario *s*, which is assumed to keep as same as that in 2015 (7.3km,13.3km, 9.9km, 13.2km, 3.6km,1.9km for bus, subway, taxi, car, cycling and walking, individually from the data of 2016 Beijing Transport Annual Report (BTRC, 2012-2020)); $P_{i,t,s,f}$ is the percentage of different fuel type vehicles *f* in one TM *i* in year *t* under a scenario *s* (Table 5.6); in another word, the percentage of different fuel type vehicles of the total population of vehicles (Table 5.7) and in this study, it is converted into the percentage of different fuel type vehicles *f* of the total distance travelled in one TM *i* in year *t* under a scenario *s* according to the percentage of different fuel type vehicles of the total population of vehicles; $I_{i,f}$ is the energy intensity of different fuels *f* of vehicles *i* (PJ/passenger.10^4 km) (for cycling and walking, $I_{i,f}$ is assumed to be zero and for different years and scenarios, $I_{i,f}$ is assumed to be the same) (Table 5.8).

The Grey Forecast model is applied to predict the total trips of residents (person-trip) in the central area of Beijing per day from 2020 to 2050 according to the total residents' trips from 2001 to 2019 (BTRC, 2012-2020) as the resident trips per day is an unclear process (BTRC, 2012-2020). By aggregating the original resident trip per day to make this variable show certain pattern, the Grey Forecast model is built:

$$DN_t = 2213.81 \times (1 - e^{0.03701583}) \times e^{-0.03701583 \times (t-1)}$$

$$(t=1, 2, 3\ldots\ldots) \quad (5.2)$$

Where DN_t is the resident trips per day and N_t will be the DN_t multiplies 365. t represents the order of years from 2001-2050. It is assumed N_t would be the same for all five scenarios. The results of N_t is showed in Figure 5.3.

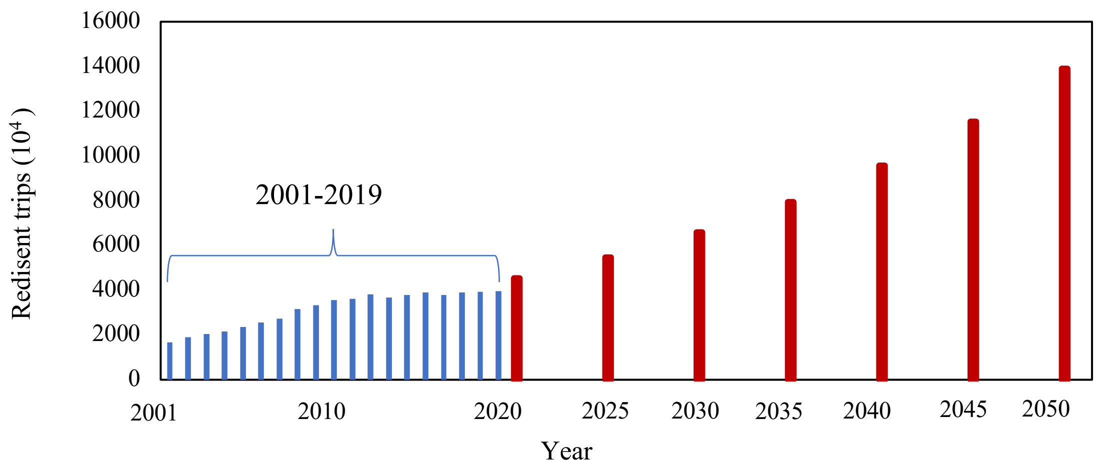


Figure 5.3 Total resident trips per day on weekdays from 2001 to 2050 (per day)

Table 5.5 Share of TMs Sits under different scenarios (%)

Year	Scenario	Bus	Subway	Taxi	Car	Cycling	Walking	Green transport
2015	Baseline	19.7	19.8	4.3	25.2	9.8	21.4	70.7
2020	BAU	15.4	16.8	2.6	22.5	12.3	30.5	75.0
2025	BAU	15.9	17.3	2.3	20.7	12.8	31.0	77.0
2030	BAU	16.4	17.8	2.1	19.0	13.3	31.5	79.0
2035	BAU	16.9	18.3	1.8	17.2	13.8	32.0	81.0
2040	BAU	17.4	18.8	1.6	15.5	14.3	32.5	83.0
2045	BAU	17.9	19.3	1.3	13.7	14.8	33.0	85.0
2050	BAU	18.4	19.8	1.1	12.0	15.3	33.5	87.0
2020	IGT	15.5	16.9	2.5	22.1	12.4	30.6	75.4
2025	IGT	16.5	17.9	2.1	18.5	13.4	31.6	79.4

Table 5.5 Share of TMs Sits under different scenarios (%) (Continued)

Year	Scenario	Bus	Subway	Taxi	Car	Cycling	Walking	Green transport
2030	IGT	17.5	18.9	1.7	14.9	14.4	32.6	83.4
2035	IGT	18.5	19.9	1.3	11.3	15.4	33.6	87.4
2040	IGT	19.5	20.9	0.9	7.7	16.4	34.6	91.4
2045	IGT	20.5	21.9	0.5	4.1	17.4	35.6	95.4
2050	IGT	21.5	22.9	0.1	0.5	18.4	36.6	99.4
2020	MEV	15.4	16.8	2.6	22.5	12.3	30.5	75.0
2025	MEV	15.9	17.3	2.3	20.7	12.8	31.0	77.0
2030	MEV	16.4	17.8	2.1	19.0	13.3	31.5	79.0
2035	MEV	16.9	18.3	1.8	17.2	13.8	32.0	81.0
2040	MEV	17.4	18.8	1.6	15.5	14.3	32.5	83.0
2045	MEV	17.9	19.3	1.3	13.7	14.8	33.0	85.0
2050	MEV	18.4	19.8	1.1	12.0	15.3	33.5	87.0
2020	IGT_MEV	15.5	16.9	2.5	22.1	12.4	30.6	75.4
2025	IGT_MEV	16.5	17.9	2.1	18.5	13.4	31.6	79.4
2030	IGT_MEV	17.5	18.9	1.7	14.9	14.4	32.6	83.4
2035	IGT_MEV	18.5	19.9	1.3	11.3	15.4	33.6	87.4
2040	IGT_MEV	19.5	20.9	0.9	7.7	16.4	34.6	91.4
2045	IGT_MEV	20.5	21.9	0.5	4.1	17.4	35.6	95.4
2050	IGT_MEV	21.5	22.9	0.1	0.5	18.4	36.6	99.4
2020	Near zero	15.5	16.9	2.5	22.1	12.4	30.6	75.4
2025	Near zero	16.5	17.9	2.1	18.5	13.4	31.6	79.4
2030	Near zero	17.5	18.9	1.7	14.9	14.4	32.6	83.4
2035	Near zero	18.5	19.9	1.3	11.3	15.4	33.6	87.4
2040	Near zero	19.5	20.9	0.9	7.7	16.4	34.6	91.4
2045	Near zero	20.5	21.9	0.5	4.1	17.4	35.6	95.4
2050	Near zero	21.5	22.9	0.1	0.5	18.4	36.6	99.4

Table 5.6 Percentage of different fuel-type vehicles in one TM under scenarios

TMs	Year	Scenario	GSL	MD	CNG	ELE
Bus	2015	Baseline	0	81.6	15.3	3.1
	2020	BAU/IGT/MEV/ IGT_MEV/Near zero	0	8.4	1.6	90
	2025-2050	BAU/IGT/MEV/ IGT_MEV/Near zero	0	0	0	100
Subway	2015	Baseline	0	0	0	100
	2020-2050	BAU/IGT/MEV/ IGT_MEV/ Near zero	0	0	0	100
Taxi/Car	2015	Baseline	99.3			0.7
	2020-2050	BAU/IGT	99.3			0.7
	2020	MEV/IGT_MEV	92.8			7.2
	2025	MEV/IGT_MEV	86.2			13.8
	2030	MEV/IGT_MEV	79.1			20.9
	2035	MEV/IGT_MEV	73.1			26.9
	2040	MEV/IGT_MEV	68			32
	2045	MEV/IGT_MEV	63.5			36.5
	2050	MEV/IGT_MEV	59.5			40.5
	2020	Near zero	92.8			7.2
	2025	Near zero	86.2			13.8
	2030	Near zero	71.4			28.6
	2035	Near zero	54.2			45.8
	2040	Near zero	37.8			62.2
	2045	Near zero	24.7			75.3
	2050	Near zero	0			100

Table 5.7 Projection of car population (10^4) in Beijing

Year	MEV/IGT_MEV			Near zero		
	Petrol cars	Electric cars	Total	Petrol cars	Electric cars	Total
2020	470.7	36.7	507.4	470.7	36.7	507.4
2025	480.7	76.7	557.4	480.7	76.7	557.4
2030	480.7	126.7	607.4	316.8	126.7	443.6
2035	480.7	176.7	657.4	208.8	176.7	385.5
2040	480.7	226.7	707.4	137.6	226.7	364.3
2045	480.7	276.7	757.4	90.7	276.7	367.4
2050	480.7	326.7	807.4	0.0	326.7	326.7

Note: From 2020 to 2050, under MEV, IGT_MEV and Near zero CO_2 emissions scenario, total quota for new cars stay 100000 annually (He et al., 2019). Under MEV, IGT_MEV and Near zero CO_2 emissions scenario, from 2020 to 2025, the quota for electric cars is 60000, 70000, 80000, 90000, 100000 respectively (He et al., 2019), and after 2025, all the quota for new cars is assumed for electric cars (Zhuang and Jiang, 2012). Under MEV and IGT_MEV scenario, after 2025, the ownerships of gasoline cars stay the same while under Near zero CO_2 emissions scenario, after 2025, the ownership of gasoline cars reduces 8% annually. The annual 8% elimination rate of present gasoline cars is set according to the BTRC 2018(BTRC, 2012-2020).

Table 5.8 Energy intensity of different fuels of vehicles

Vehicle	Energy type	MJ/passenger.km	PJ/passenger.10^4 km
Bus	GSL	0.59840	5.984×10^{-6}
	MD	0.43645	4.3655×10^{-6}
	CNG	0.65532	6.5532×10^{-6}
	ELE	0.12933	1.2933×10^{-6}
Subway	ELE	0.176	1.76×10^{-6}
Taxi	GSL	1.87	1.87×10^{-5}
Car	GSL	1.87	1.87×10^{-5}
	ELE	0.30612	3.0612×10^{-6}

Note: The data is taken from Zhuang and Jiang (2012).

Owing to the complexity of transport data including a variety of TMs, vehicle types and vehicle owners (organizations or individuals), the calculation of energy consumption for land passenger transport was based on a study (Wang et al., 2015) conducted on Beijing’s urban passenger transport in 2012. Based on this study, it assumes that in 2015, taxis and subway were using gasoline and electricity, individually, while buses are using diesel, CNG and electricity and also their percentages of different types of buses are 81.6%, 15.3% and 3.1%, respectively.

Here we apply the GAINS model to model the $PM_{2.5}$ concentration using the energy consumption of different travel modes as the data input into this model. The $PM_{2.5}$ concentration function used in this model is in equation (2.7) and (2.8).

5.2.4 $PM_{2.5}$ related health impact assessment

This study considers the long-term exposure to $PM_{2.5}$ concentration on mortality as measured by premature deaths. It is modelled by a more recent GEMM, which incorporated recent epidemiological evidence including cohort study on outdoor $PM_{2.5}$ pollution in China (Burnett et al., 2018). GEMM modeled the shape of the association between $PM_{2.5}$ and nonaccidental mortality using data from 41 cohorts from 16 countries, whose results were deemed aligned better with the census-based estimation of $PM_{2.5}$ related deaths than results of the integrated exposure-response (IER) model (Burnett et al., 2014, Xue et al., 2019), which was applied in the GBD studies. There are two versions of GEMM. One is GEMM NCD+LRI which covers risks from nonaccidental NCD and LRI and another one is GEMM 5-COD which comprises five causes of death: IHD, stroke, COPD, LC, and LRI. In this study, these two versions are applied to assess premature deaths of scenarios and premature deaths from additional nonaccidental noncommunicable diseases (ANCD) are defined via subtracting five causes of death by GEMM 5-COD from GEMM NCD+LRI. The premature deaths under scenarios are measured by sex (female and male) and age group (25-29, 30-34, 35-39, 40-44, 45-49,50-54,55-59, 60-64, 65-69,70-74,75-79, 80+). Following similar research, $PM_{2.5}$ intake is assumed to be equally harmful irrespective of the $PM_{2.5}$ composition and source and fuel of origin (Liu et al., 2017a). The number of health outcomes is estimated by multiplying the RR with the population by sex and age in the central area in Beijing and reported cause-specific mortality rate by sex and age, along with the corresponding uncertainties (95% CI) and normally the percentage of exposed population is assumed to be 1(Zhang et al., 2017d):

$$M_{e,a,g,s,t} = (RR_{e,a,i} - 1)/RR_{e,a,i} \times I_{e,a,g} \times P_{a,g,i,s,t} \quad (5.4)$$

Where $M_{e,a,g,s,t}$ is the mortality at health endpoint *e* for age specific *a* and sex specific *g* by scenario *s* in year *t* due to $PM_{2.5}$. $RR_{e,a,i}$ *is* the relative risk of a given $PM_{2.5}$ concentration in grid cell *i* for age specific *a* for health endpoint *e* , which is obtained from the GEMM (Burnett et al., 2018). $I_{e,a,g}$ is the mortality rate of a health endpoint *e* for age specific *a* and sex specific *g* in 2015 from China Health Statistics Yearbook (National Health Commission, 2016). Mortality rates for all scenarios were assumed to be the same and due to data limitations, mortality rates in China are applied to stand for Beijing's mortality rates (Figure 3.1). $P_{a,g,i,s,t}$ is the exposed population for age specific *a* and sex specific *g* in grid cell *i* in a scenario *s* in year *t*. The Beijing's central area' population for age specific *a* and sex specific *g* from 2020 to 2050 is adjusted by the population projection of China from https://www.populationpyramid.net/china/2050/**,** projection of Beijing's population under five SSPs (Jiang et al., 2017), Beijing City Master Plan (2016-2035)(PGBM, 2017) (which requests from 2035, the total resident population in Beijing is controlled under 23 million) and population distribution in six districts in Beijing in 2015 (BMBS, 2016-2020) (Figure 5.4**).**

The expression of GEMM is in equation (2.11).

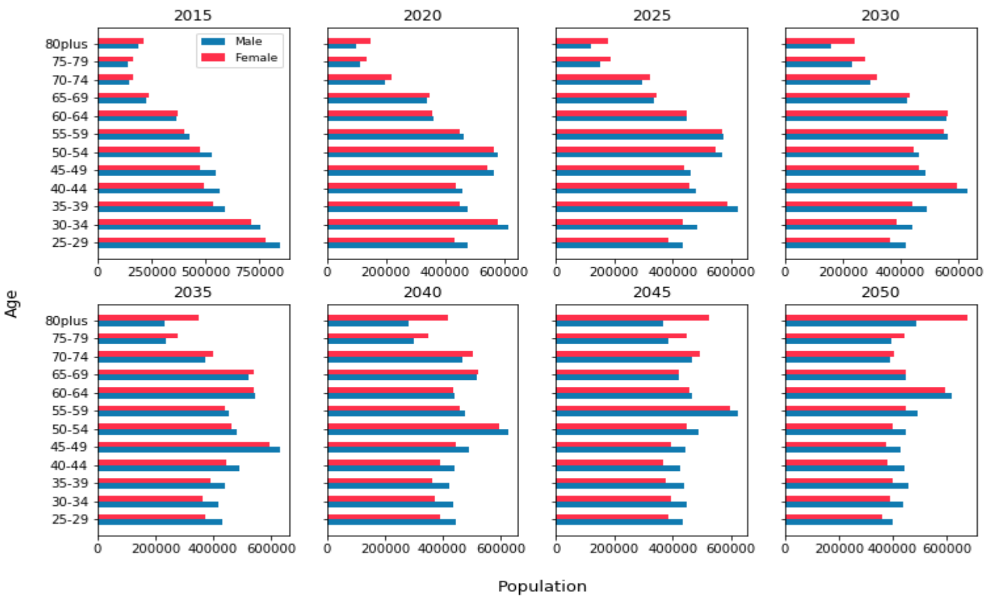


Figure 5.4 Population demographic structure in central area of Beijing for age specific and gender specific from 2015 to 2050

5.2.5 Benefits from decarbonizing urban land passenger transport

To better understand as well as compare different mitigation scenarios, two types of benefits for the four mitigation scenarios compared to BAU are considered. These include health co-benefits related to pollution and benefits of reducing CO_2. It was estimated that social cost of carbon (SCC) in China was US$ 24 (4–50) per tCO_2 in 2015 (Ricke et al., 2018).

$$B_{s,t} = VSL \times Hf_{s,t} + SCC \times C_{s,t} \quad (5.6)$$

Where $B_{s,t}$ is the benefit value provided in a scenario *s* in year *t*; VSL is the value of a statistical life from equation (5.7); H_{st} is the total premature deaths saved in a scenario *s* in year *t*; SCC is the social cost of carbon, $C_{s,t}$ is the reduced amount of CO_2 in a scenario *s* in year *t*.

In this study, monetary VSL is adopted to reflect the monetary health gains, defining the economic benefits of avoiding premature death as a valuation of increased life expectancy (National Research Council, 2008). The Beijing ag and sex-adjusted VSL in 2015,which takes account of the effects of variations in life expectancy, wealth distribution and life quality over the lifecycle is obtained from Yin et al. (2020).

5.2.6 Uncertainty analysis and sensitivity analysis

The uncertainty intervals are based on the following sources of uncertainty:

(1) Future pathways in transport sector, representing as different scenarios in this study;

(2) Uncertainty around RRs of GEMM model. For the GEMM model, estimates of. $\theta_{e,a}$ and its standard errors are obtained by using standard computer software that fit the Cox proportional hazards model. Bootstrap methods were used to obtain 95% CIs (Burnett et al., 2018). Moreover, there is another exposure-response function developed by Burnett et al. (2014), known as the IER model, which using air pollution, secondhand cigarette smoke and active smoking evidence to evaluate the $PM_{2.5}$-health endpoints exposure-response relationship. So, compare the results from the GEMM with IER results;

(3) Due to data availability, the future mortality rate of each health endpoint remains. the same as that in Beijing under each scenario.

(4) Following previous research in epidemiologic and economics literature (National Research Council, 2008), the value of a person's willingness-to-pay (WTP) and the corresponding VSL to changing his or her mortality risk in a given period by a small amount (National Research Council, 2008), does not vary with population or risk characteristics.

(5) Future total population and age/sex structure and geographic distribution of. population. Due to lack of future projection of demographic structure in Beijing and future uncertainty, the age and sex structure of Beijing from 2020 to 2050 refers to the demographic structure in China from https://www.populationpyramid.net/china/2050/. However, it is assumed

the geographic distribution of age- and sex-specific population in Beijing stays as the same as that in 2015.

The IER model incorporated risk information from multiple $PM_{2.5}$ sources, both from outdoor and indoor sources, such as secondhand smoking and heating/cooking, particle exposure from active smoking while GEMM relies solely on studies of outdoor $PM_{2.5}$ pollution. The IER model conducted cohort studies in low-polluted Europe and North America. A brief comparison of IER model and GEMM can be seen in Figure 5.5. Therefore, applying IER model in our study to compare results from the GEMM (GEMM NCD+LRI and 5-COD) can help check the range of uncertainty of our study.

The function of IER model is in equation (2.10).

	Integrated Exposure-Response (IER) Model Burnett et al. 2014	Global Exposure Mortality Model (GEMM) Burnett et al. 2018
Corhots study places	Europe and North America	Global. Includes outdoor $PM_{2.5}$ pollution in China
Pollutants' sources	Both from outdoor and indoor sources, such as second-hand smoking and heating/cooking, particle exposure from active smoking	Solely on studies of outdoor $PM_{2.5}$ pollution
Health endpoints	Age>25: ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD) , lung cancer (LC) , and diabetes mellitus. Age <5: lower respiratory infections (LRIs)	Age>25: GEMM NCD+LRI: nonaccidental noncommunicable diseases and lower respiratory infections (LRIs); GEMM 5-COD: ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and lower respiratory infections (LRIs).
Function	$RR_{e,a}(C_i) = \begin{cases} 1 & for C_i \le C_0 \\ 1+\alpha\{1-\exp(-\gamma(C_i - C_0)^{\delta}\} & for\ C_i > C_0 \end{cases}$	$RR_{e,a}(C_i) = \begin{cases} exp\left\{\frac{\theta_{e,a}\log\left(\frac{C_i - C_0}{\alpha_{e,a}}+1\right)}{1+exp\left\{-\frac{C_i - C_0 - \mu_{e,a}}{v_{e,a}}\right\}}\right\} & if\ C_i > C_0 \\ 1 & if\ C_i \le C_0 \end{cases}$

Figure 5.5 Comparison of IER model and GEMM

The value of VSL is averaged over a population to estimate the value of saving one life (Robinson et al., 2019), which stays the same value to all lives within an area, thus, the standard VSL approach neglecting age differences, which may underestimate the value of saving children's lives and overestimate the value societies place on saving adult lives (Watts et al., 2021). To solve this problem, an age-adjusted VSL is applied considering remaining life expectancy, wealth and survival rate by age from Yin et al. (2020); and the value of VSL will change by time but the value of VSL in 2015 is anchored to all scenarios in different years to better compare different scenarios.

For the sensitivity analysis, health co-benefits using additional invariant VSL across all age groups in Beijing are evaluated. A VSL of 2,027,866 RMB (US$ 325,646) in 2015 for Beijing is used from a number of contingent valuation studies for Beijing (Zhang, 2002, Hammitt and Zhou, 2006, Gao et al., 2015, Xie, 2011a) (Table 5.9). And the future geographic distribution of population can be affected by urban planning, like “Jing-Jin-Ji" integrated development policy with building Xiongan New Area to house the non-governmental functions of Beijing (Kuhn, 2019). Therefore, the sensitivity of population number on health burden is modelled with the total population in the central area of Beijing reduced by 50% under the Near zero scenario in 2050.

Table 5.9 Contingent valuation estimates of VSL for Beijing

Study	Fieldwork: city and year	VSL (RMB)	
		Mean	Median
Zhang (2002) (Zhang, 2002)	Beijing 1999	2,357,953	N/A
Hammitt and Zhou (2006) (Hammitt and Zhou, 2006)	Beijing 1999	1,929,725	358,204
Guo and Li (2015) (Gao et al., 2015)	Beijing 2011	N/A	660,204
Xie (2011) (Xie, 2011a)	Beijing 2010	1,795,920	N/A
Average (in 2015 value)		2,027,866	509203.72

5.3 Results

5.3.1 Energy consumption, air pollution emissions and $PM_{2.5}$ concentration

In 2015, total energy consumption of eight fuel types of vehicles was 110 PJ (Figure 5.6). Energy consumption for gasoline cars is much higher than other vehicles, accounting for 76% of energy consumed, followed by gasoline taxis. Under different scenarios, generally less energy amount is consumed compared to BAU during study years; and under Near zero, it consumes the least amount of energy annually compared to other scenarios.

Under the BAU and MEV scenario, the energy consumption of passenger vehicles is increasing compared to the other three scenarios. Compared to BAU, it decreases by 77%, 28%, 78%, and 80%, in 2050 under the IGT, MEV, IGT_MEV and IGT_MEV scenarios, respectively; and energy consumption's difference between BAU and other scenarios gets larger each year. Under all scenarios, energy consumption from gasoline cars decreases during the study period; for the IGT, IGT_MEV and Near zero scenarios, it decreases from the dominating position to the sub dominating position, ranging from 84% in 2020 to 0% in 2050. Only under the MEV scenario, does the energy consumption of gasoline cars dominant (65% in 2050). Starting at 2030, energy consumption of ECs becomes more pronounced under the MEV, IGT_MEV and Near zero (when the percentage of kilometer travelled by ECs takes up over 20% in the total kilometer travelled by cars in the central area of Beijing); for example, from 2030-2050, percent of energy consumption of ECs rises from 1% to 8% under IGT_MEV. But under IGT_MEV and Near zero, in 2050, the percentage of energy consumption of ECs is less than the previous year due to increasing share of public buses and subway. At the same time the percentage of energy consumed by public buses and subway (green transport) is gradually increasing under all scenarios. By 2050, the energy consumption of public buses and subway is the top consumer for each travel modes under IGT and IGT_MEV.

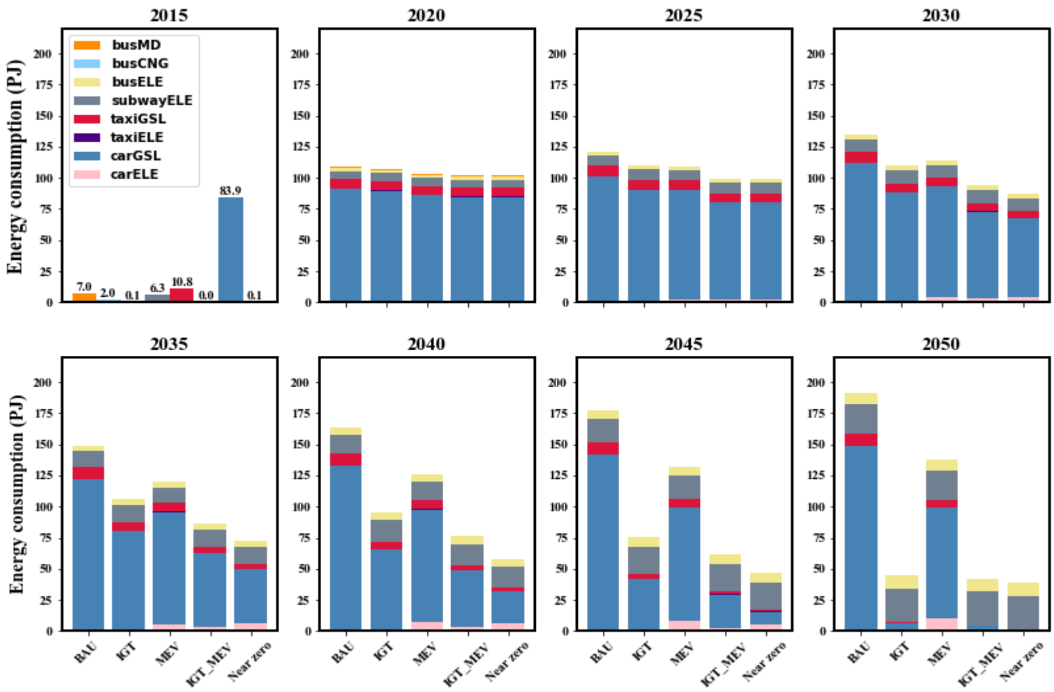
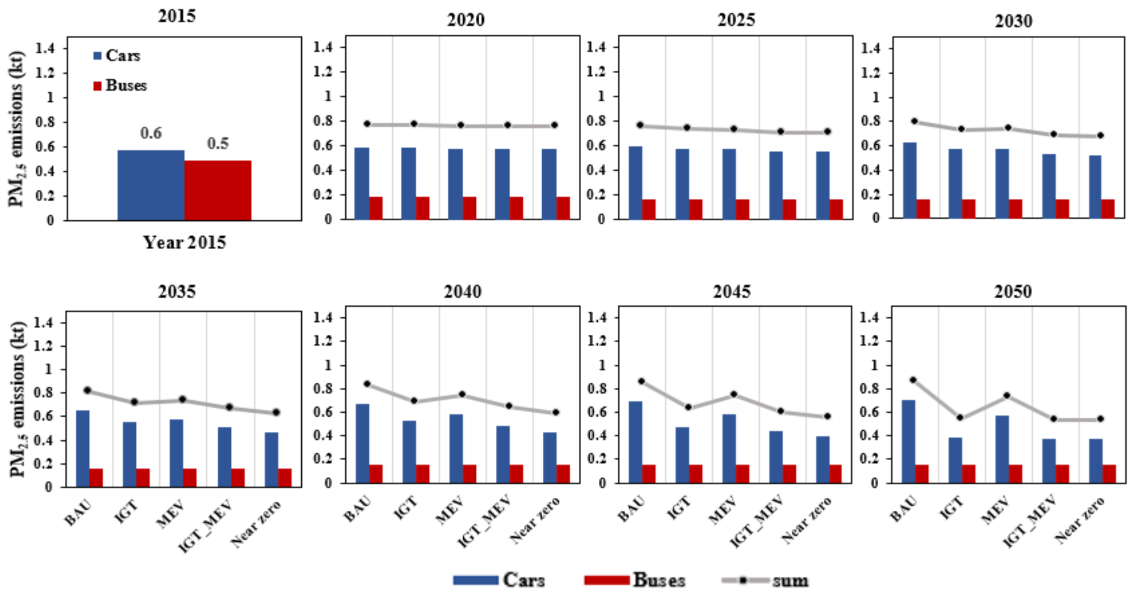


Figure 5.6 Energy consumption of passenger land TMs in Beijing in 2015 and in the future under five scenarios

Figure 5.7a illustrates the total primary $PM_{2.5}$ emissions from all passenger TMs including buses and cars in Beijing. Estimates range from 0.8 kt to 0.9 kt (increased by 13%) under BAU; from 0.8 kt to 0.6 kt under IGT (decreased by 29%); from 0.8 kt to 0.7 kt (decreased by 4%) under MEV; from 0.8 kt to 0.5 kt (decreased by 29%) under IGT_MEV and from 0.8 kt to 0.5 kt (decreased by 29%) under Near zero during 2020-2050 period. In 2050, ranking of $PM_{2.5}$ emissions under scenarios is BAU>MEV>IGT>IGT_MEV=Near zero. Compared to the BAU scenario, the CO_2 emissions from buses and cars decrease by 96%, 40%, 97% and 100% under IGT, MEV, IGT_MEV and Near zero in 2050, respectively, which means in 2050, under Near zero scenario, it achieves zero carbon emissions in the urban passenger transport (Figure 5.7b). Under the IGT, IGT_MEV and Near zero scenarios, CO_2 emissions of cars and buses decreases over time while in a BAU scenario, it is increasing over time. Under the MEV scenario, CO_2 emissions is increasing before 2035, but declines from 2035 onwards.

(a)



(b)

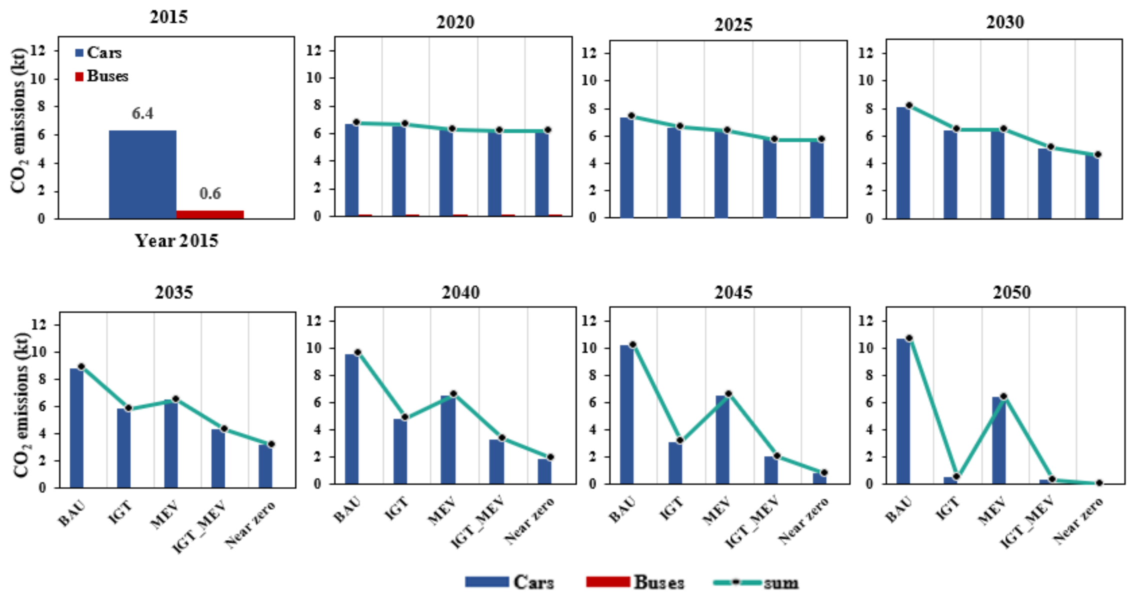
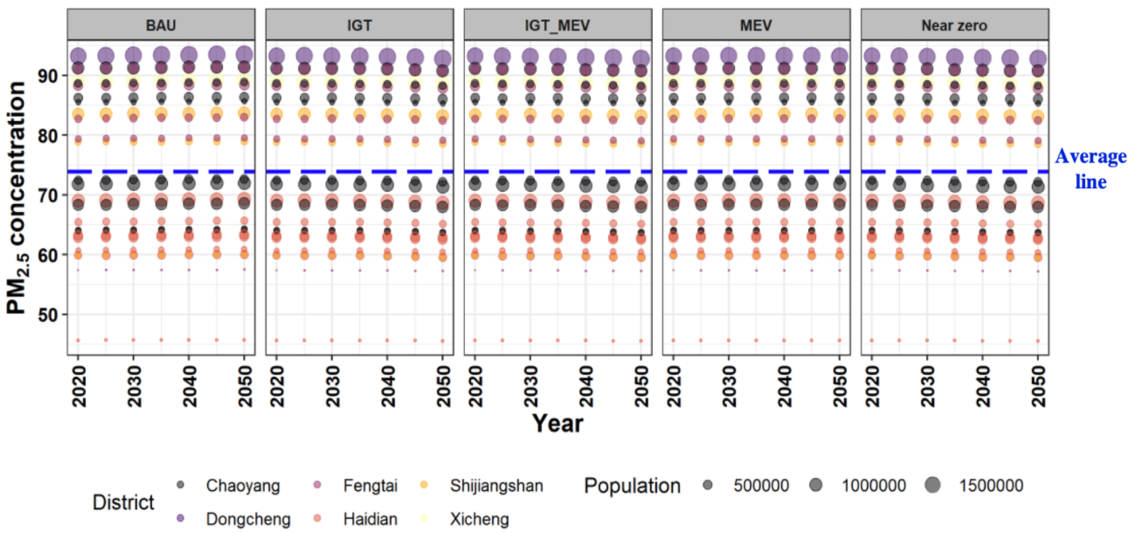


Figure 5.7 Energy consumption of passenger land TMs in Beijing in 2015 and in the future under five scenarios

(a) $PM_{2.5}$ emissions (b) CO_2 emissions

In 2015, the average population-weighted $PM_{2.5}$ concentration in the central area of Beijing was 79.4 ug/m^3 according to GAINS model. Figure 5.8a displays that most of the population in the study area is exposed to above the average $PM_{2.5}$ concentration (above the blue dashed line), located in the southeast area of Beijing. Figure 5.8b depicts a downward trend under all scenarios except for the BAU scenario. However, none of scenarios meets the China's Ambient Air Quality Standard level II (35 ug/m^3) (MEE, 2012) if other sectors except for urban passenger transport sector keep the same structure as in 2015 as assumed in this study. Compared to the BAU scenario, annual $PM_{2.5}$ concentration under each of the four scenarios is lower with Near zero (decreased by 0.45%)> IGT (0.446%)>IGT_MEV (0.43%)>MEV (0.009%) from 2020 to 2050. In general, the trend of $PM_{2.5}$ concentration of one scenario is mostly consistent with that of $PM_{2.5}$ emissions of this scenario.

(a)



(b)

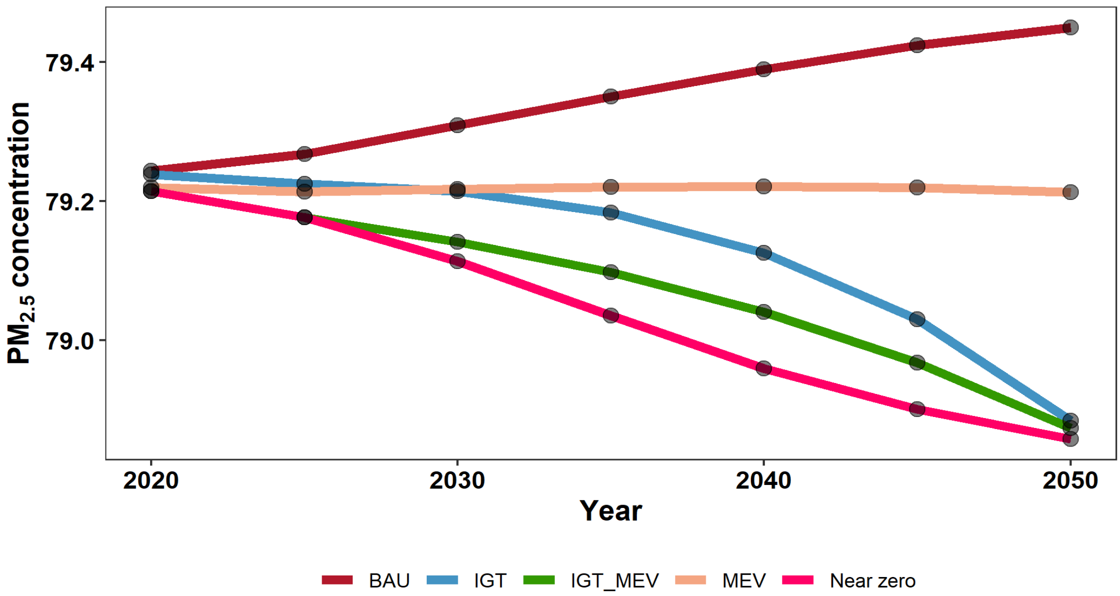


Figure 5.8 $PM_{2.5}$ concentration in the central area of Beijing under five scenarios from 2020 to 2050

(a) $PM_{2.5}$ concentration in grid cells in six districts of central Beijing under scenarios from 2020 to 2050 (the dashed line denotes average $PM_{2.5}$ concentration in six districts in corresponding year, and size of bubble represents size of population in a grid cell) (b) Average population-weighted $PM_{2.5}$ concentration in six districts of central Beijing under scenarios from 2020 to 2050

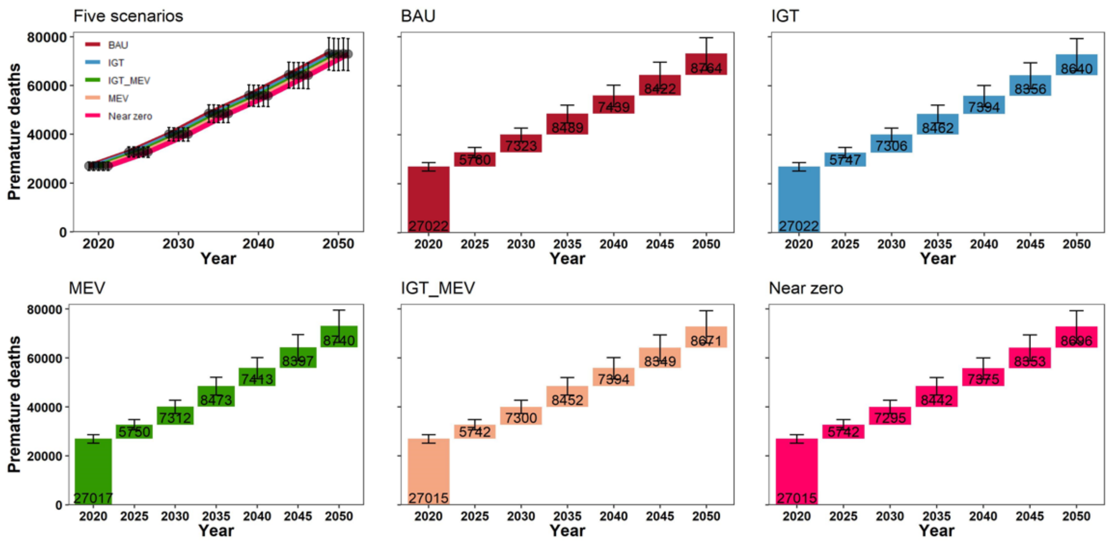
5.3.2 Premature deaths attributed to $PM_{2.5}$ exposure

Figure 5.9 presents the disease- and sex- specific and total premature deaths attributable to $PM_{2.5}$ exposure resulting from all anthropogenic activities in the central area of Beijing. Under all scenarios, the total premature deaths increase annually (Figure 5.9a). However, compared to the BAU scenario there are less premature deaths under four mitigation scenarios from 2020 to 2050, with Near zero recording the relatively lowest number of premature deaths annually (for example 72,900: 95% CI: 66,100-79,300 in 2050). The MEV scenario has more premature deaths among four mitigation scenarios since 2030.

Figure 5.9b illustrate the estimated premature mortality of five health endpoints/outcomes by sex due to $PM_{2.5}$ pollution under five scenarios. IHD and ANCD represent around 30% (31.5%-34%), 30% (26%-34%) of the total annual premature deaths, followed by LRI (20.1%-26.4%), LC (9.3%-11.2%) and Stroke

(0.8%-1%). Premature deaths, however caused by LRI (19.3%-30.2%) increased fastest among all five specific causes annually, followed by stroke (16.7%-30.6%). Males in COPD, LC, LRI, stroke and ANCD show more losses than females, but females in IHD (after 2040) loses more lives than males (Figure 5.9b). For example, under the Near zero scenario in 2050, males in IHD take up 17.3% of the total premature deaths, while males/females in stroke take up 0.5%.

(a)



(b)

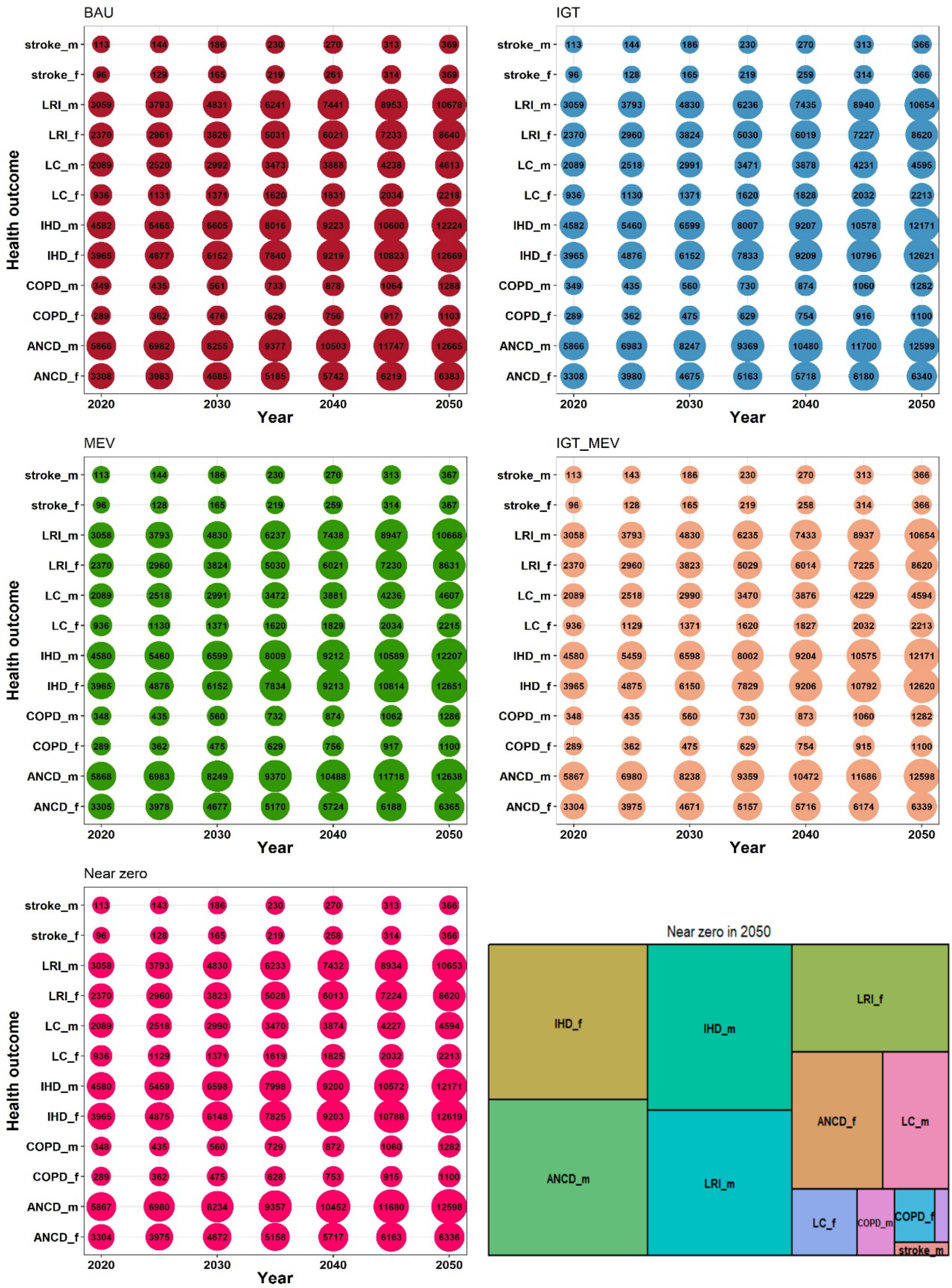


Figure 5.9 $PM_{2.5}$ attributable premature deaths under five future scenarios from 2020 to 2050

(a) Disease-specific and sex-specific premature deaths (b) Total $PM_{2.5}$ attributable premature deaths under scenarios from 2020 to 2050 and the right bottom figure shows the percent of premature deaths by sex and cause under the Near zero scenario in 2050; f represents female and m represents male

5.3.3 Economic benefits under mitigation scenarios

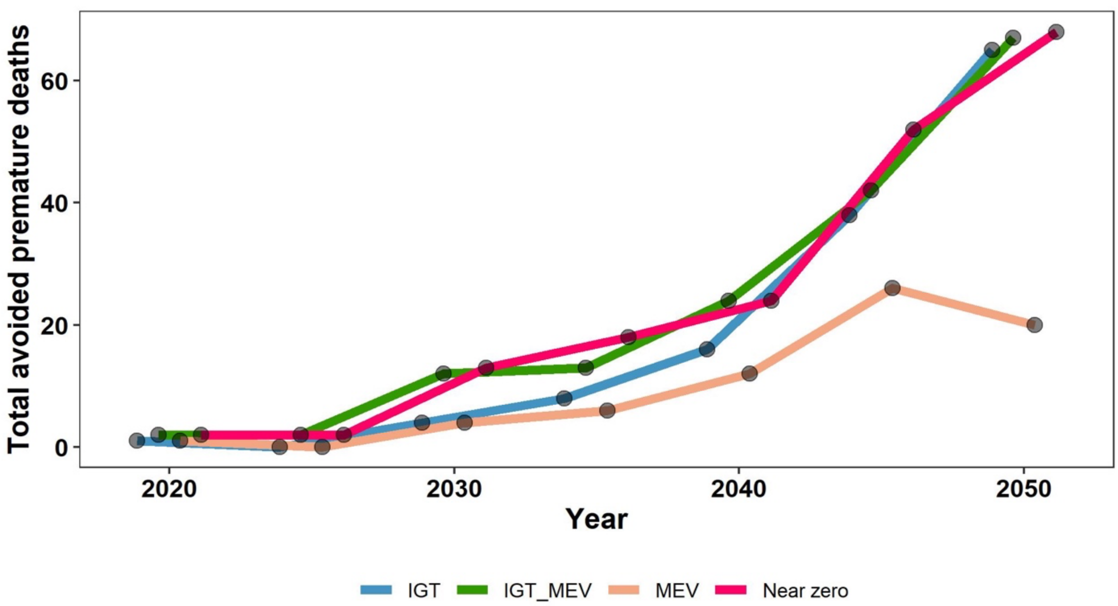
Compared to the BAU scenario, the IGT, MEV, IGT_MEV and Near zero scenarios are estimated to save 0 (95% CI: 0-13) , 5 (0-32), 7 (0-36), 7(0-36) deaths, respectively by 2020; 30 (0-100),26 (0-98), 48 (2-137), 53 (6-150) deaths, respectively by 2030; 102 (38-210), 68 (12-161), 130 (64-257), 164 (90-295) deaths, respectively by 2040; 292 (215-436), 117 (53-229), 296 (218-441), 301 (229-450) deaths, respectively by 2050 (Figure 5.10a). Among four mitigation scenarios, IGT_MEV and Near zero save the most lives over time and IGT's effect on saving lives gets more pronounced while MEV scenario's effect on saving lives gets less pronounced compared to other three scenarios (Figure 5.10a).

The population aged over 50 gains the greatest health benefits (over 84%) annually under the four mitigation scenarios (Figure 5.11b and 5.11c). Moreover, with time the older aged population, more health benefit gains. For instance, in 2025, aged 80+ group accounts for 23.1%, 20%, 24% and 24% of the total health benefits under IGT, MEV, IGT_MEV and Near zero scenarios, individually while in 2050, aged 80+ group accounts for 54%, 59%, 54% and 54%, individually (Figure 5.10c). On the other hand, younger groups (below 50-year-old) gradually avoid more premature deaths with time (Figure 5.10b and 5.10c).

Men obtain more health co-benefits than women across the study timeframe under each scenario and cumulatively, with men avoiding more deaths than women under four scenarios. However, in 80+ group, sometimes woman under four mitigation scenarios from 2020 to 2050 would gain more health co-benefits due to the effect of demographic structure (more woman than men in this age group) (Figure 5.4) outperforming mortality rate (Figure 5.10b and Figure 3.1).

The economic benefits measured by sex and age shows the same trend as avoided premature deaths. Economic benefits will get larger annually and Near zero scenario provides the largest economic benefits compared to the other three. People aged over 50+ and men gain more benefits (Figure 5.11a). For instance, under the Near zero scenario, men would gain more 4,970 US$ than women. Figure 5.11b shows lists two-type benefits under four mitigation scenarios. Monetary health co-benefits contribute the most to the total benefits. Although the value of CO_2 reduction benefits is small under scenarios, it increases annually (Figure 5.11); for example, under Near zero scenario, benefits of reducing carbon are 13 (95% CI: 2-27), 39 (7-82), 84 (14-175), 136 (23-284), 186 (31-470) and 255 (43-532) US$ from 2020 to 2050. In 2050, under the Near zero scenario, the total value from mitigation is equal to 0.01% (0-0.03%) Beijing's GDP 2015. Under IGT, IGT_MEV and Near zero scenarios, economic benefits are rising annually.

(a)



(b)

IGT
IGT_MEV
MEV
Near zero
2020
2025
2030
2035
2040
2045
2050
Age
80+
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
0
30
60
90
Avoided premature deaths
Female
Male

(c)

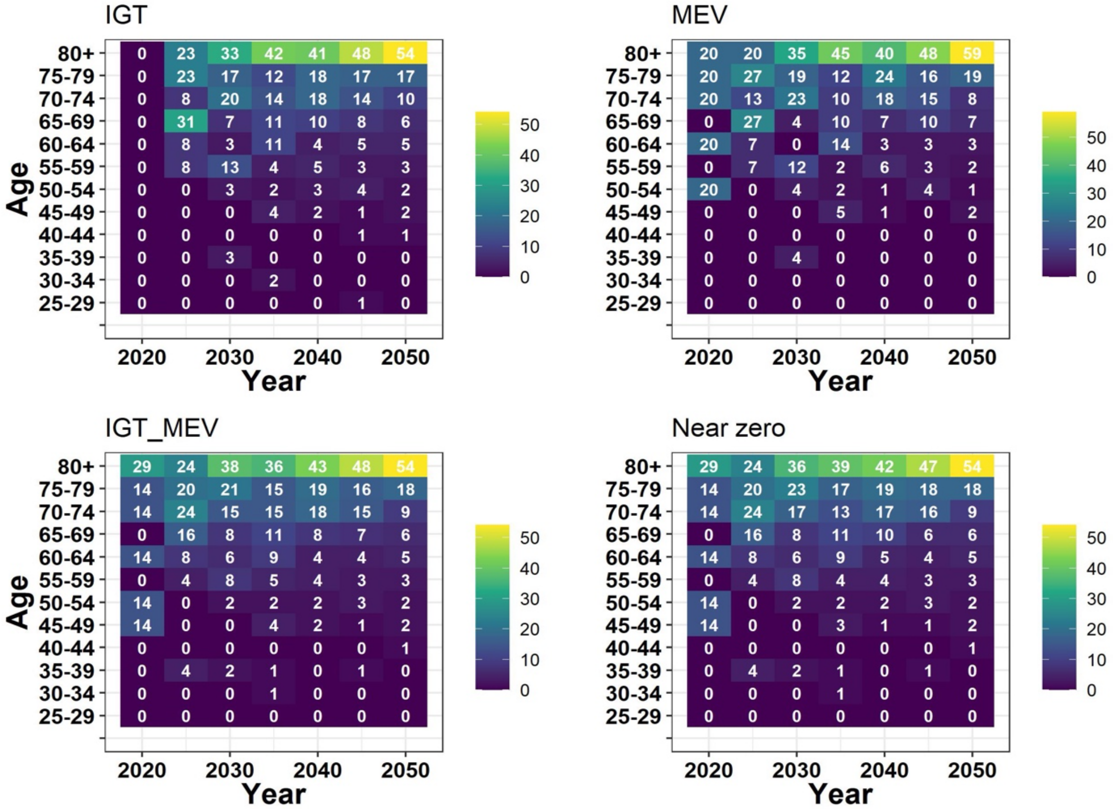


Figure 5.10 Number of avoided premature deaths attributable to $PM_{2.5}$ measured by sex and age under mitigation scenarios compared to BAU scenario from 2020 to 2050

(a) Total avoided premature deaths under scenarios (b) Detailed avoided premature deaths measured by sex and age under scenarios (c) Percentage of avoided premature deaths among population from 25-year-old to 80+ under scenarios per year from 2020 to 2050; unit: percentage

(a)

IGT
IGT_MEV
MEV
Near zero
2020
2025
2030
2035
2040
2045
2050
80+
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
Age
0
3000
6000
9000
12000
Economic benefits (thousand US$)
Female
Male

(b)

		2020	2025	2030	2035	2040	2045	2050
IGT	Health co-benefits	0 (0-0)	1,950 (0-4,300)	4,470 (0-19,300)	8,200 (181-37,700)	13,600 (1,970-54,700)	21,900 (6,000-75,200)	36,300 (15,700-96,100)
	Benefits of reducing carbon	3 (0-6)	19 (3-39)	41 (7-86)	72 (12-150)	114 (19-238)	170 (28-354)	244 (41-508)
MEV	Health co-benefits	861 (0-1,000)	2,230 (0-7,340)	3,740 (0-19,100)	6,040 (0-28,600)	8,820 (181-40,300)	11,900 (1,900-44,100)	13,700 (2,770-52,400)
	Benefits of reducing carbon	11 (2-22)	23 (4-49)	40 (7-83)	56 (9-117)	73 (12-153)	88 (15-184)	102 (17-213)
IGT_MEV	Health co-benefits	1,250 (0-384)	3,700 (0-16,700)	6,660 (181-33,700)	12,500 (960-51,900)	16,800 (3,210-66,000)	26,500 (8,080-81,700)	36,700 (16,700-98,200)
	Benefits of reducing carbon	13 (2-27)	39 (7-82)	73 (12-151)	109 (18-228)	150 (25-314)	197 (33-410)	248 (41-518)
Near zero	Health co-benefits	1,250 (0-1,300)	3,700 (0-16,700)	7,240 (0-39,800)	14,300 (1,250-60,000)	21,100 (5,840-75,500)	30,100 (10,800-88,000)	37,300 (16,900-99,600)
	Benefits of reducing carbon	13 (2-27)	39 (7-82)	84 (14-175)	136 (23-284)	186 (31-387)	226 (38-470)	255 (43-532)

Colour scale: 0 – 37,300

Figure 5.11 Economic benefits of mitigation scenarios from 2020 to 2050

(a) Economic benefits measured by sex and age under mitigation scenarios (b) Total benefit value under mitigation scenarios (thousand US$)

5.3.4 Sensitivity analysis result

In this study, variant VSLs with sex and age specific are applied to get to know the economic benefits of four mitigation scenarios from preventing premature deaths. Then the invariant VSL is adopted to do sensitivity analysis. It shows that compare to the variant VSL approach, results from invariant VSL are around 1.8 to 2.8 times larger. For example, under the Near zero scenario, in 2050, it can generate 98,019.5 (95% CI: 53,405.9-209,064.7) thousand US$ in 2050 with variant VSL while 37,341.2 (95% CI: 16,891.8-99,557.2) thousand US$ with invariant VSL, over 2.6 times (Figure 5.12).

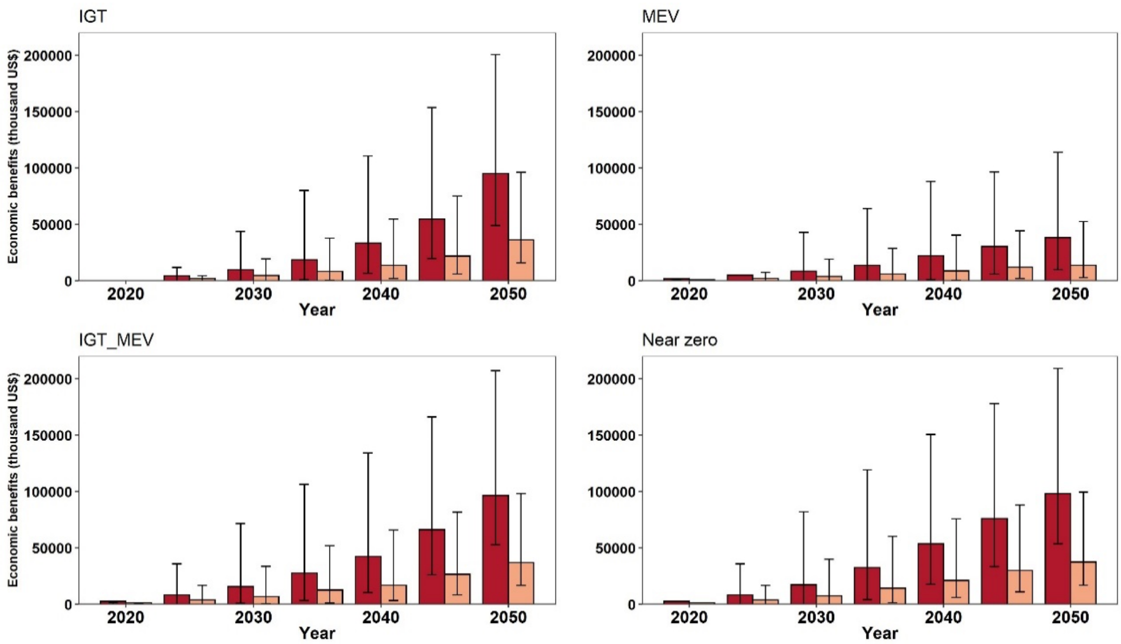


Figure 5.12 Comparison of economical health co-benefits by invariant VSL and variant VSL approach

5.3.5 Uncertainty analysis result

The IER model incorporated risk information from multiple $PM_{2.5}$ sources, both from outdoor and indoor sources, such as secondhand smoking and heating/cooking, particle exposure from active smoking while GEMM relies solely on studies of outdoor $PM_{2.5}$ pollution. The IER model conducted cohort studies in low-polluted Europe and North America.

Through modelling premature deaths under scenarios from IER, GEMM NCD+LRI and GEMM NCD 5-COD, results are showed in Figure 5.13. Generally premature deaths from GEMM NCD+LRI is relatively higher than those from IER and GEMM 5-COD because of its enhanced statistical power to characterize the shape of the $PM_{2.5}$ mortality associations and more health endpoints caused by $PM_{2.5}$ pollution exposure are included (Burnett et al., 2018). GEMM NCD+LRI results in nearly threefold premature deaths as IER and GEMM 5-COD nearly twofold as IER. For instance, in 2050, the Near zero scenario will result in 32,387 (95% CI: 22,630-40,574), 53,984 (95% CI: 47,088-59,942) and (95% CI: 66,101-

79,333) premature death modelled by IER, GEMM 5-COD and GEMM NCD+LRI, respectively.

Therefore, health impacts modelling by the GEMM tend to larger than those by the IER model. Burnett et al. (2018) pointed out these modelling differences between the GEMM and IER model reflect that $PM_{2.5}$ exposure may be related to additional causes of death rather than five causes (>25 years old) considered by the GBD and incorporation of additional sources from other, non-outdoor, particle sources results in underestimation of disease burden, especially at higher concentration, like India and China. And results from GEMM which incorporates cohort studies in China is better consistent with the census-based results in China (Xue et al., 2019). Moreover, results from Burnett et al. (2018), Yin et al. (2017) and Burnett and Cohen (2020) pointed out that the exposure-response function is the main contributor to the true uncertainty of results.

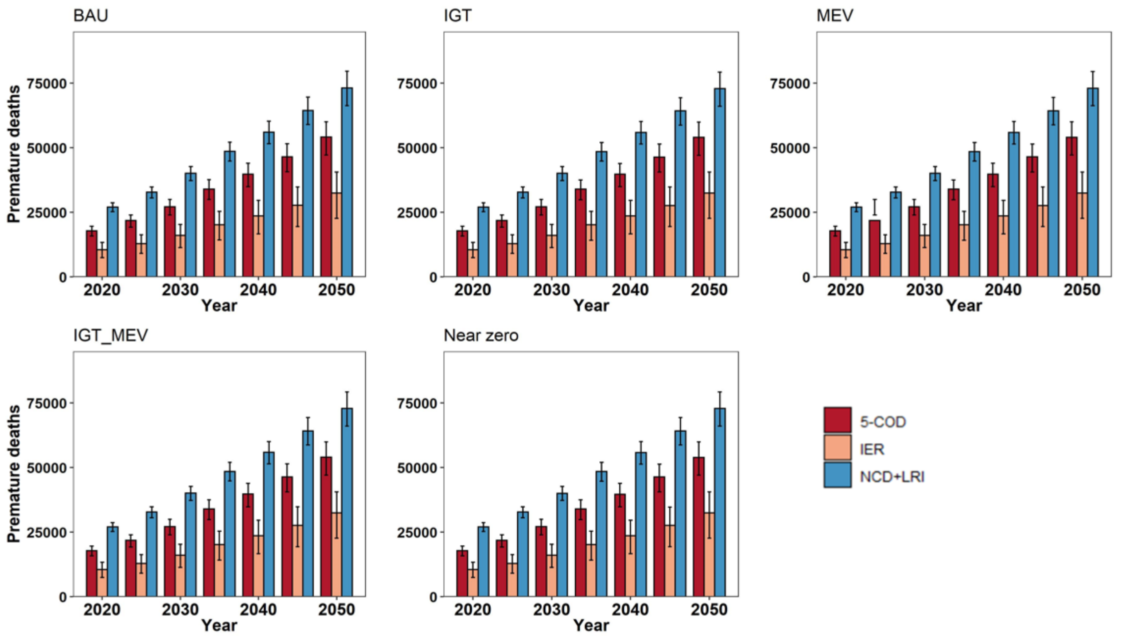


Figure 5.13 $PM_{2.5}$ attributable premature deaths under five future scenarios from 2020 to 2050 modelling from IER, GEMM NCD+LRI and GEMM NCD 5-COD

5.4 Discussion

Previous transport mitigation studies for China (Huo et al., 2014, Wu et al., 2017, Wu et al., 2011, Saikawa et al., 2011, Zhang et al., 2017c, Li et al., 2015, Ke et al., 2017, Xue et al., 2015) or other countries (Maizlish et al., 2013, Woodcock et al., 2009, Farzaneh et al., 2014, Tsoi et al., 2022, Grabow et al., 2012) have focused on a specific outcomes, primarily estimates of changes in pollution or CO_2 emissions. This study builds on those studies and provides information on multiple outcomes from the overall and sex- and age- difference of different urban transport mitigation scenarios in the passenger transport sector in Beijing: energy consumption, CO_2 emissions and $PM_{2.5}$ concentration, health co-benefits and their related monetary benefits from 2020-2050 compared to a BAU scenario. Correspondingly, this study provides the first research demonstrating that a combination of green transport and decarbonizing vehicles will have major benefits, giving a clear message in terms of policy and the benefits of such action. The Near zero scenario achieves the largest health co-benefits and economic benefits annually relative to other mitigation scenarios; in 2050, it can prevent 301 (95% CI: 229-450) cases of mortality, with US$ 37,300 (95% CI: 16,900-99,600) thousand benefits from health co-benefits and US$255.4 thousand (95% CI: 43- 532) benefits from reducing cost of abating CO_2. This study indicates increasing proportion of green transport, electrifying vehicles, less use of motor vehicles and making aggressive goals towards achieving net zero carbon emissions by the mid of this century in the transport sector can generate enormous benefits compared to the sole mitigation strategy. This finding is consistent with scenarios for other cities, such as London and Delhi, which showed that combination of active travel and lower-emission motor vehicles result in largest benefits (7,500 disability-adjusted life-years (DALY)) in London and 13,000 in Delhi for comparable sized cities) (Woodcock et al., 2009).

To date several studies have emphasized the importance of increasing EVs in the development of sustainable transport (Liang et al., 2019, Zhang et al., 2017b, Zhang and Fujimori, 2020, Ji et al., 2012, Ji et al., 2014). However, few study have estimated the impact of increased EVs and green transport. This study indicates that increasing the percentage share of green transport can provide more benefits compared to electrification of vehicles. The IGT scenario saves 0 (95% CI:0-13) life in 2020 and 292 (95% CI: 215-436) lives in 2050, with the share of green transport increasing from 75.4% in 2020 to 99.4% in 2050 (increased by 31.8%). The MEV scenario saves 5 (95% CI:0-32) lives in 2020 and 117 lives (95% CI:53-229) in 2050 with the percentage of ECs' population of the total passenger cars rising from 0.7% to 40.5% during 2020-2050 (increased by around 57 times). Comparing the IGT scenario with the IGT_MEV scenario, the effects of increasing ECs is most visible before 2050, with avoided mortality from the swap to ECs decreasing when the share of green transport reaches 99.4%. Further, comparing the IGT_MEV scenario with the Near zero scenario, it finds that by 2050, when the share of green transport has reached 99.4% only five additional lives are saved under the Near zero scenario with 100% electrification in private passenger cars compared to 40.5% electrification under the IGT_MEV scenario.

The results of the scenario analysis here suggest that when green transport already accounts for a large share in resident trips, the electrification of vehicles provides only a minor effect on the reduction of pollution and associated health burden. This finding is comparable with a scenario study in Beijing which found that public transport development should be given priority comparing to new energy and clean energy vehicles scenario (Fan et al., 2017). He and Qiu (2016) concluded that the largest reduction of pollution emission is by combining increased public buses and cycling. Furthermore, several studies have noted a shift from private vehicle to active transport is a key intervention for improving public health, physically and psychologically (Maizlish et al., 2017, Woodcock et al., 2014, Mizdrak et al., 2019, Woodcock et al., 2013, Rojas-Rueda et al., 2011, Rojas-Rueda et al., 2012). However, research by Perez et al. (2015) in Basel, Switzerland found that when active transport is already high, it produces modest benefits, and the most effective policy remains increasing zero-emission vehicles. Nevertheless, the difference in findings is mainly attributed to the difference between active transport and green transport as green transport includes active transport and public transport so that public transport plays a vital role in reducing pollutants and preventing mortality.

For health outcomes, although studies have found that women are more susceptible to air pollution (Sun et al., 2013), generally men cumulatively obtain more health co-benefit than women from our four scenarios. This is due to demographic structure of Beijing (higher male population) and the relatively higher incident rates of each of the five disease categories for men compared to women (Figure 5.4 and Figure 3.1), which can be explained by the male-female health-survival paradox. Proposed explanations for this paradox include biological differences, behavioral differences such as risk-taking and reluctance to seek and comply with medical treatment and methodological challenges, such as selective non-participation and under-reporting of health problems, and delayed seeking of treatment (Oksuzyan et al., 2008). For the age-based analysis, individuals aged 50+ and in some years female in aged 80+ in Beijing benefit more from transport mitigation owing to demographic aging and vulnerability and increased risk of the elder group exposed to air pollution (Li et al., 2018b) in Beijing. This finding in line with several studies (WHO, 2010a, Yang et al., 2013, Hu et al., 2014, Cao et al., 2011, Sun et al., 2013, Yin et al., 2020) that found that due to pre-existing illnesses and aging effect, the elderly population is particularly impacted by long-term exposure to air pollution (Sun et al., 2013) so that they gain more health co-benefits when making mitigation movements. This study also finds that as well as obtaining health co-benefits via decarbonizing transport sector in Beijing, there will be substantial benefits through a reduction in CO_2 emissions. This is in line with a study finding that stringent penetration of electric vehicles can reduce the carbon mitigation cost generated by the 2 °C climate stabilization target (Zhang and Fujimori, 2020). This finding also implies that transport-based mitigation also has a positive impact on the economic system.

Previous research suggests that the electrification of vehicles improves air quality for disadvantaged neighborhoods and thus meets social and equity goals through reduce atmospheric pollution loading in vulnerable communities, for those located near congested streets and highways (Kragh et al., 2016). However, fossil fuel powered plants are normally away from urban areas. This means that increased usage of EVs disproportionally benefits city dwellers where the highest concentration of EVs are located, while those who exposed to pollution from electricity generation predominantly reside in rural areas which are downwind of fossil power plants (Kragh et al., 2016). Ji et al. (2015) found that EVs could increase EJ challenge in China, with around 77% (41-96%) emission inhalation attributable to urban EVs use is distributed to rural communities whose incomes are average lower than city residents who use urban EVs. Also, a study suggests that electrification of transport without the replacement of fossil-fuel power plants leads to increasing CO_2 emission (Zhang and Fujimori, 2020). These previous studies suggest that a scenario for city transport based primarily on electrification does not address the fundamental issue of pollution generation, rather it displaces the pollution exposure to other areas, often outside the city. Hence, renewable power as a means to decarbonize power generation plays a key role in electrifying the transport sector (Zhang and Fujimori, 2020). In China, the percentage of renewable generation (including hydropower, nuclear, wind and solar power) was 32.1% of the total power generation in 2020 and annual increase rate of renewable power was around 10% from 2015-2020 (Table 5.10).

This suggests there is a major challenge to achieve 100% renewable power generation by 2060 for China given current rates of increase.

Table 5.10 Technology sources of electricity generation in China, 2015-2020 (TWh)

Year	Hydro power	Nuclear	Wind	Solar	Thermal power	Renewable generation	Total generation	Percentage of renewable generation
2015	11303	1708	1858	388	42842	15256	58149	26.20%
2016	11841	2133	2371	616	44371	16960	61330	27.70%
2017	11979	2481	2972	1063	47546	18495	64511	28.70%
2018	12318	2944	3660	1775	50963	20696	67692	30.60%
2019	12934	3303	4163	2194	51353	22594	73253	30.80%
2020	13550	3662	4667	2612	51742	24491	76236	32.10%

Note: Data is taken from the China Energy Statistical Yearbook(National Bureau of Statistics of China, 2011-2021), China Electricity Council (http://cec.org.cn/index.html) and Cai et al. (2021b).

There are uncertainties in our assessments. Through our uncertainty and sensitivity analysis, it finds that health assessments by IER model may underestimate the $PM_{2.5}$-related health co-benefits without considering additional nonaccidental noncommunicational diseases, which can be around twofold or threefold less than results modeling by the GEMM in this study. And the monetarized avoided premature deaths of mitigation scenarios could be around 1.8 to 2.8 times larger if using the invariant VSL. And if the population of different segments of population reduced by 50%, under the Near zero scenario, in 2050, $PM_{2.5}$-related premature deaths can reduce by 50%, showing the population number is proportionate to results of premature deaths in this integrated assessment and the distribution of future population of subpopulations is sensitive to $PM_{2.5}$-related premature death.

This research has limitations common to many scenario studies: data availability, underestimation of comprehensive health impacts, and various sources of uncertainty. First, due to a lack of data and difficulties in modeling these additional health outcomes. Wider positive health benefits of increased physical activity due to active commuting and reduction of morbidity cases are not considered nor the potential negative impacts due to increase exposure to air pollution are considered. In general, not considering these health benefits will underestimate the entire health co-benefits through active travel measures in our green transport scenarios (the IGT and IGT_MEV scenarios). Moreover, mitigation in the transport sector will also alleviate traffic congestion, reduce fossil fuel dependence, which are also benefits and should be counted in the further related study. Second, our health impact assessments conduct health co-benefits from $PM_{2.5}$ exposure but using $PM_{2.5}$ alone may underestimate the benefits of transport mitigation measures given that other sources of air pollution can also enact an adverse impact on health. Third, technology improvement and innovation in the future doesn’t be taken account of in this research because it is hard to quantify them given the complicated transport system, and technology and innovation may completely change the transport patten as well as technology part is not the research objective of this research. Fourth, assumptions of this research are applied to predict the future with limited data and plenty uncertainties, so our results should be seen as provisional and can be revised with more detailed and accurate data. But tried to make assumptions in this study more plausible based on historical data and obtained information. And still can improve our assumptions in the future, like using variant mortality rate, variant VSL and SCC by time, modelling future population distribution, the potential of adopting other motor vehicles with the development of technology, etc. Thus, given above limitations, the near future work can lead to addressing these limitations. Regardless of these limitations, the findings obtained in this study can be used to underpin future sustainable transport for Beijing as well as for other megacities (Table 5.11) if they vigorously adopt sustainable transport. The integrated method used in this study can be easily applied to similar or broader research for different research area and can be compatible with setting different future transport mitigation scenarios.

Table 5.11 Major passenger TMs in megacities

City	Country	Population (10,000)	Aera (km^2)	Major passenger TMs
Paris	France	216	105.4	metro, RER(Réseau Express Régiona), tram, bus, car, taxi, cycling
London	England	890	1,577	underground, bus, tram, car, taxi, rail, cycling
Berlin	Germany	363.4	891.9	subway, city rail, tram, bus, car, taxi, cycling
New York	United States	842	783.8	subway, ferry, bus, car, taxi, cycling
Shanghai	China	2,487.1	6,340.5	subway, tram, bus, car, taxi, cycling
Guangzhou	China	1,867.7	7,434.4	subway, tram, ferry, trolleybus, bus, car, taxi, cycling

5.5 Conclusion and policy implication

Comparing different pollution mitigation measures in the urban land passenger sector, this study demonstrates that a combination of green transport and increased EVs generate the largest health co-benefits and economic value. The study also provides evidence that developing green transport measures outperforms the electrification of passenger transport. Increases in green transport are progressive and are consistent with environmental justice: they improve access as well as health benefits for disadvantaged populations those who have sparse travel options (IEI, 2017). Examining the impact of transport-based mitigation on health across different age and sex groups, this study shows in detail who stands to benefit from the decarbonization of Beijing's transport system. This study shows that, in the context of Beijing's geography and demographic makeup, men benefit more across all mitigation strategies. While the elderly, receives the greatest impact from decarbonization in terms of avoidance of premature death, younger groups have relatively higher relative risk than the elderly when exposed to air pollution. Thus, the health impact of decarbonization among women and younger demographics is still important to consider. Our research also demonstrates a reduction in CO_2 mitigation costs via transport electrification, restricted vehicle using, phasing out internal combustion engine vehicles and so on. The comprehensive results suggest that stakeholders including transport planners, energy experts, policymakers, economists develop a joint strategy for transport electrification to reduce CO_2 emissions quickly and effectively due to the effectiveness of transport electrification policy affected by myriad factors (Zhang and Fujimori, 2020).

From a policy perspective, there are significant benefits to Beijing authorities prioritizing green transport development policies as planned in the 14th FYP (Chen, 2018). However, the effectiveness of these green transport strategies partly depends on how to let citizen adopt more green transport than motor vehicles travel at the demand side. An 'avoid–shift–improve' approach (Creutzig et al., 2018, Dalkmann and Brannigan, 2007) is encouraged, a well-established framework in developing sustainable transport for Beijing's transport development. For example, avoid in this context means reducing the need to travel, which can be achieved by advanced urban planning ('15-mintue city' is an idea to increase active travel by locating more jobs, shops and retail within active travel distance of where people live (Sutcliffe, 2020, Whittle, 2020)), teleworking, smart logistics (Creutzig et al., 2018). Shift in this context means mode shift from cars to walking, cycling and public transport (Creutzig et al., 2018), which can be achieved by cultivating citizen's travel habits to adopt more green transport, like inventing an personal carbon footprint calculator to trace how much CO_2 can be reduced by taking green transport rather than taking motor vehicles of one travel trip, advocating advantages of adopting active travel, such as tackle obesity(Saunders et al., 2013), making active travel a convenient mode like providing advanced bike sharing system and on the other hand, a carrot-and stick approach is widely implemented in cities throughout the world to increase car ownership’s costs, limit car access to city centers, etc., and increase investment in improving walking and cycling’s infrastructure (Brand et al., 2021, Nieuwenhuijsen and Khreis, 2016, Pucher and Buehler, 2017). Improve in this context refers to improving comfort of green transport; for example, increasing the safety, acceptability, appeal of (Enhanced streetscape design can make active travel pleasant (Gehl, 2001)) green transport (Woodcock et al., 2009). Furthermore, the elderly cohorts and women with elevated exposure to air pollution requires policy attention. Government authorities and civil society can, for example, promote their health awareness and take measures to improve public health care services. And our sensitivity analysis suggests that the distribution of population has a fundamental effect on health burden: radical interventions such as relocating vulnerable groups to less polluted area would likely fundamentally reduce aggregate exposure. The results also suggest that relying solely on mitigation in passenger transport cannot achieve air quality standards within China's Ambient Air Quality Standard level II (35 ug/m^3) (MEE, 2012) even with radical measures. This suggests that a comprehensive mitigation across all polluting sectors is urgently required.

Chapter 6 Conclusion

6.1 Summary

In this thesis, an integrated assessment framework coupling with the energy inventory data, Greenhouse Gas and Air pollution Interactions and Synergies (GAINS) model, Global Exposure Mortality Model (GEMM) and health economic model is applied to assess the economic loss/benefits and health burden/health co-benefits of energy consumption/switch of Chinese household consumption activities. The household sector is one of largest energy consumers in China (Fan et al., 2013) and as such has a profound impact on the production activities, energy consumption and GHG emissions (Liu et al., 2011). With increasing living standards and wealth across the Chinese population, household energy consumption is forecast to continually grow in the short and medium term (Fan et al., 2013). Therefore, deploying climate mitigation strategies in the household sector is about to take place.

To conduct this research, at the beginning, understanding the status of household consumption in the form of energy usage is important. The household energy consumption can be divided into the direct and indirect, so that firstly the analysis of the household direct energy consumption is conducted followed by the household indirect (embodied) energy consumption. And China is a typical dualistic country with substantial disparities across urban and rural areas and provinces in terms of resource and energy endowments, economic development, population densities, and lifestyles. Therefore, it is necessary to study the Chinese household direct and embodied energy consumption at regional and provincial levels to better implement climate mitigation measures in a more targeted manner. Furthermore, household embodied energy consumption is related to household different consumption activities; therefore, eight broad consumption activities (food, clothing, housing, household facilities, articles and services (abbreviated as facilities), transport and communication services (transport), education, cultural and recreation services (education), medicine and medical services (health) and miscellaneous commodities and services (miscell)) are identified for rural and urban households in this thesis and further to identify what consumption activity should be put the emphasis on mitigation strategies under the ongoing urbanization and it finds that household consumption in housing and transport and communication services activities is estimated to increase by the largest magnitude. Lastly, deploying mitigation strategies in household consumption activity in transport is conducted to better know the potential health co-benefits and economic benefits when households adopting more green transport travel or using more electric vehicles. A case study in Beijing is applied to explore mitigation scenarios of household travel pattern changes due to sufficient policies in Beijing's transport sectors and data availability.

Energy consumption of household consumption activities are attached to using different fuel types. For household direct energy consumption, solid fuels specifically coal and biomass (mainly wood and crop residues) are still important sources of energy for heating and cooking, largely in rural areas in China (Archer-Nicholls et al., 2016, Zhang and Smith, 2007, Yun et al., 2020). Combustion of solid fuels by households causes both indoor air pollution (Zhang and Smith, 2007, Clark et al., 2013) and ambient air pollution at a local or regional scale (Chen et al., 2018). Herein, after studying the rural and urban direct energy consumption, their induced $PM_{2.5}$-related premature deaths are studied in this thesis. Because primary energy tends to be more transferred into electricity for usage in China under the pledge of carbon neutrality by China's government. Hence, a scenario analysis of substituting solid fuels with electricity is applied to understand the potential health co-benefits and economic benefits across different profiles of groups (age- and sex specific) in rural and urban areas at provincial levels in China. The mitigation scenario study in Beijing, China further analyzes potential health co-benefits and economic benefits from 2020 to 20250 under four transport mitigation scenarios across different profiles of populations, which provides better implications for implementing mitigation strategies at demand side.

Major conclusions of this thesis are summarized as below:

(1) In 2015, the total household direct energy consumption and indirect was 10,500 PJ and 20,000 PJ, respectively, taking up 10.8% and 20.6% of the total energy consumption in China, showing that household embodied energy consumption was nearly 2 times than the household direct energy consumption.

(2) For the direct household energy consumption, urban household energy consumption (6,700 PJ) was nearly 1.6 times greater than the rural household energy consumption (3,800 PJ). In 2015, 17% of national premature deaths could be attributed to outdoor $PM_{2.5}$ from residential energy sector. Although urban households consumed nearly 1.6 times energy than rural households, premature deaths attributable to $PM_{2.5}$ exposure from household energy was 1.1 times higher from rural household consumption compared to urban households due to rural households using of solid fuel products.

(3) Analysis at the regional level incorporating differences between urban and rural areas and age-sex specific mortality rates by five health outcomes, finds that between 37.5% and 37.8% deaths attributable to household energy consumption were due to IHD. The population aged over 80-year-old accounts for over half the total household energy consumption-$PM_{2.5}$-related deaths (66.3% to 66.5%), with the age category 25 to 29-year-old recording the lowest. Premature mortality was higher among the male population compared to the female population, ranging from 62.3% to 62.4% of household energy consumption $PM_{2.5}$-related mortalities.

(4) The scenario analysis finds that if coal and biomass had been replaced with electricity in both urban and rural households, 28% (rural) and 6% (urban) premature deaths would have been avoided and it estimates these avoided premature deaths could bring economic benefits equal to 0.09% (95% CI: 0.08%-0.1%) GDP for rural areas and 0.006% (0.005%-0.007%) of GDP for urban areas of China.

(5) For the embodied energy consumption, urban household energy consumption (15,000 PJ) is approx. 3 times by rural household's (5,000 PJ); corresponding to 19.9 GJ/person and 9 GJ/person, respectively. Embodied

energy consumption was highest across the food (24.7% in rural and 22.9% in urban), housing (20.2% in rural and 20.9% in urban) and transport (18.6% in rural and 19.6% in urban) consumer sectors in both rural and urban households.

(6) Under the urbanization in China, categorized as aspirational, opulent and high energy intensity activities, consumption relating to housing and transport and communication services is estimated to increase by the largest magnitude for both rural and urban households. The first quintile region of China with the highest average income should take up the responsibility of reducing its own consumption level and improve its own industrial energy efficiency, especially in transport, storage and transport equipment and service sector.

(7) When adopting climate mitigation strategies in household travel patterns, a case study in Beijing, China finds that all the four alternative mitigation scenarios (IGT scenario, MEV scenario, IGT_MEV scenario, and Near zero scenario) result in reduced $PM_{2.5}$ and CO_2 emissions compared to BAU from 2020-2050. It demonstrates the effects of combination of taking green transport and using electric vehicles can gain sustainable benefits, but green transport increase plays a vital role. The Near zero scenario achieves the largest health co-benefits and economic benefits annually relative to sole mitigation strategy; in 2050, it can prevent 301 (95% uncertainty interval: 229-450) cases of mortality, with benefits from health co-benefits and benefits of reducing CO_2 (equivalent to 0.01% (0-0.03%) of Beijing's GDP 2015).

(8) Men cumulatively obtain more health co-benefit than women under four transport mitigation scenarios from 2020-2050. Individuals aged 50+ and in some years female in aged 80+ in Beijing benefit more from transport mitigation owing to demographic aging and vulnerability and increased risk of the elder group exposed to air pollution (Li et al., 2018b) in Beijing.

6.2 Research implications, limitations and future research prospect

6.2.1 Research implications

Climate mitigation strategies tend to focus on supply-side technology, underemphasizing the significant potential for mitigation through managing consumption practices (Creutzig et al., 2018, Bjørn et al., 2018) or using interactions between demand-side and supply systems to leverage mitigation action. Hence, health co-benefits and economic benefits of climate mitigation measures taking place at the demand-side of household consumption activities are studied in this thesis. And it provides new insight of economic benefits and avoided health burden across different age and gender groups at the national/regional/provinces levels in China. In this thesis, the household energy consumption analysis is split into the direct and indirect given complex consumption activities of households. And it finds that no matter the direct and indirect consumption activities of households, there is plenty of potentials to deploy mitigation strategies at households' direct and indirect consumption activities and it could bring substantial economic benefits and health co-benefits for both rural and urban populations. Since the indirect energy consumption of households in China was more than that of the direct according to the finding of this thesis, it is vital to put more efforts to conduct mitigation measures of household indirect energy consumption activities relative to households' daily consumption activities, like traveling, clothing, food, etc. Through a combination study of income elasticity of demand and energy intensity of rural and urban households' eight broad consumption activities, it also finds that embodied energy consumption of housing and transport activities are about to rise at the largest magnitude under the urbanization of China in the short and medium term. And the case study of travel pattern changes of households in Beijing, first shows that more using public transport combining with electric vehicles happening at the residents' side would generate the largest benefits in economics and health and public transport outperforms electric vehicles application. Health burden/co-benefits across sex and age-specific populations compared to other $PM_{2.5}$-related health burden studies are also studied (Maji et al., 2018, Liu et al., 2021b, Li et al., 2018a, Li et al., 2021, Song et al., 2017), it finds that the male and elderly group benefit the largest compared to other segments of populations. These findings push the climate change study into the social science area, which helps to broaden the research perspective to the effect of climate mitigation strategies on different segments of populations in the society so that it could provide more evidence to discuss about EJ issues. And climate justice or EJ has also been discussed in this thesis, that is it finds that increase in green transport can improve transport sustainability as well as increasing EJ for those who have sparse travel options (IEI, 2017); clean energy transition especially in rural areas of China would largely lower the local air pollutions and save more lives relative to clean energy transition in urban areas in China so that more clean energy transition efforts in rural areas could increase the EJ as well. And the application of regional VSL shows that disparity of VSLs among provinces is majorly attributable to the disparity of provincial economic development and the inequity of household income and it may lead to overlooking a province's loss with lower economic loss but with larger premature deaths. On the other hand, regional VSLs to quantify economic benefits of climate mitigation measures provide a quantitative value close to market price. But an enhance VSL method or another method to quantify economic value of premature deaths is needed.

Although this thesis further confirms that climate mitigation measures at demand side of households could create a large quantity of benefits (Creutzig et al., 2021), it also extends the study about mitigation strategies at different forms of energy usage (direct and indirect) and finds that for direct energy usage of households, replacing solid fuels (coal and biomass) with cleaner fuels like electricity could saliently reduce $PM_{2.5}$ pollution and avoid premature deaths while for mitigation in indirect households' consumption activities, mitigation strategies ought to be more point to point to different consumption activities. And rural-urban differences, for example in income elasticity of demand of different consumption activities, have the effect on preference on consuming different goods with the change of their income so that it is hard to project what consumption activity should be spotted to conduct mitigation measures. As per this research, via studying the income elasticity of demand of different consumption activities, it projects that housing and transport activities are the two should be implemented mitigation measures, not only at the supply side but also at the demand side. In this thesis, I uphold the idea that even if applying mitigation measures at the demand side, it is not supposed to degrade the life quality of humans. Because of this, the "nudge theory" from behavioral economics is innovatively introduced to be more efficiently and covertly guide the household consumption activities, For example, it was found that a greater number of consumers chose the renewable energy option for electricity when it was offered as the default option (Pichert and Katsikopoulos, 2008).

Lastly, all the health burden/co-benefits results are provided at a resolution at a spatial resolution of 0.1°× 0.1°, which performs a higher resolution than exited research.

6.2.2 Research limitations

There are four prime limitations in this thesis:

(1) Estimates in this thesis do not account for household energy consumption's effect on indoor air. Indeed research by Yun et al. (2020) found that the residential sector contributed to 71% of the indoor $PM_{2.5}$ concentrations and 67% of $PM_{2.5}$-induced premature deaths in 2014. As such the analysis of health burden caused by Chinese household direct energy consumption is (i) a lower bound estimate of total premature deaths and (ii) likely underestimates the impact on women as they may well have higher exposure to indoor air pollution due to their longer duration indoors in residential settings, as suggested by Hashim and Boffetta (2014).

(2) The health impact assessments conduct health co-benefits from $PM_{2.5}$ exposure but using $PM_{2.5}$ alone may underestimate the benefits of mitigation measures given that other sources of air pollution can also enact an adverse impact on health.

(3) Due to the data availability and limitation of the input-output model, products consumed in the same activity category consumed by rural and urban households are not distinguished, for example, rural and urban households may tend to consume different quality of food products, which maybe embrace different energy intensities.

(4) For the transport scenario modelling, technology improvement and innovation in the future are not be taken account of because it is hard to quantify them given the complicated transport system, and technology and innovation may completely change passengers' transport patten.

6.2.3 Future research prospect

For the future research prospect, the future work can lead to:

(1) Study the health co-benefits of clean energy transition of household in China resulting from reduction of air pollution indoor and outdoor. The indoor pollution can be monitored with the help of sensor technologies to efficiently get this source data.

(2) Do the scenario analysis to model the household embodied energy consumption change under the urbanization of China.

(3) Study driving factors of Chinese households' induced-energy/carbon emission change so as to give better suggestions of demand-side mitigation measures.

(4) Consider the health benefits with increased physical activity in the transport scenario modelling.

(5) Expand the health burden/ co-benefits attributable from $PM_{2.5}$ pollution into other sources of air pollutants. And also expand the health burden/co-benefits from mortality to morbidity.

(6) Expand the perspective of health burden/co-benefits for different sex and age segments of populations into more social dimensions, like for different income groups.

6.3 Policy implications

In general, implementing mitigation measures at the demand side would generate enormous benefits for the whole society. First, for the household direct energy consumption, it is suggested to promote clean energy transition, such as subsiding modern stoves, particularly in rural areas of China. Second, for household indirect energy consumption, a combination of mitigation measures at the supply side and demand-side is suggested, especially for housing and transport activities of households. Because it finds that the first quintile region of China has the highest average income and embodied energy consumption, it should take up the responsibility of reducing its own consumption level and improve its own industrial energy efficiency, especially in transport, storage and transport equipment and service sector; therefore, mitigation policies in the first quintile region of China should be stringent. In this thesis, it does not encourage policymakers to adopt the incentive strategies to intentionally change consumers' consuming habits as other research's policy implications but suggests to nudge consumers' habits unintentionally, like (i) optimize the defaulting options; (ii) provide visible information; (iii) provide convenience of using facilities. (iv) game design aligning with law of humans' psychology activities in order to achieve the mitigation goal more efficiently and successfully. A case study in Beijing residents' travel pattern change give us the inspiration about that the most beneficial mitigation measures lie in the "sharing" like the public transport. The sharing economy has been exploded in popularity in recent years globally, showing that our human society can transit into a resources-sharing one with saving more resources as well as reducing environmental impacts Moreover, this trend can contribute to mitigation of demand-side since sharing economy consuming largely relies on consumers' acceptance, but policymakers can support/fund more innovations of sharing economy, expanding into more facets of consumption activities and help to build better "sharing" public infrastructure. Meanwhile, taking account of different social groups' interests and disadvantages into the policy making is necessary to increase the environmental justice.

Most of China's current mitigation policies target reducing emissions on the production side by changing the energy mix and optimizing the sectoral structure(Wu et al., 2016a). Since China has pledged to achieve carbon neutrality before 2060 in 2020(Watkins, 2020), China has been putting efforts in developing low carbon, zero carbon and negative carbon technologies, like decarbonizing in the manufacturing process, phasing out fossil fuel power plants with more renewable fuel power plants such as photovoltaics, wind power plants, and promoting the carbon capture, utilization and storage (CCUS) technology, etc , but policies at the demand-side is less than supply side. Given the household sector took account of around 30-40% of the total energy consumption and nearly the same percentage of the total carbon emissions of China and with increasing living standards and wealth across the Chinese population, residential energy consumption is forecast to continually grow in the short and medium term (Fan et al., 2013).Therefore, it is inevitable for the policymakers to take actions to tackle residential sector’s pronounced carbon/energy footprint and this thesis shows that there is still a plenty of strategies can be taken to mitigate the residential sector so that China’s government can make corresponding measures suggested above to reduce carbon/energy footprint of household consumption activities.

Appendices

1.1 Self-sufficient rate of eight household consumption activities within five income regions

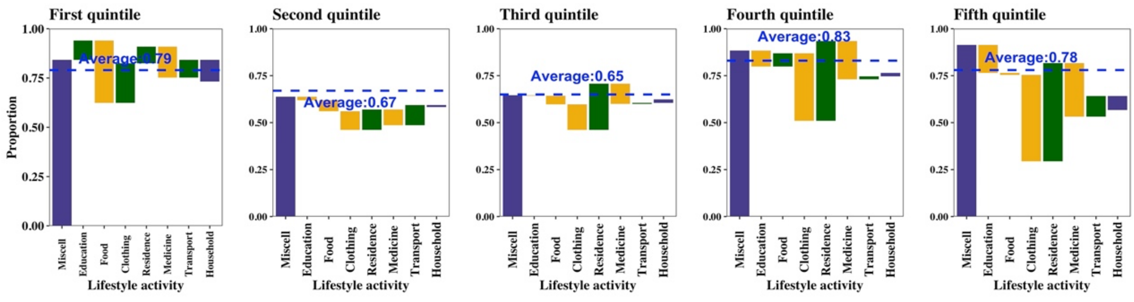


Figure A.1 Self-sufficient rate of eight household consumption activities within five income regions

1.2 Beijing Government's measures to tackle problems in transport

Beijing government has implemented several policies, measures and regulations to reduce energy consumption, carbon emissions, air pollution and traffic jams in transport sector. It can be categorized into six: (1) public transport. Beijing government has provided more public transport infrastructure, including more subway line and bus lanes and subsiding the public transport and it aims to take pressure off roads and increase the share of public transport as well as increasing the total green travel (BTRC, 2012-2020). Due to developing public transport, it not only eased the traffic jam but decreased the energy use and GHG (greenhouse gas) emission. The CO_2 emission in transport sector in Beijing has dropped from 15.2% in 2007 to 0.38% in 2010; (2) traffic control measures. Beijing's government has also taken restrictive measures to limit the number of cars on the road, like Beijing's even-odd rule, which stipulates that only cars with even- or odd-numbered license plates can be on the road on any given day (it alternates) and a lottery system to limit new car registrations and using quota for new car registration; (3) fuel quality and emission control on vehicles. Beijing regulated the NO_X emissions from heavy diesel vehicles, implemented stricter standard for gasoline and diesel of vehicles (like DB11/238-2016 and DB11/239-2016) and eliminated old motor vehicles and diesel freight with high emissions; (4) alternative fuel and advanced vehicles. Beijing has put a lot of efforts to promote electric vehicles usage. In 2020, population of electric vehicles has increased to 0.4 million, increased by around 14 times than 2015 (BTRC, 2012-2020). And more charging stations for electric cars was built. More renewable buses have been replaced the old public buses every year; (5) technology application. Beijing has used big data, cloud computing, Internet + and other new technologies to analyze transport structure of Beijing and surrounding areas to give plans for managing transport of Beijing in order to make it more intelligent, efficient and scientific (BTRC, 2012-2020). What's more, it also promoted energy-saving technologies for vehicles and made regulations for better use these technologies, for example, technical specifications for energy saving in rail transit (1T/1486-2017) was published in 2017 (BTRC, 2012-2020); (6) economic incentives. For example, subsiding for a user who buys electric cars. Many have proven to be successful but the total growth of vehicles in Beijing annually is challenging policymakers and still put a lot of burden on traffic, carbon emissions and air pollution.

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